Financial Decisions of Households under Uncertainty

Inaugural-Dissertation

zur Erlangung des Grades eines Doktors
der Wirtschafts- und Gesellschaftswissenschaften

durch

die Rechts- und Staatswissenschaftliche Fakultät der
Rheinischen Friedrich-Wilhelms-Universität Bonn

vorgelegt von

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Bonn

2021

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Tag der mündlichen Prüfung:	22. Januar 2021

Acknowledgements

I would like to thank my advisors Hans-Martin von Gaudecker and Armin Falk for their guidance and support throughout the last years. I benefited a lot from being exposed to their different approaches to science. I would also like to thank Thomas Dohmen for insightful discussions and for being part of my dissertation committee.

The time as a PhD student was not always easy. A big thank you goes to my friends and colleagues at BGSE, in particular Jana Hofmeier, Lukas Kießling, Thomas Neuber, and Axel Wogrolly. You made this time very enjoyable overall.

I benefited tremendously from the great environment at the Bonn Graduate School of Economics, the support from the Institute for Applied Microeconomics, the Institute of Labor Economics, and the Collaborative Research Center Transregio 224. Besides, I want to thank Britta Altenburg, Simone Jost, Silke Kinzig, Vanessa Pollari, and Andrea Reykers, who helped me on various administrative matters over the years.

Finally, I want to thank my family – Klaus, Elli, Caroline – for their lifelong support! Thank you, Giulia, for enduring me over all those years and sharing your life with me!

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Introduction

Understanding decision making of households has always been a key challenge of economic research. Some of the most relevant household choices are financial decisions regarding savings since these insure household consumption against income shocks and are an important component of retirement income in many countries. Depending on the investment decision (e.g., savings account, housing, or stocks) the household faces a substantial financial risk. A very cautious investment strategy, however, can lead to large forgone gains – especially in the long-run (Barth, Papageorge, and Thom, 2019). The key characteristic of these decision situations is that the returns of some financial investments are uncertain. How households make decisions under this kind of uncertainty, is the motivating question of this thesis.

Based on standard economic theory, the risk households take when choosing how to invest their savings, is most importantly determined by the level of risk aversion and wealth. It has been shown, however, that those determinants can neither explain the low levels of stock holding nor the large individual heterogeneity that is observed (Barberis, Huang, and Thaler, 2006; Guiso and Sodini, 2013). This thesis studies three alternative components that might play a role for households' financial decision making: subjective beliefs about the development of the stock market (Chapter 1), loss aversion measured by lottery choices (Chapter 2), and attitudes towards ambiguity (Chapter 3).

Besides the focus on financial decision making under uncertainty, the chapters share two common features: While many empirical studies on decisions under risk and uncertainty are conducted in the laboratory using student samples, I make use of representative samples. To understand the preferences and behaviour across the full population, representative subject pools are naturally better suited. In the domain of financial decision making, which is of less relevance for most students, this is crucial. Furthermore, data from household surveys can be often combined with a rich set of asset and background variables, which allows me to examine the relations between preference parameters and other variables, and help to control for alternative explanations. These advantages, however, come with a cost: it is challenging to make the survey design comprehensible for such heterogeneous subject pools.

An important challenge of studies using self-reported data is the presence of measurement error, which I explicitly consider in all three chapters. In the first chapter, I examine measurement error in self-reported asset data by comparing them to high-quality administrative data. Conversely, in Chapters 2 and 3, we consider measurement error during the elicitation of preference parameters. We take great care to model and estimate these deviations and increase the precision of estimated parameters by making use of repeated elicitations.

Chapter 1: "Stock Market Beliefs and Portfolio Choice in a Representative Sample" combines repeated elicitations of beliefs about the evolution of stock prices and administrative data on asset holdings to study their relation in a sample drawn from the Dutch population. I find a positive and robust association between stock market expectations and portfolio risk in cross-sectional data. Furthermore, I show that changes in expectations over time are positively related to changes in portfolio risk which demonstrates that cross-sectional correlations are not solely driven by a time-invariant, unobserved third variable. The results suggest in a representative sample that subjective beliefs might be an important driver of portfolio choice. Repeating the analysis with self-reported data only reveals that survey data yield similar results for the cross-sectional analysis – despite large differences between self-reported and administrative asset data on the individual level. This indicates the usefulness of wide-spread survey data on assets and wealth for research in contexts in which no administrative asset data are available.

In **Chapter 2: "Individual Preferences over Risk and Portfolio Choice"** that is joint work with Hans-Martin von Gaudecker, Arthur van Soest, and Erik Wengström, we assess the relation between experimental data on choices over monetary gambles and portfolio choices. First, we estimate preference parameters for the experimental lottery choices and show that they are related to portfolio choice. Second, we estimate a full utility specification which explains both small-stake decisions in experiments and large-stake portfolio choices. This specification incorporates first-order risk aversion and "narrow framing". We empirically account for preference heterogeneity by a finite mixture model. In the aggregate, the model fits observed behaviour well in both domains. On the individual level, we find that our model helps to predict choices within the same domain. For a sizeable fraction of the population, however, the imposed structural relation of behaviour across domains is too tight. When taking individual lottery choices into account, the portfolio choice prediction improves for two thirds of the subjects. But overall the model prediction, judged by the implied likelihood, gets worse relative to those that only include socio-demographic variables for determining the preference type of an individual. We discuss explanations and implications of this negative result.

Chapter 3: "The Distribution of Ambiguity Attitudes" that is joint work with Hans-Martin von Gaudecker and Axel Wogrolly analyzes the stability and distribution of ambiguity attitudes. We employ four waves of data from a survey instrument with high-powered incentives. Structural estimation of random utility models yields three individual-level parameters: Ambiguity aversion, likelihood insensitivity or perceived level of ambiguity, and the variance of decision errors. We demonstrate that these parameters are very heterogeneous but fairly stable over time and across domains. These contexts span financial markets—our main application—and climate change. The interpretation of the ambiguity parameters are interdependent and the precision of their estimates depends on decision errors. To describe heterogeneity in these three dimensions, we adopt a discrete classification approach. A third of our sample comes rather close to the behaviour of expected utility maximisers. Half of the sample is characterized by a high likelihood insensitivity, with thirty percent ambiguity averse and twenty percent making ambiguity seeking choices for most events. For the remaining eighteen percent, we estimate sizeable error parameters, which implies that no robust conclusions about their ambiguity attitudes are possible. Predicting group membership with a large number of observed characteristics shows reasonable patterns.

In summary, this thesis studies various components of financial decision making of households. The results suggest that subjective beliefs and loss aversion are important determinants of investment decisions of households. Ambiguity attitudes seem to be more stable than previously thought, both across time and domains.

Future research that examines the combined effect of ambiguity attitudes, risk attitudes, and subjective beliefs on portfolio choice seems particularly promising. Similar analyses could also prove fruitful in other, non-financial domains, in which important decisions under uncertainty are made. Those include school choice, migration choices, and various labour market decisions.

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Chapter 1

Stock Market Beliefs and Portfolio Choice in a Representative Sample

1.1 Introduction

This paper combines repeated elicitations of beliefs about the evolution of the stock market and administrative data on asset holdings in a representative data set. I find that stock market expectations and portfolio risk are positively and robustly related, both in the cross-section and over time.

The decision of individuals and households how much risk to take when investing their savings entails potential long-term consequences, especially with respect to retirement savings. However, standard theory based on risk aversion and wealth level can neither explain the low levels of stock holding nor the large individual heterogeneity (Mankiw and Zeldes, 1991; Barberis, Huang, and Thaler, 2006; Campbell, 2006; Guiso and Sodini, 2013). Differences in subjective beliefs about the future performance of the stock market could play a key role to fill this knowledge gap.

Survey measures of stock market beliefs have been criticized as noisy and depending on framing (e.g., Cochrane, 2011). This study demonstrates that beliefs are meaningful enough to predict actual behavior – even in a representative sample in which a substantial amount of people show little comprehension of financial markets and numerical concepts (see e.g., van Rooij, Lusardi, and Alessie, 2011, for results in a similar sample).

Recent research shows the relevance of subjective beliefs for financial choices in various areas such as borrowing decisions (Malmendier and Nagel, 2016), saving decisions (Heimer, Myrseth, and Schoenle, 2019), and corporate investment plans (Gennaioli, Ma, and Shleifer, 2016). Concerning their relationship with chosen portfolio risk, two strands of the literature can be identified: Merkle and Weber (2014), Ameriks, Kézdi, Lee, and Shapiro (2019), and Giglio, Maggiori, Stroebel, and Utkus (2019) utilize administrative asset data, but their analyses are confined to samples of wealthy stock-holders. These samples are well-suited to answer a range of questions, for instance with respect to asset pricing. However, for several important economic questions such as the distributional effects of pension reforms or foregone equity premium by households, it is crucial to understand portfolio choice for the whole population.

A second literature (Dominitz and Manski, 2007; Hurd, Rooij, and Winter, 2011; Kézdi and Willis, 2011; Drerup, Enke, and von Gaudecker, 2017) focuses on representative samples and shows that stock market expectations are related to portfolio risk in the cross-section using self-reported asset data. I also examine a representative sample and make two key contributions by using, first, high-quality administrative asset data and, second, repeated elicitations of beliefs which allows me to analyze belief changes and portfolio changes over time.

The administrative data used in this study are provided by Statistics Netherlands (CBS) and includes detailed records for the universe of Dutch households. I link this data to a Dutch household panel (LISS) that is representative of the Dutch adult population. The LISS contains measures of stock market beliefs, self-reported asset data, and additional control variables such as risk aversion, and financial numeracy. By combining individual characteristics elicited in a survey and high-quality administrative data about wealth, asset allocation, and household composition, I utilize the individual advantages of both types of data.

The importance of using administrative asset data is motivated by the literature on survey response error, as well as by empirical evidence for my sample showing substantial deviations between survey and administrative asset data (see below). Duncan and Hill (1985), Bound and Krueger (1991), and Bound, Brown, Duncan, and Rodgers (1994) were one of the first to compare self-reported and administrative records as a mean to gauge the amount of measurement error of self-reported data. They focus on income and find substantial differences. Concerns about the reliability of survey data have been recently renewed (Gottschalk and Huynh, 2010; Meyer, Mok, and Sullivan, 2015; Bollinger, Hirsch, Hokayem, and Ziliak, 2019; Meyer and Mittag, 2019). While much less is known about the reliability of self-reported asset data, some evidence (Hill, 2006; Johansson and Klevmarken, 2007; Akers and Chingos, 2014) indicates that there are also large deviations between self-reported and administrative data in this context. These potential deviations lead Campbell, Jackson, Madrian, and Tufano (2011) to stress the need for high-quality administrative asset data for understanding households' financial decision making. This study is a step in this direction.

Focusing on my sample, I analyze differences between self-reported and administrative data and find both substantial non-response in the survey data and individual differences between survey and administrative data that I interpret as response error. Wealth information is missing for 41 % of the households, and non-response is strongly related to having low wealth, among other characteristics. For response error, debts are strongly underreported on average, which leads to wealth being overreported. Response error in wealth is mean-reverting in the sense that poor households tend to deviate more upwards than wealthier households and systematically related to other household characteristics. For the share of risky financial assets, the main dependent variable of the later analysis, I find no relation between response error and characteristics of the household. However, risky financial assets are underreported on the extensive margin: about 10 % of the subjects report not having any risky assets despite possessing any according to the administrative data while only 2 % of the subjects deviate in the other direction.

Next, I turn to the relation between stock market beliefs and portfolio risk. Beliefs over the distribution of stock market returns are elicited using an incentivized survey tool that has been designed specifically for the use in internet panels. I extract the expected value and standard deviation of beliefs by fitting a log-normal distribution on the individual level. As main measure of portfolio risk, I make use of the share of risky financial assets of total financial assets. To look at the extensive margin, I also consider a dummy variable indicating whether the household possesses any risky assets and, to look at the intensive margin, I make use of the risky asset share in the subset of households that hold any risky assets.

In the cross-section, the expected value is positively related to portfolio risk which is robust to adding a rich set of control variables. Increasing the expected value by one standard deviation is associated with a 3.5 percentage points higher predicted probability to hold any risky assets and an increase in the predicted risky asset share of 1.5 percentage points. This corresponds to half of the effect size of risk aversion. I do not find a statistically significant effect of the standard deviation of the belief distribution, which aligns well with findings by Kézdi and Willis (2011) and Giglio et al. (2019).

The relation found in cross-sectional data is a good indicator that stock market beliefs might be an important component of portfolio choice. However, the findings could be potentially biased by a third variable (e.g., personality or family background) which drives both beliefs and portfolio choice and is either unobserved or measured with substantial noise. To address this issue, I leverage a specific feature of my belief data: Subjects have the option to update their beliefs half a year after the first elicitation. This allows me to compare changes in beliefs to changes in portfolios and thereby to control for time-invariant, unobserved other variables. An effect of belief changes on portfolio changes have been previously shown for experimental investment tasks (Drerup and Wibral, 2020) and wealthy stock-holder samples (Merkle and Weber, 2014; Giglio et al., 2019).

I find that changes in expected stock market development are predictive of changes in portfolio risk. While there is no relation on the extensive margin of portfolio risk, an increase in the expected value by one standard deviation predicts an increase in the risky asset share of 0.9 percentage points. The findings demonstrate that the cross-sectional correlation between stock market expectations and portfolio risk is not solely driven by a time-invariant, unobserved third variable. Although no strict causal interpretation is justified, this demonstrates that beliefs are an important component of portfolio choice. I do not find an effect for the extensive margin of risky asset holding, which is consistent with Giglio et al. (2019). They show that belief changes have little to no explanatory power for the extensive margin of trading, but they explain both the direction and magnitude of trading conditional on a trade occurring. The relation of the standard deviation of beliefs is again more noisy and, if anything, positive. This surprising finding vanishes when subjects that updated their belief the most are excluded.

While I cannot conduct the dynamic analysis with self-reported asset data, which is only elicited bi-yearly, I repeat the cross-sectional regressions using survey data alone. Finding out if self-reported asset data are well-suited to understand the determinants of portfolio choice in the general population, is a relevant question for future research. If yes, it justifies relying on survey data for similar types of questions, especially in the many contexts and countries in which administrative tax data on wealth are unavailable. Conversely, if the relations implied by self-reported data turn out to be biased, much more caution seems advisable. Despite a smaller sample and the aforementioned measurement error, I find patterns consistent with my previous findings. This indicates that wide-spread survey data on assets and wealth can replicate results based on high-quality administrative data.

Section 3.2 describes the belief elicitation and the different sources of asset data before differences between self-reported and administrative asset data are examined in Section 1.3. I then focus on the main analysis and look at stock market beliefs in the cross-section (Section 1.4) and over time (Section 1.5). Section 2.8 concludes and outlines opportunities for future research.

1.2 Data

To examine the relation of stock market beliefs on portfolio risk, I use three data sources that I discuss in turn: stock market beliefs elicited in the Longitudinal Internet Studies for the Social Sciences (LISS), asset and background data based on administrative records from Statistics Netherlands (CBS), and self-reported background data from the LISS.

1.2.1 Stock market beliefs

To answer the main research question, expectations of households for the risky assets they hold in their portfolio or consider purchasing are needed. I make use of beliefs about the development of the most important stock market index in the Netherlands, the AEX, which is likely a good proxy for beliefs about different investments in the Dutch or international stock market.

The beliefs are elicited in the LISS panel, which is an internet-based household panel administered by CentERdata (Tilburg University). Participating households are representative of the Dutch population (see below) and financially compensated for their participation. The panel allows researchers to run individual surveys tailored to specific research questions. During the first elicitation in August 2013 participants are asked about the value of a 100 EUR investment in the AEX in one year. The procedure is based on a survey tool by Delavande and Rohwedder (2008) which was explicitly designed for usage in Internet experiments. To elicit the full distribution of beliefs, subjects place 100 balls into 7 partitions in an iterative procedure.

The survey was sent to the self-reported financial deciders of 2978 households who either reported total financial assets of at least EUR 1000 or whose financial assets observation was missing in 2012. 2311 subjects filled out the complete first questionnaire. The answers are incentivized such that every tenth participant is payed-out up to 100 EUR one year later, depending on the accuracy of their prediction about the performance of the stock market. Payoffs are calculated based on the binarized scoring rule (Hossain and Okui, 2013), an incentive-compatible method for a wide range of utility functions.

When analyzing the relation of beliefs and portfolio choice, I make use of the expected value (μ_1) and the standard deviation (σ_1) of the belief distributions. The expected value is a key component of portfolio choice models and the interpretation is straightforward. The standard deviation, however, can play a role for at least two reasons: an observed high standard deviation of the belief distribution could be either an expression of actual high dispersion of the perceived return distribution and therefore a measure of perceived risk. On the other hand, it can express uncertainty over the distribution of expectations (Ben-David, Fermand, Kuhnen, and Li, 2018). For both interpretations, a negative relation to portfolio risk is expected if subjects are on average risk averse and ambiguity averse, respectively.

I calculate the parameters by fitting a log-normal distribution for each individual to the cumulative distribution function of the observed belief distribution. As the outer bins are open intervals, estimates of μ_1 and σ_1 for subjects with a high share of balls in these bins are potentially unreliable. In my main specification, I exclude all subjects with more than 80 % of the probability mass in the two outer bins (1.5% of the sample).

Summary statistics for the resulting parameters are presented in Table 1.2.1, and Figure 1.2.1 shows the joint distribution together with histograms for each parameter. Subjects expect on average that the AEX increases by 2.5%. While the distribution of μ_1 is roughly normally distributed, the distribution of σ_1 has a substantial mass at values close to zero and a large right tail.

More details about the distribution of beliefs, the estimation of the log-normal distribution, and correlations between beliefs and demographic variables are given in Appendix 1.D. Most notably, subjects slightly underestimate the expected value

Table 1.2.1. Summary statistics of belief parameters

	Observations	Mean	Std. dev.	$q_{0.1}$	$q_{0.5}$	$q_{0.9}$
μ_1	1720	2.51	4.9	-2.21	1.84	8.19
σ_1	1720	6.24	3.27	2.23	5.96	9.82

Notes: The expected value (μ_1) and standard deviation (σ_1) are based on the first elicitation of beliefs and calculated by fitting a log-normal distribution.

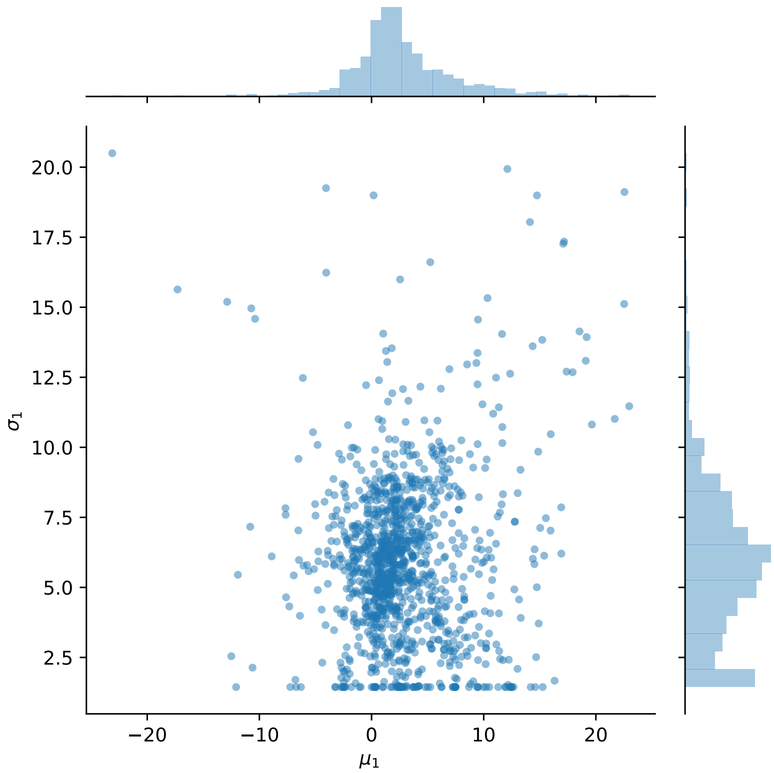

Figure 1.2.1. Joint distribution of belief parameters

Notes: On the top and the right of the scatter plot are the histograms of the respective marginal distributions. Sample: Participants with at most 80 balls in the two outer bins.

and strongly underestimate the standard deviation of beliefs compared to empirical frequencies. Furthermore, subjects with higher μ_1 tend to be male, went to university, have a higher numeracy, and a lower risk aversion. On the other hand, a lower σ_1 is associated with unmarried couples and high numeracy subjects. These findings align well with previous studies (e.g., Manski, 2004; Hurd, 2009). Drerup, Enke, and von Gaudecker (2017), as well as Drerup and Wibral (2020) use the same belief data and give a more detailed description of the elicitation procedure.

Apart from the results reported in the paper, I replicate the analyses using two alternative specifications in Appendix 1.C: First, I increase the sample and exclude only subjects if all 100 balls are put in the outer bins. Second, I make use of a non-parametric splines estimation based on Bellemare, Bissonnette, and Kröger (2012) to obtain the expected value and standard deviation of the distribution.

After half a year, in March 2014, another questionnaire is addressed to the participants in which they can update their belief about the performance between August 2013 and 2014. They receive information about the performance during the first half of the period together with the belief they entered in August 2013 and can adjust their belief accordingly. The opportunity to change the beliefs is incentivized and unexpected by the subjects. Figure 1.2.2 depicts the timing of the two belief elicitations.

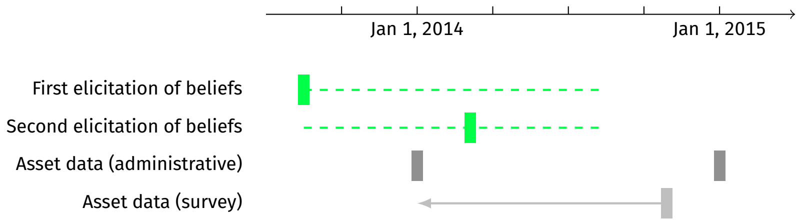

Figure 1.2.2. Timeline of data collection

Notes: The beliefs are elicited twice: in August 2013 and March 2014. Both questionnaires asked for the development of the AEX over the same time frame: August 2013 until August 2014. Administrative asset data is collected at the beginning of 2014 and 2015. Survey asset data is collected in autumn 2014 for the beginning of 2014.

I calculate the belief parameters of the second elicitation μ_2 and σ_2 in the same way. Summary statistics of the updating of beliefs are presented in Section 1.5.

1.2.2 Asset and background data

1.2.2.1 Administrative data

The second component needed for the analysis is asset data, in particular about portfolio risk, which in my main analysis is based on administrative records provided by Statistics Netherlands (CBS). The data cover a wide range of characteristics for the whole Dutch population and include among others gender, age, and income on the individual level, as well as the household composition. In contrast to administrative data in most other countries, the CBS data also contain detailed financial information about wealth, total financial assets, as well as a split between save assets (bank and savings accounts) and risky assets (shares, bonds, funds, etc.). The financial information is available on the household level and based on yearly tax records associated with the balances on January 1st of the respective year.

CBS provides an income equivalence scale that is based on the number of adults and children in the household. The factors are calibrated based on a budget survey (e.g., the factor for a couple without children is 1.37). I use this equivalence scale to standardize all asset and income variables. I make use of gross income as no measure of net income exists that is directly comparable between survey and administrative data. Finally, two measures of portfolio risk are calculated: A dummy variable indicating whether the household possesses any risky assets and the share of risky financial assets of total financial assets.

While the administrative data also contain information about the achieved level of education, this variable is missing for 58 % of the sample, especially for older persons that finished education before the collection of comprehensive administrative data started. Therefore, I do not use administrative educational information, but make use of the self-reported measures in the LISS panel (see below). For the subjects with available administrative educational information from both sources, the data sources agree in 78 % of the cases, where some diverging answers seem to be driven by a different aggregation of sub-categories. All analyses are based on background variables referring to the year 2013 and asset variables referring to the end of 2013. When focusing on the updating of beliefs in Section 1.5, I also use information from one year later.

The LISS data can be linked to the CBS data for 1890 of 2311 households that participate in the belief elicitation survey.[1] Table 1.2.2 summarizes how the number of observations in the final sample emerge: 1884 subjects can be linked to complete administrative income and asset data of which 28 put more than 80 % of the probability mass in the two outermost bins and are, therefore, excluded. In all regressions analyzing portfolio choice, only those 1720 households holding financial assets of at least EUR 1000 are considered. When examining the dynamics of beliefs, I can make use of 1489 observations that participated in both waves.

Table 1.2.3 shows summary statistics of the main dataset. The gender split is even. Subjects are on average 58 years old with the 10 %-percentile at 36 and the 90 %-percentile at 77 years. The share of risky financial assets is 10 % on average.

I compare my full sample (without restrictions and equivalisation of asset and income variables) with statistics of the Dutch population based on publications by Statistics Netherlands[2] and my own calculations with CBS data to see how representative my sample is. The share of 45 to 64-year-olds is 40 % which is similar to the fraction in the Dutch population, excluding individuals aged below 20. My sample contains fewer individuals aged 20 to 44 than in the population (21 % compared

1. The incomplete linkage is mostly caused by households that object to do so. While this might potentially introduce a bias in the administrative data, Sakshaug and Kreuter (2012) assess the linkage non-consent bias in a similar setting and find that it is very low compared to other sources of error like non-response or measurement error of the survey. I do not consider the non-consent bias further in this study and focus all analyses on the subset of households that can be linked to administrative records.

2. Statistical yearbook of the Netherlands 2014: https://www.cbs.nl/-/media/imported/documents/2014/27/2014-statistical-yearbook-of-the-netherlands.pdf?la=en-gb

Table 1.2.2. Observations in final sample

Complete first elicitation	2311
(Thereof) linked to admin data	1890
(Thereof) complete income data	1884
(Thereof) at most 80 % of prob mass in outer events	1856
(Thereof) financial assets $\geq$ EUR 1000	1720
(Thereof) complete second elicitation	1489

Notes: The analyses of differences between self-reported and administrative asset data relies on 1884 observations. For the cross-sectional analyses, 1720 subjects are used. When examining changes in beliefs, 1489 observations remain.

Table 1.2.3. Main dataset

	Observations	Mean	Std. dev.	$q_{0.1}$	$q_{0.5}$	$q_{0.9}$
Female	1720	0.47				
Couple	1720	0.68				
Married	1720	0.58				
Has children at home	1720	0.30				
Education: lower secondary and below	1718	0.28				
Education: upper secondary	1718	0.33				
Education: tertiary	1718	0.38				
Age	1720	58.07	15.15	36	60	77
Gross income (thousands)	1720	2.92	1.72	1.15	2.65	4.88
Financial assets (thousands)	1720	50.50	97.61	3.43	19.82	117.18
Wealth (thousands)	1720	132.99	274.08	-14.1	65.52	344.71
Has risky financial assets	1720	0.29				
Share of risky assets	1720	0.10	0.22	0	0	0.43

Notes: The education variable is taken from the LISS survey. All other variables are based on administrative records (CBS). All income and wealth variables are aggregated on the household level and equivalised.

to 42 %) and more aged 65 to 85 (33 % compared to 16 %). Tertiary education is also more common in my sample (38 % compared to 29 %). Concerning financial variables, my sample is somewhat richer (mean wealth EUR 160,000 compared to EUR 137,000) and more households hold any risky assets (28 % compared to 18 %). Subjects in my sample also have a somewhat higher income (mean gross household income EUR 5750, median EUR 4873) compared to the Dutch population (mean EUR 5237, median EUR 3982). These differences are in part expected given the focus on financial deciders in each household and the fact that some households are more likely than others to respond to a survey about stock market expectations. Nevertheless, the sample represents a good cross-section of the Dutch population, especially compared to studies using student samples or samples restricted to stockholders.

1.2.2.2 Survey data

The study also makes use of survey data to leverage additional individual variables not present in administrative data. Besides, the survey data allows me to assess the difference between self-reported and administrative asset data. Asset data in the LISS panel are elicited every other year. I employ the wave that was collected in October and November 2014. The subjects are asked about their financial and non-financial assets, as well as their debts on 31st December 2013, the same date the administrative data is based on.[3] Again, Figure 1.2.2 shows the timeline of the elicitation of asset data.

For each asset class (e.g., safe financial assets), subjects are first asked if they possess any assets of this category. In a second step, they are asked for the total balance on all accounts of this category. If they refuse or are unable to answer, they are presented a list of intervals and asked to select the bin in which the total value most likely falls. In case the subject refuse to answer again, the item is classified as missing. Otherwise, I use the midpoint of the interval as response value. The asset classes are then aggregated such that for instance, total financial assets consist of safe and risky financial assets and wealth consists of financial assets plus non-financial assets minus debts. Every household member aged 16 years or older is asked for their personal assets. Additionally, the self-reported financial decider of the household is asked to enter the joint assets of the household. The household definition in the LISS is comparable to the administrative data. In a few households, however, not all members participate in the survey. For each household, I aggregate the individual LISS asset data based on the CBS household composition data and use the CBS equivalence scale to standardize all financial variables. This is done to ensure that observed differences in asset data are driven by the individual responses of the household members and the effect of differences in observed household composition is minimized. A household-level financial variable is missing if either no household member filled out the questionnaire or if one of the household members entered an invalid response.

All mentioned asset variables contained in the administrative records are also available in the survey data, including the split between safe and risky financial assets. I, hence, construct a second set of data that is solely based on survey information which can be used to compare administrative and self-reported measures. Summary statistics are reported in Table 1.A.1 in the Appendix.

3. Note that one wealth component, owner-occupied housing wealth and the respective mortgages, is elicitated in a separate questionnaire administered also in October and November 2014.

The survey also allows me to use additional information not present in the administrative data. I make use of the following two:

Risk Aversion. A natural driver of portfolio risk is the aversion towards risk. The study employs the average of three standardized risk aversion measures that are based on Falk, Becker, Dohmen, Huffman, and Sunde (2016): a quantitative lottery choice task and two qualitative risk questions for general decisions under risk and financial decisions, respectively. The resulting risk aversion index is standard normalized.

Financial Numeracy. The ability to reason quantitatively is potentially important for investment decisions, the elicitation of stock market expectations, and the updating of those after new information. A set of questions by van Rooij, Lusardi, and Alessie (2011) is used to elicit numeracy for basic financial calculations. The numeracy measure is standard normalized.

1.3 Difference between self-reported and administrative asset data

Self-reported data can deviate from the true value caused for instance by cognitive or motivational limitations of the respondent or social desirability considerations (Bound, Brown, and Mathiowetz, 2001). This section discusses the observed differences between self-reported and administrative asset data. I first focus on item non-response analyzing the magnitude and how it is related to individual characteristics. For households for which both self-reported and administrative data is available, I then look at the difference between the two measures, which I interpret as response error.

Deviations in self-reported asset data may bias estimates of the drivers of portfolio risk in at least two ways. First, measurement error of portfolio risk can lead to a bias if it is non-standard, i.e., either correlated with the true value or correlated with other variables of interest. Second, a high share of missing observations can be problematic if the non-response is not randomly distributed. In that case, the estimated relation could be different from the population of interest whenever wealth is added as an important control variable.

The analysis in this section is based on the sample of subjects that participated in the belief elicitation and can be linked to administrative records. In contrast to the later analysis, households with financial assets below EUR 1000 are not excluded.

Income data are frequently log-transformed to, among others, reduce the effect of outliers. This proves difficult for asset variables as the logarithm is only defined for strictly positive values and wealth is negative for a substantial share of the population. To circumvent this problem, I make use of the inverse hyperbolic sine transformation $\left(\text{ihs}(x) = \ln\left(x + \sqrt{x^2+1}\right)\right)$ (see e.g. Pence, 2006; Bellemare and Wichman, 2020). The ihs-transformation is similar to the natural logarithm for positive values in the sense that it approximates $\ln(2x)$, but allows for zero values ($\text{ihs}(0) = 0$) and, in case of the wealth variable, even negative values (where it approximates $-\ln(-2x)$).

While I highlight the most interesting deviations between self-reported and administrative asset data in this section, Table 1.A.2 in the Appendix reports differences in more detail and for more variables.

1.3.1 Non-response

A well-known characteristic of survey data is non-response to particular items or a whole questionnaire. For simplicity, I do not differentiate between the two in the following. Table 1.3.1 shows the number of missing observations for several asset variables. Information about financial assets is missing for 28 % of the sample. Wealth, which includes financial assets, non-financial assets like housing, and debts is missing for even 41 % of the sample. In contrast, observations for labor income are available for almost all subjects as this variable is part of the background data set of the LISS, which is asked every month.

Concerning the later analyses, non-response leads to no bias if it is randomly distributed. In that case, only the power to detect relations between variables is decreased. In contrast, non-response that is correlated to observed or unobserved characteristics, makes the obtained results unrepresentative of the population of interest which potentially leads to biased estimates. Comparing the means (based on CBS data) between observations that are missing and non-missing in the LISS, reveals that for several variables a bias exists. For wealth, LISS respondents are substantially and significantly richer ($\text{ihs}(\text{wealth}) = 8.9$) than the missing sample ($\text{ihs}(\text{wealth}) = 6.6$), which implies that poor households are less likely to report complete wealth data. Furthermore, households with more debt or with risky financial assets are less likely to report the respective quantity. One reason for this finding could be that truthfully reporting a zero is trivial while filling out the respective questionnaire is more demanding when people have substantial wealth of a specific category.

Since wealth is an aggregate of the other asset variables, wealth is missing whenever any other asset variable is missing. I, hence, focus on missing wealth observations and examine in Table 1.3.2 which other observed characteristics of the households are related to it. The first column reveals that negative wealth is highly predictive of missing self-reported wealth. In columns 2 and 3, it is shown that older, more educated, and high numeracy households are substantially more likely to report wealth information. The hypothesis of random non-response can be rejected (p-value < 0.001 for F-test). The R^2 for the full set of covariates is 0.081 which indicates that they explain a substantial part of the observed variation. Importantly, however, missing wealth information is not related to the holding of risky assets.

Table 1.3.1. Missing observations for asset variables and income

		Present in LISS	Missing in LISS	Difference
		(1)	(2)	(3)
Wealth	Observations	1107	770	
	Mean	8.901	6.638	-2.263
		(0.226)	(0.336)	(0.405)
Total fin. assets	Observations	1383	501	
	Mean	10.262	10.190	-0.072
		(0.051)	(0.087)	(0.101)
Debts	Observations	1350	534	
	Mean	7.259	10.190	2.931
		(0.157)	(0.191)	(0.247)
Has rfa	Observations	1695	192	
	Mean	0.260	0.406	0.146
		(0.011)	(0.036)	(0.038)
Share rfa	Observations	1289	587	
	Mean	0.101	0.086	-0.015
		(0.006)	(0.009)	(0.011)
Income	Observations	1837	47	
	Mean	8.385	8.242	-0.143
		(0.027)	(0.111)	(0.114)

Notes: The first row for each variable shows the number of observations that are non-missing and missing in the LISS panel. 'rfa' stands for risky financial assets. The second row reports the mean according to CBS data in the two respective groups and the difference in the last column. Standard errors are in parentheses. Different total number of observations for the variables stem from missing observations in the CBS data. All variables except the portfolio risk variables (has rfa and share rfa) are ihs-transformed.

Bollinger et al. (2019) analyze non-response of self-reported income and find a U-pattern in non-response with higher non-reporting in both tails of the income distribution. While I can replicate this finding for wealth data in the lower tail, I do not find evidence for increased non-reporting of rich households. This does not change, when I look at more than four wealth groups (not shown).

Note that the high rate of missing values for the wealth variable is, in part, a result of my strict way of aggregating the individual survey responses in the household. In case a household member reports that they possess a certain asset class, but refuse to say how much, this variable is set to missing for the whole household. Under a relaxed policy in which the responses of the remaining household members were used instead, the missing rate would be lower, but the mean of the wealth variable would be lower, as well. This trade-off between sample size and accuracy is typical when working with self-reported data.

Table 1.3.2. Missing wealth information and individual characteristics

	Missing wealth obs.		
	(1)	(2)	(3)
Has risky financial assets	0.021	0.023	0.025
	(0.027)	(0.027)	(0.028)
Couple		0.009	0.026
		(0.042)	(0.044)
Married		0.003	-0.001
		(0.041)	(0.042)
Has children at home		0.002	0.013
		(0.030)	(0.031)
Age between 41 and 55		-0.031	-0.034
		(0.039)	(0.043)
Age between 56 and 70		-0.208***	-0.184***
		(0.040)	(0.044)
Age above 70		-0.238***	-0.241***
		(0.046)	(0.049)
Education: upper secondary		-0.051*	-0.018
		(0.030)	(0.031)
Education: tertiary		-0.127***	-0.084***
		(0.030)	(0.032)
Income between 1600 and 2500		-0.031	0.013
		(0.033)	(0.034)
Income between 2500 and 3500		-0.021	0.044
		(0.034)	(0.035)
Income above 3500		0.022	0.092**
		(0.035)	(0.038)
Wealth below 0	0.159***	0.093**	0.062
	(0.035)	(0.037)	(0.040)
Wealth between 50k and 200k	-0.023	0.009	0.015
	(0.029)	(0.029)	(0.030)
Wealth above 200k	-0.039	0.030	0.023
	(0.034)	(0.035)	(0.036)
Financial numeracy			-0.082***
			(0.013)
Risk aversion			-0.001
			(0.012)
N	1884	1882	1617
R^2	0.019	0.056	0.081

Notes: The dependent variable is a dummy that indicates if the wealth variable is missing in the survey data set. Robust standard errors in parentheses. * $- p < 0.1$, ** $- p < 0.05$, *** $- p < 0.01$

1.3.2 Response error

Next, I focus on households that are responding to the survey and focus on the difference between self-reported and administrative quantities which I interpret as response error.[4]

Under the assumption of classical measurement error, response error in the dependent variable does not introduce a bias (despite lowering the power), but error in an independent variable gives rise to attenuation bias. These well-known results do not apply if the measurement error is correlated with the true value or with other variables. In that general case, response error in the dependent variable can introduce a bias, too. That is for example the case if the measurement error of the dependent variable is mean-reverting or correlated with the independent variable of interest. See e.g. Bound, Brown, Duncan, et al. (1994) for a more extensive discussion.

Table 1.3.3 reports some statistics regarding the response error of several variables. Columns 2 and 3 reveal that there are large deviations between self-reported and administrative data. While 21 % of subjects report wealth that is more than 20 % below the administrative quantity, 47 % of respondents deviate upwards by more than 20 %. Both measures of portfolio risk tend to be rather reported too low than too high: About 10 % of the sample falsely report not having any risky assets while only 2 % deviate in the other direction.

The next columns report the mean of the administrative variable, the survey variable, and the individual response error. The respective standard errors are shown in parentheses. The mean response error is significantly different from 0 for all variables except the risky asset share. Financial assets, income, and debts are underreported, the latter leading to wealth being overreported. The underreporting of debts is also found by earlier studies (Karlan and Zinman, 2008; Brown, Haughwout, Lee, and van der Klaauw, 2011). Strikingly the share of subjects that report having any risky assets is just 0.18 while this share is 0.26 for the CBS data. A substantial share of subjects do not report the risky assets they possess. Note that for the sample with total financial assets exceeding EUR 1000 that is used for the main analysis later, the difference is much smaller (0.29 vs 0.24). The difference for the risky asset share is not significant indicating that risky assets are not underreported over the full distribution, but rather some individuals falsely claiming to not have any risky financial assets. This interpretation is confirmed by Table 1.A.2.

To understand the potential bias introduced by response error, the second to last column in Table 1.3.3 shows the correlation coefficient between the response error and the administrative quantity. The response error is strongly mean-reverting for

4. It seems intuitive that most reasons for measurement error in survey data do not apply to administrative records as most components are directly reported by banks and it would be a criminal offense for a household to hide part of their wealth.

Table 1.3.3. Response error

	N	Share rel. dev. < −20 %	Share rel. dev. > 20 %	Mean CBS	Mean LISS	Mean dev.	Corr. b/w dev. and CBS	λ
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Wealth	1107	0.205	0.47	8.901	9.522	0.621	-0.538	0.69
				(0.226)	(0.202)	(0.189)		
Total fin. assets	1383	0.395	0.262	10.262	9.388	-0.874	-0.039	0.271
				(0.051)	(0.095)	(0.082)		
Debts	1350	0.161	0.107	7.259	6.559	-0.699	-0.237	0.8
				(0.157)	(0.162)	(0.093)		
Has rfa	1695	0.104	0.021	0.260	0.177	-0.083	-0.546	0.757
				(0.011)	(0.009)	(0.008)		
Share rfa	1289	0.137	0.08	0.101	0.093	-0.008	-0.405	0.657
				(0.006)	(0.006)	(0.005)		
Income	1837	0.317	0.068	8.385	8.194	-0.192	-0.275	0.574
				(0.027)	(0.031)	(0.024)		

Notes: The first column shows the number of observations that are non-missing in the LISS data set. Columns 2 and 3 report the share of observations for which the relative deviation ($\frac{a^{LISS}-a^{CBS}}{|a^{CBS}|}$) (using untransformed values) is below −20 % and above 20 %, respectively. Division by a zero value is thereby treated as ∞ if the numerator is positve and $-\infty$ if it is negative. The next columns show the mean of the administrative variable, the mean of the survey variable and the mean of the individual response error. The respective standard errors are in parentheses. The last columns report the correlation coefficient between response error and administrative value and the reliability index λ introduced in equation 1.3.1. All variables except the portfolio risk variables (has rfa and share rfa) are ihs-transformed.

all variables except total financial assets meaning that households with a high value tend to underreport while households with a low value tend to overreport. Note that for the portfolio risk variables this effect is mechanical since a dummy variable can, on the individual level, only deviate in one direction.

In the last column of Table 1.3.3, the reliability

$$\lambda = \frac{\operatorname{cov}\left(X_j^{\text{Admin}}, X_j^{\text{Survey}}\right)}{\operatorname{Var}\left(X_j^{\text{Survey}}\right)} \tag{1.3.1}$$

is shown for each variable. Thereby, $1-\lambda$ is a measure of the attenuation bias introduced when this variable is used as independent variable (Bound and Krueger, 1991). The reliability of wealth is 0.69, slightly above the reliability of household income.

Table 1.3.4. Response error and individual characteristics

	|Dev. ihs(wealth)|	Dev. ihs(wealth)	|Dev. share rfa|	Dev. share rfa
	(1)	(2)	(3)	(4)
Has risky financial assets	0.606*	0.761**	0.150***	-0.093***
	(0.360)	(0.366)	(0.014)	(0.016)
Couple	1.950**	-0.453	0.012	-0.004
	(0.830)	(0.861)	(0.018)	(0.021)
Married	-2.168***	0.186	-0.013	0.015
	(0.812)	(0.849)	(0.018)	(0.021)
Has children at home	1.065**	-0.032	0.024*	0.017
	(0.502)	(0.521)	(0.013)	(0.014)
Age between 41 and 55	-0.419	0.954	-0.012	-0.039*
	(0.906)	(0.930)	(0.019)	(0.021)
Age between 56 and 70	-0.159	2.190**	-0.011	-0.017
	(0.851)	(0.863)	(0.017)	(0.020)
Age above 70	0.157	2.119**	0.007	-0.033
	(0.872)	(0.890)	(0.019)	(0.021)
Education: upper secondary	-0.253	0.166	0.016	0.010
	(0.375)	(0.388)	(0.012)	(0.014)
Education: tertiary	-0.406	-0.539	-0.008	0.011
	(0.370)	(0.382)	(0.012)	(0.013)
Income between 1600 and 2500	0.405	-0.346	-0.015	-0.003
	(0.452)	(0.480)	(0.013)	(0.015)
Income between 2500 and 3500	-0.201	0.133	-0.011	-0.007
	(0.446)	(0.463)	(0.015)	(0.017)
Income above 3500	-0.091	0.150	-0.001	0.028
	(0.485)	(0.507)	(0.016)	(0.018)
Wealth below 0	8.107***	11.476***	0.049***	-0.006
	(0.914)	(0.930)	(0.018)	(0.020)
Wealth between 50k and 200k	-0.689*	-0.654	0.006	0.006
	(0.387)	(0.411)	(0.010)	(0.011)
Wealth above 200k	-1.285***	-0.648	0.010	0.004
	(0.391)	(0.412)	(0.014)	(0.016)
Financial numeracy	-0.175	0.672***	-0.008	0.009
	(0.228)	(0.233)	(0.006)	(0.007)
Risk aversion	-0.019	-0.268*	-0.001	-0.005
	(0.144)	(0.149)	(0.005)	(0.005)
N	1060	1060	1208	1208
R^2	0.284	0.348	0.180	0.070

Notes: The dependent variable is the difference between the self-reported and administrative value. In columns 1 and 3, the respective absolute value is used as dependent variable. Robust standard errors in parentheses. $* - p < 0.1, ** - p < 0.05, *** - p < 0.01$

Finally, we look at how these differences are related to other characteristics of the households. Table 1.3.4 shows for wealth and the risky asset share the regression of the response error and the absolute value of it. For wealth, the error is higher (not in absolute terms) for households with risky assets, old respondents, and subjects with high numeracy. The strongest effect, however, is that households with negative wealth tend to deviate upwards on average.[5] Response error for reporting any risky assets is positive related to high-income households, as well as high numeracy and low risk-aversion subjects (not shown). Conversely, for the risky asset share, no strong predictors for response error can be found (an F-test reveals that the variables other than the dummy 'has risky financial assets' are not jointly significant; p-value=0.129). Having strictly negative wealth predicts an increase in the absolute value of risky asset share response error though which can be expected as a lower level of financial assets leads to more variation of the risky asset share over time.

In summary, for the variables that I will use in the subsequent analysis, strong deviations between survey and administrative data is found: the wealth variable is missing for a large share of respondents, most strongly for respondents with negative wealth. Furthermore, those low-wealth households that do respond overreport their wealth and response error of the wealth variable is clearly not exogenous to other variables. The measures of portfolio risk, however, are unrelated to asset variables being missing. Having any risky assets is in the full sample strongly underreported and related to other characteristics of the household. On the other hand, the share of risky assets is very similar over the data sets and the individual measurement error seems to be unrelated to other variables.

Appendix 1.B presents regressions of wealth and portfolio risk on demographic variables based on either of the two data sets. Comparing the results gives a first understanding of the relevance of the measurement error just discussed. Altogether, the revealed predictors of wealth and portfolio risk are very similar. However, some associations are missed, most strongly with respect to holding negative wealth.

1.4 Stock market beliefs in the cross-section

I now focus on the relation of stock market beliefs and portfolio choice in a static setting. To get a first impression, I split the sample into five groups based on the quintiles of the expected value of stock market belief. Figure 1.4.1 shows the mean risky asset share of each group. The mean portfolio risk increases over the groups

5. The strong effect of having strictly negative wealth is supported by the ihs-transformation since deviations towards zero lead to a higher response error than deviations of the same untransformed value away from zero. When using a different metric that values deviations in both directions equally, the relative deviation ($\frac{a^{LISS}-a^{CBS}}{|a^{CBS}|}$), the results, however, do not change (not shown).

from below 4.8 % for the most pessimistic to 14.5 % for the most optimistic group. This difference is significant and the means of the groups in between align well with this pattern.

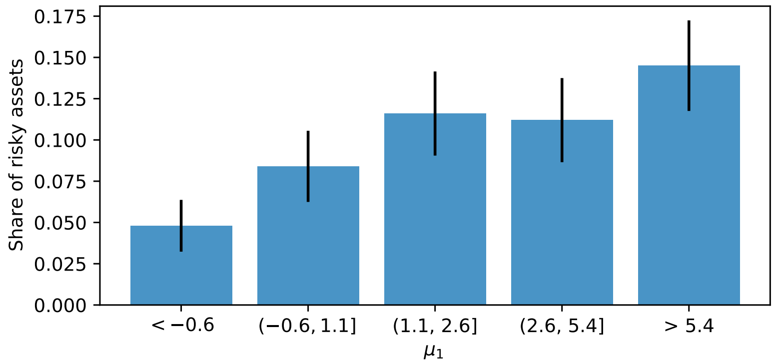

Figure 1.4.1. Risky asset share and stock market expectations

Notes: μ_1 is based on the first elicitation of beliefs and separated in five quintiles. The bars show the mean risky asset share for each bin while the thin black lines depict 95 % confidence intervals.

To look at the relation more deeply, I run the following regression:

$$a_{2013,i} \;=\; \beta_0 + \beta_1\mu_{1,i} + \beta_2\sigma_{1,i} + \beta X_{2013,i} + \epsilon_i$$

where μ_1 and σ_1 are the expected value and standard deviation of elicited stock market beliefs, X is a collection of background characteristics measured in 2013, and a_{2013} is one of the two measures of portfolio risk measured at the end of 2013: a dummy variable indicating whether the household possesses any risky assets ('has rfa') or the share of risky assets of the total financial assets ('share rfa'). While the first measure allows for analyses of the decision to hold any risky investments (extensive margin), the risky asset share is a finer proxy of actual portfolio risk. Besides, I also analyze the risky asset share for the subset of households that hold any risky assets. This analysis allows me to look at the intensive margin separately.

Regression results are shown in Table 1.4.1. The belief parameters are standardized. μ_1 is positively related to both the extensive margin of stock ownership and the share of risky assets. An expected value that is higher by one standard deviation is related to a 3.5 percentage points higher predicted probability to hold any risky assets based on column 2 and an increase in the risky asset share of 1.5 percentage points (column 4). Compared to the effect of risk aversion, the absolute effect size is between 50 % (risky asset share) and 75 % (extensive margin) of it. For the sample of stock-holders, the coefficients are similar, but insignificant due to the reduced sample size.

The relation with σ_1 is insignificant. This is also the case for interactions of σ_1 and μ_1 (not shown) which would be expected when interpreting σ_1 as uncertainty of the expectation. Based on the negative effect of risk aversion, risk considerations seem to be important for the portfolio decision. The standard deviation of beliefs, however, seems to be an insufficient proxy of perceived financial risk for my sample of representative subjects.

Table 1.4.1. Portfolio choice and stock market beliefs

	Has rfa		Share rfa			
	(1)	(2)	(3)	(4)	(5)	(6)
μ_1	0.045***	0.035***	0.021***	0.015***	0.023*	0.013
	(0.011)	(0.012)	(0.005)	(0.006)	(0.013)	(0.014)
σ_1	-0.008	0.000	-0.002	0.000	0.001	0.001
	(0.013)	(0.014)	(0.007)	(0.007)	(0.016)	(0.017)
Financial numeracy		0.018		0.001		-0.010
		(0.011)		(0.006)		(0.024)
Risk aversion		-0.044***		-0.029***		-0.053***
		(0.012)		(0.006)		(0.016)
N	1718	1482	1718	1482	500	425
R^2	0.138	0.137	0.107	0.112	0.073	0.102
Subset: has risky assets	No	No	No	No	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: For the first two columns, the dependent variable is the dummy indicating whether any risky assets are in the portfolio, while the remaining columns utilize the share of risky assets as dependent variable. In the last two columns, the sample is restricted to households with any risky assets. The belief variables (expected value μ_1 and standard deviation σ_1) are only based on the first elicitation and standardized. Demographic controls are household composition, education, age, gross income, and wealth. The full regression table is shown in Table 1.A.3. All variables except education, beliefs, numeracy, and risk aversion are based on administrative records. Robust standard errors in parentheses.
* – $p < 0.1$, ** – $p < 0.05$, *** – $p < 0.01$

To examine the robustness of this finding, I repeat the analysis for two alternative specifications in the Appendix: First, I relax the restriction that at most 80 % of the probability mass of the belief distribution is in the two extreme bins and include subjects that put more mass into those bins (Table 1.C.1). Second, I make use of an alternative, non-parametric method to estimate μ_1 and σ_1 (Table 1.C.2). The results do barely change. I, hence, conclude that in the cross-section there is a robust relationship between the expected value of stock market beliefs and portfolio choice, both in the extensive margin and the actual risky asset share. The standard deviation of stock market beliefs does not seem to play an important role.

Survey data set. Table 1.4.2 shows the same regression as Table 1.4.1, for the data set based solely on survey answers. Despite the response error and the substantially lower sample size, the relations between belief parameters and portfolio risk measures are very similar. Surprisingly, the effects for the restricted set of stock-holds are even stronger and significant for the survey data. To differentiate the effects of the changing sample and the difference in responses, Table 1.A.5 presents regressions using administrative data for the restricted sample of those subjects that are also part of the survey data set. The coefficients are in between the ones presented here, indicating that both factors play a role. Overall, the survey data set seems to be capable of uncovering the important relations.

Table 1.4.2. Portfolio choice and stock market beliefs (survey data set)

	Has rfa		Share rfa			
	(1)	(2)	(3)	(4)	(5)	(6)
μ_1	0.044***	0.038***	0.022***	0.019**	0.045**	0.042**
	(0.014)	(0.015)	(0.008)	(0.008)	(0.020)	(0.021)
σ_1	-0.005	-0.004	-0.005	-0.006	-0.025	-0.035
	(0.016)	(0.017)	(0.010)	(0.011)	(0.029)	(0.031)
Financial numeracy		0.025*		0.006		-0.012
		(0.015)		(0.008)		(0.038)
Risk aversion		-0.051***		-0.029***		-0.062***
		(0.013)		(0.007)		(0.021)
N	960	923	960	923	281	268
R^2	0.152	0.171	0.109	0.125	0.089	0.124
Subset: has risky assets	No	No	No	No	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The same regressions as in Table 1.4.1 are shown for the data set that uses survey data only. Demographic controls are household composition, education, age, gross income, and wealth. The full regression table is shown in Table 1.A.4. Robust standard errors in parentheses.
* $- p < 0.1$, ** $- p < 0.05$, *** $- p < 0.01$

1.5 Updating of stock market beliefs

1.5.1 Distribution and determinants of updating of beliefs

Half a year after the first elicitation, subjects participate in another questionnaire in which they can update their prediction of the stock market development. Information about the performance during the first half of the period together with the belief distribution they entered in August 2013 are presented and they can adjust their beliefs accordingly. The change in the reported distribution is depicted in Figure 1.5.1. Subjects become overall more optimistic, which is in line with the actual AEX performance of +5 %, above both the mean historic 6-month performance and the mean expected value at $t = 1$. However, the adjustment seems to be lower than what would be expected when rationally taking the performance into account (see below) and roughly 45 % of the subjects do not adjust their belief at all.

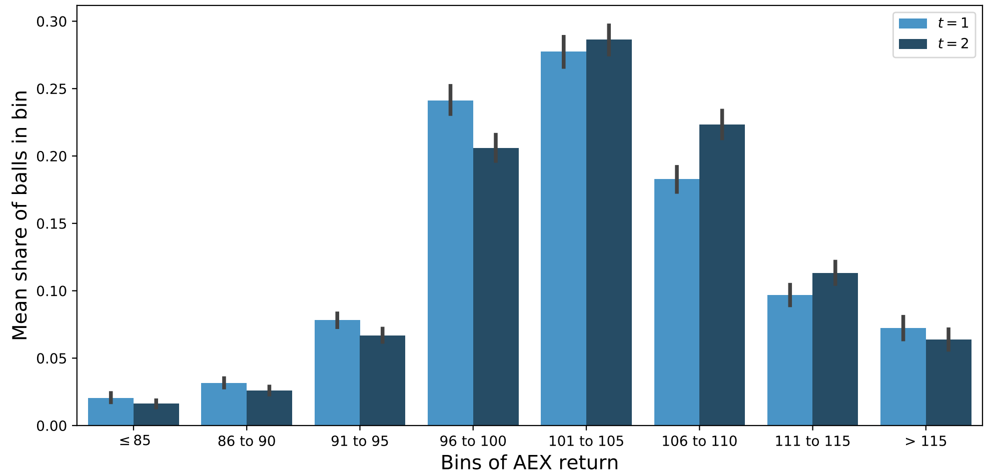

Figure 1.5.1. Mean share of balls in each bin in the first and second elicitation

Notes: The figure shows the average number of balls that are put in each bin during the first elicitation (light blue) and during the second elicitation (dark blue). The black lines depict 95 % confidence intervals for each mean.

For the beliefs of the second elicitation, μ_2 and σ_2 are calculated in the same way as the equivalent parameters from time $t = 1$. Figure 1.5.2 shows the distribution of the difference between μ_2 and μ_1. The expected value increases for 40 % of the subjects and decreases for 16 % of the subjects. A large share of adjustments changed the expected value by no more than 5 percentage points while 7 % of the subjects updated more strongly.

Next, I look at the relationship between changes in beliefs and individual characteristics. The first two columns in Table 1.5.1 reveal that not changing the beliefs is associated with younger, less educated, and low-numeracy subjects. For the subset of participants that do change their belief, high-income households tend to update their expected value more positively while less educated households and those with negative wealth tend to increase the standard deviation of beliefs.

A different interpretation of beliefs in the second period would be to take the AEX return during the first six months into account when calculating the expected value: If a subject expected +2 % during the first elicitation and did not change this response during the second elicitation, the implied expected value for the second part of the incentivized period, is roughly −3 % since the return so far was already +5 %. The data, however, strongly suggests that participants do not give responses according to that alternative interpretation. First, many people do not change their beliefs which would be expected after the positive stock market development. Sec-

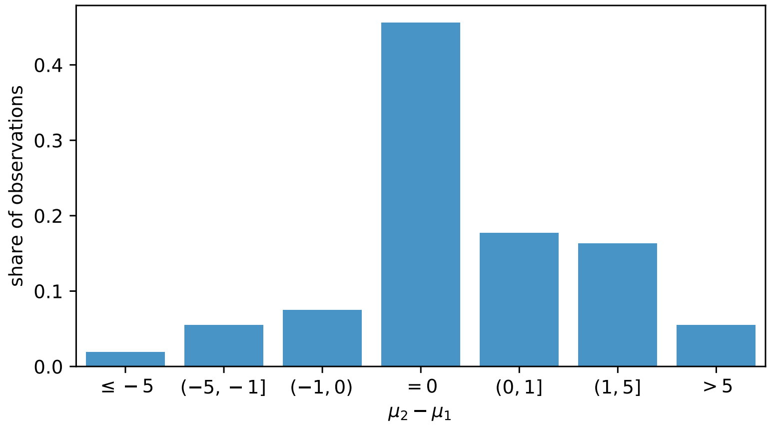

Figure 1.5.2. Distribution of changes in stock market expectations

Notes: The sample is split in seven groups based on the change in the respective expected value ($\mu_2 - \mu_1$). The respective numbers are shown in Table 1.A.6.

ond, the distribution of expected values would be strongly in the negative domain and, hence, implausibly different from beliefs in the first period. An unrealistically high level of expected mean-reverting would be necessary to explain this. I, hence, rely on the interpretation as an update of the first belief elicitation as described above.

1.5.2 Updating of beliefs and portfolio risk

In the last part of the study, I examine how changes in beliefs are related to changes in the chosen portfolio risk. Figure 1.5.3 shows the mean change in the risky asset share for five bins. The two groups with positive expectation changes do also increase their risky asset share on average (+0.4 and +0.8 percentage points). These changes are significant compared to the group that decreased their expectation the most.

Next, I run the following first difference regression:

$$a_{2014,i} - a_{2013,i} = \beta_0 + \beta_1 \left(\mu_{2,i} - \mu_{1,i}\right) + \beta_2 \left(\sigma_{2,i} - \sigma_{1,i}\right) + \beta \left(X_{2014,i} - X_{2013,i}\right) + \epsilon_i$$

The changes of belief parameters are standardized based on the respective $t = 1$ distribution. Table 1.5.2 reveals that changes in the expected value are positively related to changes in the risky asset share. A one standard deviation increase in the expected values is associated with an increase of the risky share by 0.9 percentage points (column 4). The effect size does not change if I control for income and wealth changes (column 5). However, no relation with the extensive margin is detected, which corresponds well to the findings by Giglio et al. (2019). To look at the intensive margin, the sample in the last three columns is restricted to households

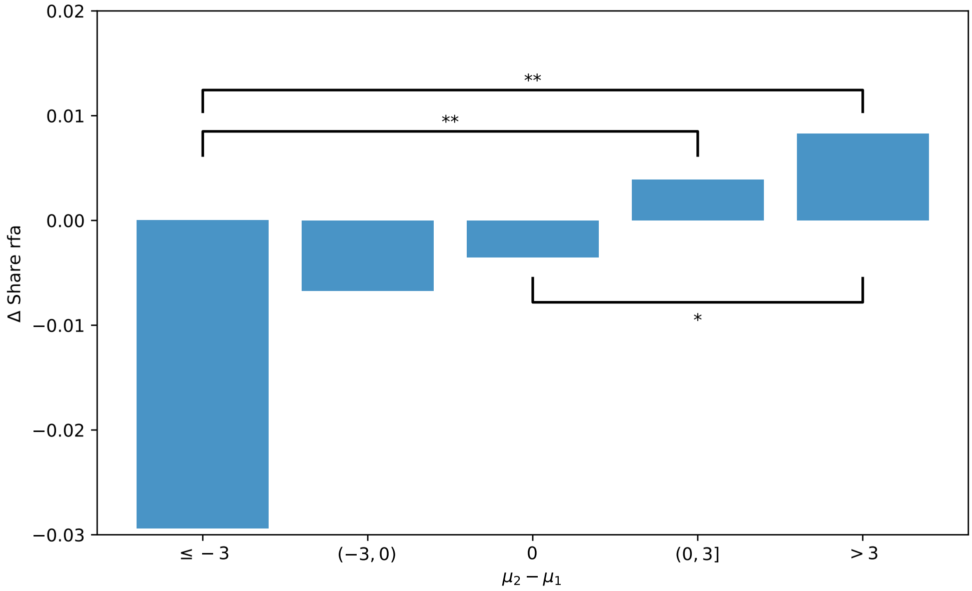

Figure 1.5.3. Changes in expectation and changes in portfolio risk

Notes: The changes in the expected value are grouped in five bins. The figure shows the mean change of the risky asset share for each bin. Brackets indicate significance levels between the group means. * – $p < 0.1$, ** – $p < 0.05$, *** – $p < 0.01$

that hold risky assets in both periods. The coefficient is slightly higher than in the full sample, although it is only significant at the 10 %-level.

Surprisingly, changes in the standard deviation of beliefs also tend to be associated with positive portfolio changes although it is only significant for the stockholder subset and at the 10 % level. The coefficient is of a similar size as for the expected value, but with larger standard errors. In columns 3, 6, and 9 the 2.5 % strongest changes in μ and σ on both ends of the distribution are dropped. For column 6 and 9, the effect of μ increases, and the coefficient of σ becomes insignificant and even negative. This suggests that the finding for the standard deviation is driven by outliers.

Finally, I again make sure in the Appendix that the results are very similar for less restrictive sample selection (Table 1.C.3) and non-parametric belief parameter estimation (Table 1.C.4). Note that a similar analysis of changes in the portfolio risk is not possible for the survey data set as the asset data is only collected every other year.

Table 1.5.1. Updating of beliefs

	$\mu_2 \neq \mu_1$		$\mu_2 - \mu_1$		$\sigma_2 - \sigma_1$	
	(1)	(2)	(3)	(4)	(5)	(6)
μ_1	-0.000	-0.012	-0.472***	-0.477***		
	(0.013)	(0.014)	(0.057)	(0.059)		
σ_1	-0.006	0.007			-0.453***	-0.460***
	(0.013)	(0.014)			(0.059)	(0.060)
Female	-0.039	-0.002	0.057	0.081	0.045	0.022
	(0.028)	(0.030)	(0.049)	(0.055)	(0.047)	(0.050)
Age between 41 and 55	0.039	0.056	-0.030	0.001	-0.098	-0.093
	(0.046)	(0.049)	(0.083)	(0.093)	(0.069)	(0.077)
Age between 56 and 70	0.086*	0.118**	-0.094	-0.050	-0.011	-0.013
	(0.049)	(0.051)	(0.084)	(0.095)	(0.069)	(0.078)
Age above 70	0.080	0.118**	-0.053	-0.000	-0.070	-0.068
	(0.054)	(0.057)	(0.107)	(0.119)	(0.088)	(0.098)
Education: upper secondary	0.061*	0.037	0.037	0.003	-0.160***	-0.172***
	(0.035)	(0.036)	(0.073)	(0.079)	(0.062)	(0.066)
Education: tertiary	0.139***	0.092**	-0.006	-0.023	-0.256***	-0.259***
	(0.036)	(0.037)	(0.067)	(0.070)	(0.057)	(0.060)
Income between 1600 and 2500	0.029	0.024	0.205**	0.212**	-0.045	-0.021
	(0.039)	(0.040)	(0.083)	(0.086)	(0.067)	(0.073)
Income between 2500 and 3500	0.041	0.015	0.239***	0.254***	-0.054	-0.029
	(0.040)	(0.042)	(0.079)	(0.083)	(0.069)	(0.076)
Income above 3500	0.057	0.035	0.224***	0.240***	0.056	0.074
	(0.042)	(0.044)	(0.080)	(0.085)	(0.069)	(0.076)
Wealth below 0	0.004	0.025	0.020	-0.039	-0.180**	-0.183**
	(0.045)	(0.046)	(0.083)	(0.087)	(0.075)	(0.081)
Wealth between 50k and 200k	0.043	0.025	-0.004	-0.000	-0.046	-0.054
	(0.033)	(0.034)	(0.061)	(0.065)	(0.052)	(0.055)
Wealth above 200k	0.081**	0.041	-0.016	-0.029	-0.018	-0.013
	(0.038)	(0.039)	(0.067)	(0.072)	(0.062)	(0.066)
Financial numeracy		0.115***		0.076*		-0.031
		(0.014)		(0.040)		(0.037)
Risk aversion		0.010		-0.015		0.017
		(0.014)		(0.026)		(0.025)
N	1488	1357	809	742	809	742
R^2	0.033	0.072	0.371	0.376	0.415	0.423
Subset: $\mu_2 \neq \mu_1$	No	No	Yes	Yes	Yes	Yes
Household composition controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: In the first two columns, the dependent variable is a dummy variable indicating whether the expected value changed at all. The next columns are restricted on those individuals that did change their beliefs. Columns 3 and 4 utilize changes in μ and the last two columns changes in σ as dependent variable. Robust standard errors in parentheses. $* - p < 0.1, ** - p < 0.05, *** - p < 0.01$

Table 1.5.2. Updating of beliefs and portfolio choice

	Δ Has rfa			Δ Share rfa					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\mu_2 - \mu_1$	0.010	0.010	0.011	0.009**	0.009**	0.016**	0.014*	0.014*	0.035
	(0.009)	(0.009)	(0.014)	(0.004)	(0.004)	(0.007)	(0.008)	(0.008)	(0.022)
$\sigma_2 - \sigma_1$	0.012	0.013	0.011	0.010	0.010	-0.005	0.032*	0.031*	-0.014
	(0.011)	(0.011)	(0.017)	(0.006)	(0.006)	(0.010)	(0.018)	(0.019)	(0.030)
Δ Income between 1600 and 2500		-0.021	-0.022		-0.012	-0.013		-0.003	-0.007
		(0.043)	(0.044)		(0.014)	(0.014)		(0.019)	(0.020)
Δ Income between 2500 and 3500		-0.015	-0.016		-0.001	-0.001		0.013	0.012
		(0.046)	(0.047)		(0.017)	(0.017)		(0.038)	(0.038)
Δ Income above 3500		0.020	0.024		0.002	0.008		0.015	0.023
		(0.047)	(0.048)		(0.020)	(0.021)		(0.050)	(0.052)
Δ Wealth below 0		-0.067**	-0.075**		-0.013	-0.014		-0.011	-0.011
		(0.033)	(0.036)		(0.015)	(0.017)		(0.061)	(0.060)
Δ Wealth between 50k and 200k		-0.002	-0.015		0.026	0.025		0.018	0.025
		(0.031)	(0.030)		(0.017)	(0.018)		(0.049)	(0.053)
Δ Wealth above 200k		0.014	0.003		0.019	0.017		0.013	0.010
		(0.038)	(0.038)		(0.028)	(0.028)		(0.074)	(0.076)
N	1489	1489	1365	1489	1489	1365	396	396	364
R^2	0.002	0.010	0.010	0.006	0.013	0.010	0.018	0.020	0.012
Subset: has risky assets	No	No	No	No	No	No	Yes	Yes	Yes
Without strongest updaters	No	No	Yes	No	No	Yes	No	No	Yes

Notes: For the first three columns, the dependent variable is the difference between the end of 2014 and 2013 in the dummy indicating whether any risky assets are in the portfolio. The next columns use the change in the risky asset share. In the last three columns, the sample is restricted on those households that hold any risky assets in both years. In columns 3, 6, and 9 the 2.5 % strongest changes in μ and σ on both ends of the distribution are dropped. The changes in the expected value $\mu_2 - \mu_1$ and the standard deviation $\sigma_2 - \sigma_1$ of beliefs are standardized based on the respective $t = 1$ distribution. All variables except education, beliefs, numeracy, and risk aversion are based on administrative records. Robust standard errors in parentheses. * – $p < 0.1$, ** – $p < 0.05$, *** – $p < 0.01$

1.6 Conclusion

This study shows that stock market expectations and portfolio risk are positively related in a representative data set and makes two contributions: First, I make use of administrative asset data complementing recent efforts to do so for samples of wealthy stock-holders (e.g., Giglio et al., 2019). This is especially relevant as precedent analysis shows substantial differences between self-reported asset data and administrative records.

Second, I document that changes in beliefs over time are related to changes in portfolio risk. This analysis demonstrates that cross-sectional correlations between stock market expectations and portfolio risk are not solely driven by an unobserved time-invariant third variable and suggests that subjective beliefs might be an important driver of portfolio choice.

The estimated effects in the cross-section are very similar when using an alternative data set based on survey data alone. This indicates the usefulness of wide-spread survey data on assets and wealth for research in contexts in which no administrative asset data is available.

While I find a robust relation between stock market expectations and portfolio choice, it cannot be ruled out that it is actually portfolio risk driving beliefs instead of the other way around. This reverse-causality could for instance originate by the mechanism that risky assets for some households performed better than for others which might increase both the risky asset share, as well as stock market expectations. Shedding more light on this question will require (quasi-)experimental variation of beliefs or portfolio risk.

Similar to several earlier studies, I find no robust relationship between the standard deviation of belief and chosen portfolio risk. Disentangling the two interpretations of the standard deviation as perceived risk or perceived uncertainty about expectations would be very fruitful. Direct measures of perceived risk and/or perceived ambiguity could prove helpful in this matter. For a full understanding of different components of beliefs and related measures, the estimation of a more complex decision model containing the expected value, standard deviation, risk aversion, and potentially ambiguity parameters would be necessary. The linear model used in this study highlights the relevance of the expectations, but falls short to uncover the full picture of relations between belief and preference parameters.

While I consider measurement error in self-reported asset data, I do not account for error in the belief elicitation. Although great care is taken to keep the elicitation procedure comprehensible for the heterogeneous subject pool and the choices are incentivized, it is indisputable that some measurement error is present which makes the coefficients found in the analysis a lower bound. More than two elicitations of beliefs would help to differentiate true beliefs from measurement noise and obtain more precise estimates.

Despite not being the main focus of this study, interesting facts about the differences between self-reported and administrative asset data have been discovered: Most importantly, debts are strongly under-reported – both in terms of non-response and response error. This implies that studies focusing on borrowing and debts need to be more cautious about relying on survey data. It would be fruitful for future research to look deeper at the extend and the determinants of response error for asset variables.

Finally, this study ignores potential error in administrative data (see e.g. Kapteyn and Ypma, 2007). While most causes of response error in survey data seem to not apply to administrative data, the size and effect of the linkage error could be examined further. The fact that the regressions of interest lead to very similar results for both data sets is in this sense reassuring for both types of data.

Appendix 1.A Some additional tables

Table 1.A.1. Survey dataset

	Observations	Mean	Std. dev.	$q_{0.1}$	$q_{0.5}$	$q_{0.9}$
Female	1183	0.41				
Couple	1183	0.69				
Married	1183	0.60				
Has children at home	1183	0.29				
Education: lower secondary and below	1138	0.26				
Education: upper secondary	1138	0.31				
Education: tertiary	1138	0.43				
Age	1183	59.13	14.96	37	61	77
Gross income (thousands)	1167	2.63	1.57	1.13	2.38	4.26
Financial assets (thousands)	1183	53.89	260.02	2.58	18.25	109.71
Wealth	973	168.94	399.81	2.39	92.21	399.33
Has risky financial assets	1183	0.24				
Share risky assets	1183	0.10	0.22	0	0	0.42

Notes: All variables are based on the LISS survey.

Table 1.A.2. CBS data, LISS data, difference between the data sets

		N	Mean	Std. dev.	$q_{0.1}$	$q_{0.5}$	$q_{0.9}$	share equals to 0
		(1)	(2)	(3)	(4)	(5)	(6)	(7)
	CBS	1884	2.648	4.499	0	0	10.546	0.725
	CBS (LISS sample)	1692	2.509	4.405	0	0	10.394	0.741
Risky fin. assets	CBS (missing)	192	3.873	1.163				
	LISS	1692	1.799	3.957	0	0	9.965	0.824
	LISS - CBS	1692	-0.710	3.236	-3.801	0	0	0.732
	CBS	1884	10.066	1.878	7.877	10.337	12.001	0.006
	CBS (LISS sample)	1386	10.080	1.870	7.918	10.341	11.997	0.006
Save fin. assets	CBS (missing)	498	10.027	1.902				
	LISS	1386	9.206	3.583	6.305	10.151	11.939	0.058
	LISS - CBS	1386	-0.874	3.091	-3.061	-0.087	0.927	0.009
	CBS	1884	10.243	1.918	8.051	10.479	12.294	0.006
	CBS (LISS sample)	1383	10.262	1.904	8.094	10.476	12.278	0.006
Total fin. assets	CBS (missing)	501	10.190	1.958				
	LISS	1383	9.388	3.542	6.377	10.282	12.16	0.056
	LISS - CBS	1383	-0.874	3.063	-2.993	-0.09	0.789	0.007
	CBS	1884	8.089	5.569	0	11.492	12.821	0.305
	CBS (LISS sample)	1350	7.259	5.757	0	10.97	12.742	0.368
Debts	CBS (missing)	534	10.190	4.417				
	LISS	1350	6.559	5.965	0	10.505	12.714	0.444
	LISS - CBS	1350	-0.699	3.435	-2.448	0	0.225	0.475
	CBS	1884	7.968	8.389	-10.321	11.686	13.409	0
	CBS (LISS sample)	1107	8.901	7.526	-9.329	11.85	13.445	0
Wealth	CBS (missing)	770	6.638	9.330				
	LISS	1107	9.522	6.723	0	11.972	13.527	0.014
	LISS - CBS	1107	0.621	6.279	-1.179	0.155	1.814	0.001
	CBS	1887	0.275	0.447	0	0	1	0.725
	CBS (LISS sample)	1695	0.260	0.439	0	0	1	0.74
Has rfa	CBS (missing)	192	0.406	0.492				
	LISS	1695	0.177	0.382	0	0	1	0.823
	LISS - CBS	1695	-0.083	0.343	-1	0	0	0.876
	CBS	1876	0.096	0.218	0	0	0.417	0.723
	CBS (LISS sample)	1289	0.101	0.219	0	0	0.424	0.706
Share rfa	CBS (missing)	587	0.086	0.216				
	LISS	1289	0.093	0.220	0	0	0.413	0.774
	LISS - CBS	1289	-0.008	0.181	-0.086	0	0.023	0.683
	CBS	1884	8.382	1.155	7.727	8.549	9.178	0.013
	CBS (LISS sample)	1837	8.385	1.163	7.733	8.552	9.181	0.013
Income	CBS (missing)	47	8.242	0.764				
	LISS	1837	8.194	1.332	7.533	8.409	8.995	0.02
	LISS - CBS	1837	-0.192	1.044	-0.44	-0.142	0.077	0.009

Notes: Summary statistics for different samples of several asset and wealth variables: CBS data, CBS data of all households with non-missing observations in the LISS, CBS data of all households that are missing in the LISS, LISS data, individual difference between LISS and CBS data. The last column reports the share of observations that are equal to 0.

Table 1.A.3. Portfolio choice and stock market beliefs (main data set)

	Has rfa			Share rfa					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
μ_1	0.065***	0.045***	0.035***	0.028***	0.021***	0.015***	0.017	0.023*	0.013
	(0.012)	(0.011)	(0.012)	(0.005)	(0.005)	(0.006)	(0.012)	(0.013)	(0.014)
σ_1	-0.024*	-0.008	0.000	-0.007	-0.002	0.000	0.003	0.001	0.001
	(0.014)	(0.013)	(0.014)	(0.008)	(0.007)	(0.007)	(0.016)	(0.016)	(0.017)
Female		-0.047**	-0.015		-0.012	0.001		0.008	0.031
		(0.022)	(0.024)		(0.011)	(0.012)		(0.028)	(0.033)
Couple		-0.018	0.008		-0.027	-0.025		-0.074	-0.101*
		(0.039)	(0.043)		(0.019)	(0.020)		(0.053)	(0.055)
Married		0.006	-0.017		0.006	0.009		0.003	0.048
		(0.038)	(0.041)		(0.018)	(0.019)		(0.048)	(0.050)
Has children at home		0.032	0.019		0.003	0.000		-0.017	-0.015
		(0.028)	(0.029)		(0.013)	(0.013)		(0.034)	(0.035)
Age between 41 and 55		0.092***	0.098**		0.060***	0.063***		0.119**	0.132***
		(0.035)	(0.039)		(0.016)	(0.017)		(0.047)	(0.049)
Age between 56 and 70		0.008	0.029		0.020	0.035*		0.084*	0.112**
		(0.038)	(0.041)		(0.017)	(0.018)		(0.051)	(0.053)
Age above 70		0.070*	0.091**		0.057***	0.070***		0.141**	0.162**
		(0.041)	(0.045)		(0.020)	(0.021)		(0.061)	(0.064)
Education: upper secondary		0.023	0.015		-0.006	-0.007		-0.064	-0.063
		(0.028)	(0.030)		(0.013)	(0.014)		(0.039)	(0.044)
Education: tertiary		0.125***	0.128***		0.048***	0.054***		0.010	0.025
		(0.030)	(0.033)		(0.015)	(0.016)		(0.039)	(0.043)
Income between 1600 and 2500		0.004	0.022		-0.004	0.009		-0.040	-0.003
		(0.029)	(0.031)		(0.014)	(0.015)		(0.046)	(0.048)
Income between 2500 and 3500		0.004	0.008		0.001	0.006		-0.014	-0.000
		(0.031)	(0.034)		(0.016)	(0.016)		(0.045)	(0.047)
Income above 3500		0.045	0.035		0.005	0.009		-0.035	-0.019
		(0.033)	(0.036)		(0.016)	(0.017)		(0.043)	(0.046)
Wealth below 0		0.016	0.016		0.037**	0.040**		0.131**	0.153**
		(0.034)	(0.038)		(0.017)	(0.019)		(0.054)	(0.060)
Wealth between 50k and 200k		0.123***	0.126***		0.044***	0.050***		0.026	0.053
		(0.025)	(0.027)		(0.011)	(0.012)		(0.038)	(0.041)
Wealth above 200k		0.344***	0.314***		0.148***	0.125***		0.078*	0.070
		(0.032)	(0.034)		(0.017)	(0.017)		(0.041)	(0.044)
Financial numeracy			0.018			0.001			-0.010
			(0.011)			(0.006)			(0.024)
Risk aversion			-0.044***			-0.029***			-0.053***
			(0.012)			(0.006)			(0.016)
N	1720	1718	1482	1720	1718	1482	501	500	425
R^2	0.021	0.138	0.137	0.016	0.107	0.112	0.004	0.073	0.102
Subset: has risky assets	No	No	No	No	No	No	Yes	Yes	Yes

Notes: Full version of Table 1.4.1. Robust standard errors in parentheses.
$* - p < 0.1, ** - p < 0.05, *** - p < 0.01$

Table 1.A.4. Portfolio choice and stock market beliefs (survey data set)

	Has rfa			Share rfa					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
μ_1	0.062***	0.044***	0.038***	0.030***	0.022***	0.019**	0.039***	0.045**	0.042**
	(0.013)	(0.014)	(0.015)	(0.007)	(0.008)	(0.008)	(0.015)	(0.020)	(0.021)
σ_1	-0.009	-0.005	-0.004	-0.008	-0.005	-0.006	-0.014	-0.025	-0.035
	(0.016)	(0.016)	(0.017)	(0.009)	(0.010)	(0.011)	(0.020)	(0.029)	(0.031)
Female		-0.063**	-0.036		-0.024*	-0.010		0.002	0.046
		(0.027)	(0.028)		(0.014)	(0.014)		(0.043)	(0.044)
Couple		-0.044	-0.051		-0.012	-0.014		-0.010	0.001
		(0.040)	(0.040)		(0.023)	(0.024)		(0.087)	(0.094)
Married		0.006	0.020		-0.008	-0.002		-0.017	-0.012
		(0.040)	(0.040)		(0.024)	(0.026)		(0.084)	(0.091)
Has children at home		0.006	0.000		0.026	0.026		0.026	0.026
		(0.037)	(0.038)		(0.020)	(0.021)		(0.056)	(0.059)
Age between 41 and 55		0.005	-0.006		-0.002	-0.006		0.006	0.006
		(0.049)	(0.051)		(0.026)	(0.028)		(0.080)	(0.089)
Age between 56 and 70		-0.025	-0.028		0.007	0.012		0.051	0.068
		(0.046)	(0.049)		(0.023)	(0.025)		(0.074)	(0.082)
Age above 70		-0.016	-0.001		0.029	0.042		0.085	0.113
		(0.049)	(0.052)		(0.026)	(0.028)		(0.082)	(0.089)
Education: upper secondary		-0.021	-0.020		0.002	0.006		-0.003	-0.001
		(0.033)	(0.034)		(0.017)	(0.018)		(0.055)	(0.059)
Education: tertiary		0.088**	0.087**		0.053***	0.054***		0.059	0.058
		(0.038)	(0.038)		(0.019)	(0.020)		(0.049)	(0.051)
Income between 1600 and 2500		-0.019	-0.016		-0.008	-0.006		0.029	0.027
		(0.031)	(0.032)		(0.015)	(0.016)		(0.053)	(0.054)
Income between 2500 and 3500		0.023	0.019		0.015	0.014		0.083	0.067
		(0.040)	(0.041)		(0.022)	(0.023)		(0.059)	(0.064)
Income above 3500		0.088*	0.085*		0.035	0.034		0.068	0.057
		(0.049)	(0.050)		(0.024)	(0.025)		(0.058)	(0.060)
Wealth below 0		-0.010	-0.009		0.023	0.027		0.068	0.050
		(0.050)	(0.052)		(0.030)	(0.033)		(0.128)	(0.155)
Wealth between 50k and 200k		0.117***	0.128***		0.057***	0.060***		0.109*	0.108*
		(0.031)	(0.031)		(0.016)	(0.017)		(0.056)	(0.059)
Wealth above 200k		0.296***	0.287***		0.123***	0.119***		0.110**	0.102*
		(0.038)	(0.038)		(0.020)	(0.020)		(0.056)	(0.060)
Financial numeracy			0.025*			0.006			-0.012
			(0.015)			(0.008)			(0.038)
Risk aversion			-0.051***			-0.029***			-0.062***
			(0.013)			(0.007)			(0.021)
N	1183	960	923	1183	960	923	360	281	268
R^2	0.020	0.152	0.171	0.017	0.109	0.125	0.020	0.089	0.124
Subset: has risky assets	No	No	No	No	No	No	Yes	Yes	Yes

Notes: Full version of Table 1.4.2. Robust standard errors in parentheses.
$* - p < 0.1$, $** - p < 0.05$, $*** - p < 0.01$

Table 1.A.5. Portfolio choice and stock market beliefs (main data for obs in survey data set)

	Has rfa			Share rfa					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
μ_1	0.058***	0.039**	0.028*	0.028***	0.022***	0.018**	0.023*	0.028*	0.024
	(0.015)	(0.016)	(0.016)	(0.007)	(0.007)	(0.007)	(0.013)	(0.016)	(0.017)
σ_1	0.008	0.019	0.025	-0.001	-0.001	-0.002	-0.010	-0.015	-0.021
	(0.019)	(0.018)	(0.019)	(0.009)	(0.009)	(0.010)	(0.017)	(0.022)	(0.024)
Female		-0.068**	-0.046		-0.018	-0.004		0.013	0.044
		(0.029)	(0.031)		(0.013)	(0.014)		(0.037)	(0.041)
Couple		-0.035	-0.016		-0.028	-0.022		-0.053	-0.051
		(0.059)	(0.060)		(0.026)	(0.028)		(0.072)	(0.075)
Married		-0.010	-0.018		0.005	0.006		0.008	0.014
		(0.057)	(0.058)		(0.025)	(0.026)		(0.066)	(0.069)
Has children at home		-0.003	-0.010		-0.010	-0.013		-0.024	-0.018
		(0.037)	(0.038)		(0.016)	(0.016)		(0.044)	(0.046)
Age between 41 and 55		0.074	0.089		0.049**	0.059***		0.135*	0.179**
		(0.053)	(0.054)		(0.022)	(0.022)		(0.070)	(0.072)
Age between 56 and 70		0.034	0.057		0.023	0.037*		0.084	0.130**
		(0.053)	(0.055)		(0.019)	(0.019)		(0.066)	(0.065)
Age above 70		0.101*	0.140**		0.066***	0.087***		0.160**	0.219***
		(0.057)	(0.060)		(0.023)	(0.023)		(0.080)	(0.081)
Education: upper secondary		0.011	0.011		0.000	0.000		-0.027	-0.044
		(0.037)	(0.038)		(0.016)	(0.016)		(0.052)	(0.056)
Education: tertiary		0.139***	0.138***		0.063***	0.063***		0.054	0.043
		(0.040)	(0.041)		(0.018)	(0.018)		(0.049)	(0.050)
Income between 1600 and 2500		0.035	0.043		0.003	0.006		-0.035	-0.035
		(0.038)	(0.039)		(0.017)	(0.018)		(0.064)	(0.065)
Income between 2500 and 3500		0.037	0.028		0.006	0.001		-0.011	-0.033
		(0.041)	(0.042)		(0.020)	(0.020)		(0.064)	(0.066)
Income above 3500		0.091**	0.073		0.020	0.011		-0.016	-0.026
		(0.046)	(0.047)		(0.021)	(0.022)		(0.061)	(0.061)
Wealth below 0		0.014	0.024		0.028	0.032		0.092	0.108
		(0.050)	(0.052)		(0.022)	(0.024)		(0.079)	(0.086)
Wealth between 50k and 200k		0.116***	0.115***		0.052***	0.051***		0.074	0.066
		(0.033)	(0.034)		(0.013)	(0.014)		(0.046)	(0.051)
Wealth above 200k		0.317***	0.311***		0.137***	0.134***		0.095*	0.091
		(0.041)	(0.042)		(0.021)	(0.021)		(0.050)	(0.056)
Financial numeracy			0.028*			0.011			0.003
			(0.016)			(0.007)			(0.031)
Risk aversion			-0.050***			-0.028***			-0.049**
			(0.015)			(0.007)			(0.021)
N	1183	960	923	1181	958	921	360	281	268
R^2	0.017	0.147	0.164	0.016	0.130	0.151	0.008	0.079	0.115
Subset: has risky assets	No	No	No	No	No	No	Yes	Yes	Yes

Notes: The same regressions as in Table 1.A.3 are shown. Data are also based on the main data set, but the sample is restricted to the survey data set. Robust standard errors in parentheses.
$* - p < 0.1, ** - p < 0.05, *** - p < 0.01$

Table 1.A.6. Distribution of changes in expectations

≤ -5	$(-5,-1]$	$(-1,0)$	$=0$	$(0,1]$	$(1,5]$	>5
0.019	0.055	0.075	0.456	0.177	0.163	0.055

Notes: Shows numbers depicted in Figure 1.5.2

Appendix 1.B Relations of portfolio risk, wealth, and demographics based on self-reported and administrative data

In this section, several regressions are shown in which asset variables enter as dependent and/or independent variable. I compare the estimated relations for the data sets based on administrative data and survey data, respectively.

In Table 1.B.1, I look at the relationship of wealth and other demographic characteristics. The first and third columns are regressions on the dummy variable if household wealth is strictly negative. Based on CBS data, this is predicted by being young, low education and high income. Only the first relation is also found based on self-reported data (column 3). In the next columns, I focus on the subset of households with non-negative wealth and use ihs-transformed wealth as dependent variables. Age, education, and income are predictive in both data sets whereas the effects for age and income seem to be stronger in the LISS data set. Couple households are associated with higher wealth according to administrative data which is not visible in the survey data.

Next, I focus on explaining portfolio risk in Table 1.B.2. The effects are very similar across data sets showing a strong positive relationship with education and wealth. Exceptions are that the CBS data implies that negative wealth households hold a higher risky asset share (compared to low wealth households) while LISS data reveals a relation with high income. Furthermore, only in the administrative data, a relation between age and portfolio risk can be detected: both middle-age and subjects above 70 hold more risky assets compared to young participants.

In sum, while the most important relations found in the administrative data are also visible in survey data, some associations are missed. Most of these deviations are related to households with negative wealth.

Table 1.B.1. Wealth variables by demographics

	Has neg. wealth	ihs(wealth)	Has neg. wealth	ihs(wealth)
	(Admin)	(Admin)	(Survey)	(Survey)
Couple	0.041	0.701***	0.052	-0.791
	(0.036)	(0.151)	(0.036)	(0.679)
Married	-0.030	-0.163	-0.015	1.287*
	(0.035)	(0.141)	(0.036)	(0.665)
Has children at home	0.020	-0.092	-0.003	-0.125
	(0.024)	(0.106)	(0.026)	(0.420)
Age between 41 and 55	-0.257***	0.879***	-0.147***	1.825**
	(0.036)	(0.156)	(0.047)	(0.882)
Age between 56 and 70	-0.409***	1.564***	-0.255***	3.187***
	(0.033)	(0.150)	(0.042)	(0.797)
Age above 70	-0.435***	1.585***	-0.259***	2.950***
	(0.034)	(0.167)	(0.043)	(0.820)
Education: upper secondary	-0.017	0.370***	-0.022	0.657*
	(0.020)	(0.115)	(0.019)	(0.368)
Education: tertiary	-0.064***	0.640***	-0.009	0.623*
	(0.020)	(0.108)	(0.020)	(0.350)
Income between 1600 and 2500	0.015	0.024	-0.031	1.184***
	(0.021)	(0.133)	(0.021)	(0.417)
Income between 2500 and 3500	0.058**	0.581***	0.042	1.861***
	(0.023)	(0.125)	(0.028)	(0.438)
Income above 3500	0.111***	0.689***	0.011	2.161***
	(0.025)	(0.131)	(0.029)	(0.482)
N	1882	1563	1093	957
R^2	0.182	0.164	0.103	0.097
Subset: non-negative wealth	No	Yes	No	Yes

Notes: The first two columns are based on the main data set that uses administrative variables. The last two columns are based on the data set that uses survey data only. The first and third column use a dummy if household wealth is strictly negative as dependent variable. In the second and fourth column, the sample is restricted to households with non-negative wealth and the dependent variable is ihs-transformed wealth. Robust standard errors in parentheses. * – $p < 0.1$, ** – $p < 0.05$, *** – $p < 0.01$

Table 1.B.2. Portfolio risk by demographics

	Has rfa	Share rfa	Has rfa	Share rfa
	(Admin)	(Admin)	(Survey)	(Survey)
Couple	0.001	-0.018	-0.035	-0.008
	(0.036)	(0.018)	(0.036)	(0.022)
Married	0.001	0.003	0.007	-0.011
	(0.035)	(0.017)	(0.036)	(0.023)
Has children at home	0.029	0.002	-0.007	0.016
	(0.026)	(0.012)	(0.033)	(0.019)
Age between 41 and 55	0.086***	0.057***	0.010	-0.001
	(0.032)	(0.015)	(0.043)	(0.024)
Age between 56 and 70	0.013	0.022	-0.029	0.001
	(0.034)	(0.016)	(0.041)	(0.023)
Age above 70	0.069*	0.055***	-0.012	0.023
	(0.037)	(0.018)	(0.044)	(0.025)
Education: upper secondary	0.030	-0.001	-0.007	0.006
	(0.025)	(0.012)	(0.029)	(0.016)
Education: tertiary	0.138***	0.053***	0.094***	0.055***
	(0.027)	(0.014)	(0.034)	(0.019)
Income between 1600 and 2500	0.022	-0.000	0.010	0.000
	(0.026)	(0.013)	(0.026)	(0.014)
Income between 2500 and 3500	0.028	0.007	0.058	0.029
	(0.029)	(0.014)	(0.035)	(0.021)
Income above 3500	0.084***	0.019	0.123***	0.047**
	(0.030)	(0.015)	(0.042)	(0.023)
Wealth below 0	0.003	0.032**	0.005	0.028
	(0.029)	(0.014)	(0.040)	(0.025)
Wealth between 50k and 200k	0.117***	0.041***	0.117***	0.060***
	(0.024)	(0.011)	(0.028)	(0.016)
Wealth above 200k	0.354***	0.151***	0.315***	0.135***
	(0.031)	(0.017)	(0.036)	(0.020)
N	1882	1871	1092	1039
R^2	0.134	0.101	0.147	0.100

Notes: The first two columns are based on the main data set that uses administrative variables. The last two columns are based on the data set that uses survey data only. For each data set three regression are shown with the dependent variable being, first, the dummy if any risky assets are in the portfolio, and, second, the share of risky assets. Robust standard errors in parentheses.
* $- p < 0.1$, ** $- p < 0.05$, *** $- p < 0.01$

Appendix 1.C Main regressions for alternative specifications

I replicate the main results regarding the relation of stock market beliefs and chosen portfolio risk using two alternative specifications: First, I increase the sample and exclude only subjects if all 100 balls are put in the outer bins.

Second, I make use of a non-parametric splines estimation that estimates μ_1 and σ_1 without functional form assumptions. I approximate the observed cumulative distribution function using a spline consisting of several cubic polynomials. The method is based on Bellemare, Bissonnette, and Kröger (2012) and described in more detail by Drerup and Wibral (2020). Since the method requires all bins to be bounded, I set the bounds of the outer bins to the 2.5 % and 97.5 % quantiles of the empirical distribution of the AEX.

In the cross-section, the coefficients and significance levels are almost unchanged. For the analysis over time, the results are also very similar. In particular, the main result in column 5 remains unchanged. Two minor changes can be detected. First, when dropping the 2.5 % strongest updaters of μ and σ in column 6, the coefficient of the change in expectations is no longer significant although the coefficient increases similarly as in the main specification. Second, when using non-parametric estimates of the belief parameters, the effects on the intensive margin are slightly smaller and no longer significant on the 10 %-level.

Table 1.C.1. Portfolio choice and stock market beliefs (less restrictive)

	Has rfa		Share rfa			
	(1)	(2)	(3)	(4)	(5)	(6)
μ_1	0.041***	0.029**	0.018***	0.012**	0.021	0.012
	(0.013)	(0.013)	(0.006)	(0.005)	(0.016)	(0.016)
σ_1	-0.018	-0.010	-0.007	-0.004	-0.002	-0.002
	(0.013)	(0.013)	(0.006)	(0.006)	(0.016)	(0.017)
Female	-0.052**	-0.018	-0.014	-0.001	0.005	0.029
	(0.021)	(0.024)	(0.010)	(0.011)	(0.028)	(0.033)
Couple	-0.016	0.010	-0.026	-0.024	-0.077	-0.103*
	(0.039)	(0.043)	(0.019)	(0.020)	(0.052)	(0.055)
Married	0.005	-0.017	0.006	0.010	0.008	0.052
	(0.038)	(0.041)	(0.018)	(0.019)	(0.047)	(0.050)
Has children at home	0.028	0.016	0.002	-0.001	-0.016	-0.012
	(0.028)	(0.029)	(0.013)	(0.013)	(0.034)	(0.035)
Age between 41 and 55	0.092***	0.099**	0.060***	0.063***	0.121**	0.132***
	(0.035)	(0.039)	(0.016)	(0.017)	(0.047)	(0.049)
Age between 56 and 70	0.004	0.024	0.019	0.034*	0.088*	0.115**
	(0.037)	(0.041)	(0.017)	(0.018)	(0.051)	(0.053)
Age above 70	0.065	0.086*	0.054***	0.067***	0.139**	0.162**
	(0.041)	(0.045)	(0.020)	(0.021)	(0.061)	(0.064)
Education: upper secondary	0.021	0.012	-0.008	-0.009	-0.065*	-0.064
	(0.027)	(0.030)	(0.013)	(0.014)	(0.039)	(0.043)
Education: tertiary	0.127***	0.127***	0.048***	0.053***	0.009	0.023
	(0.030)	(0.032)	(0.015)	(0.016)	(0.039)	(0.043)
Income between 1600 and 2500	0.003	0.022	-0.006	0.008	-0.045	-0.007
	(0.029)	(0.031)	(0.014)	(0.015)	(0.046)	(0.048)
Income between 2500 and 3500	0.004	0.007	0.001	0.006	-0.013	0.001
	(0.031)	(0.034)	(0.016)	(0.016)	(0.045)	(0.047)
Income above 3500	0.047	0.038	0.006	0.009	-0.036	-0.021
	(0.033)	(0.036)	(0.016)	(0.017)	(0.043)	(0.046)
Wealth below 0	0.016	0.016	0.037**	0.041**	0.131**	0.152***
	(0.034)	(0.038)	(0.017)	(0.019)	(0.053)	(0.059)
Wealth between 50k and 200k	0.118***	0.120***	0.042***	0.048***	0.027	0.053
	(0.025)	(0.027)	(0.011)	(0.012)	(0.038)	(0.040)
Wealth above 200k	0.344***	0.314***	0.148***	0.126***	0.082**	0.074*
	(0.032)	(0.034)	(0.017)	(0.017)	(0.041)	(0.043)
Financial numeracy		0.019*		0.002		-0.011
		(0.011)		(0.006)		(0.024)
Risk aversion		-0.046***		-0.029***		-0.054***
		(0.012)		(0.006)		(0.016)
N	1731	1494	1731	1494	504	429
R^2	0.135	0.134	0.104	0.110	0.071	0.100
Subset: has risky assets	No	No	No	No	Yes	Yes

Notes: Conversely to the main specification, I exclude subjects only if all 100 balls are put in the outer bins during the belief elicitation. Otherwise, the same specification as in Table 1.4.1 is used. The threshold was 80 in the main specification. Robust standard errors in parentheses.
$* - p < 0.1$, $** - p < 0.05$, $*** - p < 0.01$

Table 1.C.2. Portfolio choice and stock market beliefs (non-parametric splines estimation)

	Has rfa		Share rfa			
	(1)	(2)	(3)	(4)	(5)	(6)
μ_1	0.046***	0.038***	0.021***	0.015***	0.022*	0.011
	(0.011)	(0.011)	(0.005)	(0.005)	(0.013)	(0.013)
σ_1	-0.006	0.001	-0.004	-0.002	-0.009	-0.008
	(0.011)	(0.011)	(0.006)	(0.006)	(0.014)	(0.015)
Female	-0.047**	-0.015	-0.012	0.001	0.008	0.031
	(0.021)	(0.024)	(0.011)	(0.012)	(0.028)	(0.033)
Couple	-0.019	0.007	-0.027	-0.025	-0.075	-0.102*
	(0.039)	(0.043)	(0.019)	(0.020)	(0.053)	(0.055)
Married	0.006	-0.016	0.006	0.009	0.005	0.050
	(0.038)	(0.041)	(0.018)	(0.019)	(0.048)	(0.050)
Has children at home	0.031	0.020	0.003	0.000	-0.016	-0.013
	(0.028)	(0.029)	(0.013)	(0.013)	(0.034)	(0.035)
Age between 41 and 55	0.093***	0.099**	0.061***	0.064***	0.121**	0.134***
	(0.035)	(0.039)	(0.016)	(0.017)	(0.047)	(0.049)
Age between 56 and 70	0.009	0.030	0.020	0.036**	0.086*	0.113**
	(0.038)	(0.041)	(0.017)	(0.018)	(0.051)	(0.053)
Age above 70	0.070*	0.091**	0.056***	0.069***	0.141**	0.162**
	(0.041)	(0.045)	(0.020)	(0.021)	(0.061)	(0.064)
Education: upper secondary	0.022	0.015	-0.007	-0.008	-0.064	-0.062
	(0.028)	(0.030)	(0.013)	(0.014)	(0.040)	(0.044)
Education: tertiary	0.126***	0.128***	0.048***	0.054***	0.011	0.026
	(0.030)	(0.033)	(0.015)	(0.016)	(0.039)	(0.043)
Income between 1600 and 2500	0.004	0.022	-0.004	0.009	-0.041	-0.003
	(0.029)	(0.031)	(0.014)	(0.015)	(0.046)	(0.048)
Income between 2500 and 3500	0.004	0.008	0.001	0.006	-0.014	-0.000
	(0.031)	(0.034)	(0.016)	(0.016)	(0.045)	(0.047)
Income above 3500	0.045	0.036	0.005	0.009	-0.036	-0.020
	(0.033)	(0.036)	(0.016)	(0.017)	(0.043)	(0.046)
Wealth below 0	0.015	0.015	0.037**	0.040**	0.132**	0.153**
	(0.034)	(0.038)	(0.017)	(0.019)	(0.054)	(0.060)
Wealth between 50k and 200k	0.122***	0.125***	0.044***	0.050***	0.025	0.052
	(0.025)	(0.027)	(0.011)	(0.012)	(0.038)	(0.041)
Wealth above 200k	0.344***	0.315***	0.147***	0.125***	0.077*	0.069
	(0.032)	(0.034)	(0.017)	(0.017)	(0.041)	(0.044)
Financial numeracy		0.017		0.001		-0.011
		(0.011)		(0.006)		(0.024)
Risk aversion		-0.044***		-0.029***		-0.055***
		(0.012)		(0.006)		(0.016)
N	1719	1483	1719	1483	501	426
R^2	0.139	0.138	0.107	0.113	0.072	0.102
Subset: has risky assets	No	No	No	No	Yes	Yes

Notes: Conversely to the main specification, I use belief parameters that are non-parametrically estimated. Otherwise, the same specification as in Table 1.4.1 is used. Robust standard errors in parentheses.
$* - p < 0.1, ** - p < 0.05, *** - p < 0.01$

Table 1.C.3. Updating of beliefs and portfolio choice (less restrictive)

	Δ Has rfa			Δ Share rfa					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\mu_2 - \mu_1$	0.009	0.010	0.014	0.008*	0.009**	0.015	0.019*	0.019*	0.027
	(0.008)	(0.009)	(0.018)	(0.004)	(0.004)	(0.010)	(0.010)	(0.011)	(0.029)
$\sigma_2 - \sigma_1$	0.010	0.011	0.013	0.009	0.009	0.003	0.029*	0.029*	0.009
	(0.010)	(0.010)	(0.020)	(0.006)	(0.006)	(0.016)	(0.016)	(0.017)	(0.045)
Δ Income between 1600 and 2500		-0.021	-0.022		-0.012	-0.012		-0.003	-0.001
		(0.043)	(0.044)		(0.014)	(0.014)		(0.019)	(0.020)
Δ Income between 2500 and 3500		-0.015	-0.016		-0.001	0.001		0.013	0.023
		(0.045)	(0.047)		(0.017)	(0.017)		(0.038)	(0.038)
Δ Income above 3500		0.019	0.023		0.002	0.003		0.013	0.016
		(0.046)	(0.048)		(0.020)	(0.022)		(0.050)	(0.052)
Δ Wealth below 0		-0.067**	-0.075**		-0.013	-0.014		-0.014	-0.008
		(0.033)	(0.036)		(0.015)	(0.017)		(0.056)	(0.060)
Δ Wealth between 50k and 200k		-0.002	-0.015		0.026	0.025		0.020	0.025
		(0.031)	(0.030)		(0.017)	(0.018)		(0.049)	(0.052)
Δ Wealth above 200k		0.014	0.003		0.019	0.018		0.009	0.014
		(0.038)	(0.038)		(0.027)	(0.028)		(0.074)	(0.076)
N	1500	1500	1377	1500	1500	1377	400	400	370
R^2	0.002	0.010	0.010	0.005	0.011	0.008	0.015	0.018	0.007
Subset: has risky assets	No	No	No	No	No	No	Yes	Yes	Yes
Without strongest updaters	No	No	Yes	No	No	Yes	No	No	Yes

Notes: Conversely to the main specification, I exclude subjects only if all 100 balls are put in the outer bins during on of the belief elicitations. Otherwise, the same specification as in Table 1.5.2 is used. The threshold was 80 in the main specification. Robust standard errors in parentheses. * $- p < 0.1$, ** $- p < 0.05$, *** $- p < 0.01$

Table 1.C.4. Updating of beliefs and portfolio choice (non-parametric splines estimation)

	Δ Has rfa			Δ Share rfa					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\mu_2 - \mu_1$	0.007	0.007	0.021	0.009**	0.009**	0.012	0.012	0.012	0.008
	(0.008)	(0.009)	(0.018)	(0.004)	(0.004)	(0.010)	(0.009)	(0.009)	(0.027)
$\sigma_2 - \sigma_1$	0.013	0.013	0.007	0.008	0.008	-0.009	0.020	0.018	-0.038
	(0.010)	(0.010)	(0.012)	(0.006)	(0.006)	(0.009)	(0.018)	(0.018)	(0.028)
Δ Income between 1600 and 2500		-0.021	-0.022		-0.012	-0.012		-0.002	-0.004
		(0.043)	(0.044)		(0.014)	(0.014)		(0.018)	(0.017)
Δ Income between 2500 and 3500		-0.014	-0.016		-0.001	0.001		0.013	0.027
		(0.046)	(0.047)		(0.017)	(0.017)		(0.038)	(0.037)
Δ Income above 3500		0.019	0.021		0.001	0.003		0.009	0.013
		(0.047)	(0.048)		(0.020)	(0.021)		(0.050)	(0.052)
Δ Wealth below 0		-0.067**	-0.076**		-0.014	-0.014		-0.010	-0.006
		(0.033)	(0.037)		(0.015)	(0.017)		(0.060)	(0.059)
Δ Wealth between 50k and 200k		-0.002	-0.016		0.026	0.025		0.021	0.029
		(0.031)	(0.030)		(0.017)	(0.018)		(0.049)	(0.052)
Δ Wealth above 200k		0.014	-0.001		0.019	0.017		0.015	0.012
		(0.038)	(0.038)		(0.028)	(0.028)		(0.074)	(0.075)
N	1490	1490	1374	1490	1490	1374	397	397	364
R^2	0.002	0.009	0.010	0.004	0.010	0.009	0.008	0.010	0.010
Subset: has risky assets	No	No	No	No	No	No	Yes	Yes	Yes
Without strongest updaters	No	No	Yes	No	No	Yes	No	No	Yes

Notes: Conversely to the main specification, I use belief parameters that are non-parametrically estimated. Otherwise, the same specification as in Table 1.5.2 is used. Robust standard errors in parentheses. * $- p < 0.1$, ** $- p < 0.05$, *** $- p < 0.01$

Appendix 1.D Belief elicitation

This appendix gives more information on the distribution of stock market beliefs, the estimation of the belief parameters, and correlations between beliefs and demographic variables.

During the elicitation, participants are asked for the value of a 100 EUR investment into the AEX one year later where the value includes fees of EUR 0.30. Subjects split 100 balls between the events that the AEX goes up or down, respectively. Afterwards, each half is divided further until the 7 bins are filled. See Figure 1.D.1 for an example of a filled-out response. Drerup, Enke, and von Gaudecker (2017), as well as Drerup and Wibral (2020) give a more detailed description of the elicitation procedure.

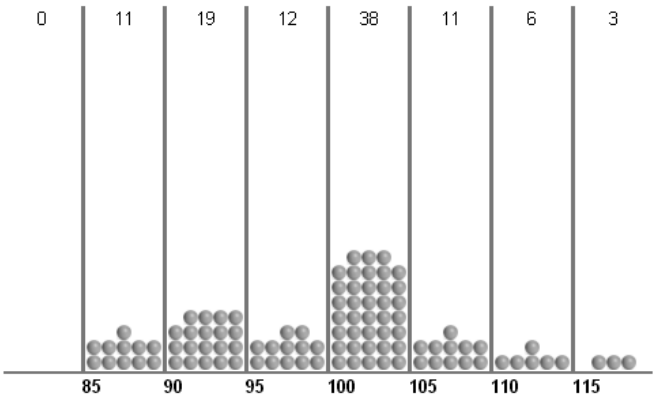

Figure 1.D.1. Survey tool

Notes: One example of an elicited belief distribution after all iteration steps. Subjects are asked for the value of a 100 EUR investment in the AEX in one year.

As also noted by Drerup, Enke, and von Gaudecker (2017) the belief distributions are rather pessimistic compared to empirical frequencies. This is also found by Hurd (2009). Besides, the probability mass in the tail events is much lower than empirically observed (see Figure 1.D.2).

When analysing the relation of beliefs and portfolio choice, I make use of the expected value (μ_1) and the standard deviation (σ_1) of the elicited distribution. These values are obtained by fitting a log-normal distribution. In particular, I minimize the sum of squared errors between the cumulative distribution function of a log-normal distribution with parameters $\widehat{\mu}_1$ and $\widehat{\sigma}_1$ and the observed cumulative distribution function

$$\min_{\widehat{\mu}_1, \widehat{\sigma}_1} \sum_i \left(\Phi\left(\frac{\ln(x_i) - \widehat{\mu}_1}{\widehat{\sigma}_1} \right) - F^{obs}(x_i) \right)^2 \tag{1.D.1}$$

where Φ is the cumulative distribution function of the standard normal distribution and the x_i are the threshholds of the bins (0.85, 0.9, ...). The expected value and

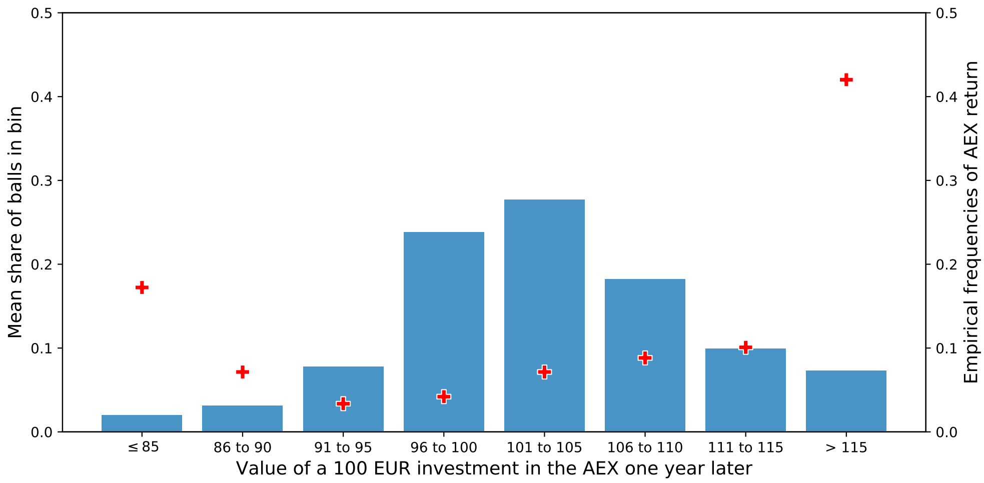

Figure 1.D.2. Mean share of balls in each bin during the first elicitation

Notes: The red crosses depict historical frequencies calculated based on the yearly performance in each month between October 1992 and July 2013.

standard deviation of the estimated distribution are obtained by

$$\mu_1 = \exp\left(\widehat{\mu}_1 + \frac{\widehat{\sigma}_1^2}{2}\right) \tag{1.D.2}$$

$$\sigma_1 = \sqrt{\left(\exp\left(\widehat{\sigma}_1^2\right) - 1\right)\exp\left(2\widehat{\mu}_1 + \widehat{\sigma}_1^2\right)} \tag{1.D.3}$$

Table 1.D.1 shows the relation of stock market beliefs and demographics. Subjects with higher μ_1 tend to be male, went to university, have a higher numeracy, and a lower risk aversion. On the other hand, a lower σ_1 is associated with unmarried couples and high numeracy subjects. These findings align well with previous studies (e.g., Manski, 2004; Hurd, 2009).

Table 1.D.1. Stock market beliefs

	μ_1		σ_1	
	(1)	(2)	(3)	(4)
Female	-0.313***	-0.208***	0.074	0.033
	(0.051)	(0.056)	(0.052)	(0.056)
Couple	-0.043	-0.049	-0.104	-0.209**
	(0.086)	(0.091)	(0.088)	(0.093)
Married	0.034	0.059	0.103	0.199**
	(0.079)	(0.083)	(0.083)	(0.088)
Has children at home	0.030	0.031	-0.053	-0.019
	(0.061)	(0.064)	(0.064)	(0.065)
Age between 41 and 55	0.075	0.078	0.022	0.093
	(0.074)	(0.083)	(0.078)	(0.087)
Age between 56 and 70	0.043	0.041	-0.054	-0.043
	(0.085)	(0.093)	(0.086)	(0.093)
Age above 70	-0.113	-0.030	-0.078	-0.050
	(0.102)	(0.114)	(0.102)	(0.114)
Education: upper secondary	0.105	0.070	-0.062	-0.071
	(0.068)	(0.072)	(0.070)	(0.076)
Education: tertiary	0.239***	0.153**	-0.082	-0.044
	(0.065)	(0.070)	(0.065)	(0.069)
Income between 1600 and 2500	0.008	0.020	-0.006	0.012
	(0.074)	(0.081)	(0.080)	(0.088)
Income between 2500 and 3500	0.070	-0.004	-0.025	-0.033
	(0.073)	(0.081)	(0.079)	(0.086)
Income above 3500	0.143*	0.123	-0.094	-0.107
	(0.077)	(0.085)	(0.080)	(0.089)
Wealth below 0	0.122	0.155*	0.052	0.033
	(0.080)	(0.090)	(0.077)	(0.085)
Wealth between 50k and 200k	0.005	-0.009	-0.068	-0.052
	(0.062)	(0.066)	(0.063)	(0.067)
Wealth above 200k	0.084	0.058	-0.054	-0.033
	(0.073)	(0.079)	(0.077)	(0.083)
Financial numeracy		0.106***		-0.113***
		(0.026)		(0.030)
Risk aversion		-0.121***		-0.051
		(0.030)		(0.031)
N	1718	1482	1718	1482
R^2	0.059	0.079	0.009	0.027

Notes: Dependent variables are the belief parameters. The expected value is used in the first two columns and the standard deviation in the last two. All variables except education, beliefs, numeracy, and risk aversion are based on administrative records. Robust standard errors in parentheses.
* – $p < 0.1$, ** – $p < 0.05$, *** – $p < 0.01$

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Chapter 2

Individual Preferences over Risk and Portfolio Choice*

Joint with Hans-Martin von Gaudecker, Arthur van Soest, and Erik Wengström

2.1 Introduction

Portfolio choices are an important component of household and individual decisions concerning life cycle saving and consumption smoothing under uncertainty, in particular when retirement savings have a component of individual choice. According to economic theory, such decisions are driven by the perceived distributions of returns to various types of assets and other future outcomes such as earnings or inflation, as well as the decision maker's risk preferences. It is well-known that the observed stock market participation rates for private households are much lower than what standard economic theories would predict (see e.g., Mankiw and Zeldes, 1991; Guiso and Sodini, 2013). We examine to which extend this "stock market participation puzzle" can be explained by differences in preferences.

We use data on choices over monetary gambles from an experiment with small-stake gambles and real incentives in a large representative sample of the Dutch adult population. For a large subsample of the experimental sample, we have rich background information including details on the composition of household wealth. Our data set, hence, contains both repeated decisions between small-stake gambles and detailed information on household portfolios for the same respondents. The paper exploits this unique data set in two steps: First, structural preference parameters are estimated using only the experimental data and the relation to individual portfolio choice is established. Second, we estimate a utility specification based on Barberis, Huang, and Thaler (2006) which explains both small-stake decisions in experiments and large-stake portfolio choices. We empirically account for preference heterogeneity with a finite mixture model.

There is now a large literature on eliciting and estimating risk preferences (see e.g., Dohmen, Falk, Huffman, Sunde, Schupp, et al., 2011). An approach that has become particularly popular with economists is to infer such preferences from small-stakes, potentially incentivised, choices in controlled risky environments (Holt and Laury, 2002; Andersen, Harrison, Lau, and Rutström, 2006; Choi, Fisman, Gale, and Kariv, 2007; Gaudecker, Soest, and Wengström, 2011). The general findings are that there is a lot of heterogeneity in risk preferences and that the average individual behaves in a risk-averse manner. The latter fact is add odds with classical economic theory (Rabin, 2000). The idea behind Rabin's famous calibration theorem is if curvature of the utility function alone was responsible for small-stake risk taking, this would imply absurd behaviour for higher stakes. A potential solution has been proposed by Barberis, Huang, and Thaler (2006) (henceforth BHT), based on preferences with first-order risk aversion (Epstein and Zin, 1990; Segal and Spivak, 1990) and "narrow framing" of risks (Kahneman and Lovallo, 1993). The first property implies a kink in the utility function at some reference point, which leads to aversion even to infinitesimal risks; the second means that risky prospects are evaluated in isolation from other (background) risks, such as uncertain future prices or incomes.[1] BHT show that plausible parameterizations of this type of preferences can help in explaining the "stock market participation puzzle". An advantage of BHT preferences is that they can be used to measure risk aversion in a controlled setting with small stakes while still being relevant for decisions in other domains with the much larger stakes that play a role in real life decisions, such as portfolio choice. This allows us to identify the impact of certain kinds of preference heterogeneity on portfolio choice without recurring to external assumptions such as the completeness of markets or rational expectations, which are often considered implausible.

It is not obvious that individuals that behave more risk-averse when deciding about 10 € gambles also behave more risk-averse when choosing how to invest their wealth – compared to other individuals. Dohmen et al. (2011) establish a qualitative relation between risky choice experiments, survey questions, and several measures of risky real-world behaviour including portfolio choice. This paper explores if we can also estimate a parametric relationship, i.e. a utility specification that incorporates both small-stake and large-stake decisions.

To fit observed aggregate behaviour in both domains, we find that we need a scaling parameter that leads to higher first-order risk aversion for portfolio choices compared to lottery choices. On the individual level, our model helps to predict choices within the same domain. When we use individual lottery choices to determine the preference type of an individual and predict portfolio choice, we obtain mixed results. The average absolute deviation of the predictions improve relative to those that only include socio-demographic variables to determine the preference

1. "Narrow framing" is in the literature also referred to as "narrow bracketing".

type. Also the likelihood contribution for two thirds of the subjects increases. For a sizeable fraction of the population, however, the link between behaviour with small and large stakes is too tight such that the overall model predictions, judged by the implied likelihood, get worse. We discuss explanations and implications of this negative result.

The remainder of the paper is organized as follows. In Section 2.2 we present the portfolio data and our experiment. Section 2.3 establishes a relation between preference parameters estimated from experimental choices and portfolio choice. We summarise the theory behind the BHT preference specification in Section 2.4. Section 2.5 introduces our empirical specification and we present our aggregate results in Section 3.4. In Section 2.7 individual level predictions are calculated and compared to individual level predictions based solely on demographic characteristics, Section 2.8 concludes.

2.2 Data

Our analysis is based on the CentERpanel, a Dutch general-purpose household survey that is administered via the Internet. To avoid selection problems due to lack of Internet access, respondents without a computer are equipped with a set-top box for their television set (and with a TV if they do not have one) so that the survey also covers households that do not have Internet access. The panel consists of roughly 2,000 households who are representative of the Dutch population in terms of observable characteristics. It comes with very detailed information on household wealth and portfolio allocations, as well as rich demographic and socio-economic background characteristics. We conducted a risky choice experiment with real incentives with this panel in late 2005.

2.2.1 Household wealth and portfolio data

The CentERpanel is host to the Dutch National Bank Household Survey (DHS), which contains very detailed questionnaires about the households' wealth holdings. The questions are asked to the member of the household who is best acquainted with the financial matters of the household. They are administered in spring around the time when income tax statements are prepared for the preceding year, and accordingly ask for wealth holdings at the end of that preceding year. We use data from 2006 and 2005 in case the former is not available.

We consider liquid financial assets excluding debts and use standard definitions for classifying assets to be safe or risky. See Table 2.C.1 in the Appendix for details. A unique feature of the dataset is that households are not only asked for the number of stocks and mutual funds they possess, but also to report each item's name and the quantity held. Gaudecker (2015) connects each portfolio constituent to its time series of returns and estimates the risk-return characteristics of household portfolios directly from the data. This implies that covariances between different items' returns are appropriately taken into account and there is no need to invoke any assumptions about the properties of asset classes (that is, assumptions of the form "directly held stocks have an annual standard deviation of 25 %.").

We use the estimates of Gaudecker (2015) and classify the risky asset holdings on the basis of the household portfolio standard deviations. More precisely, we assume that households can observe the volatility of their entire portfolios and hold homogeneous beliefs about the return per unit of risk. We use the Sharpe ratio of the MSCI Europe, which has an annual excess return $\mu_b = 5.77\%$ over the 1-month EURIBOR rate ($\mu_{\mathrm{rf}} = 4.65\%$) in the period from January 1983 until July 2009. Along with its standard deviation $\sigma_b = 16.7\%$ this implies a Sharpe ratio $S_b = {}^{\mu_b}/_{\sigma_b}$ of 35%.

Our econometric implementation requires a discretisation of the observed portfolios into risk categories. We use the calculated portfolio standard deviations and construct four risk groups using the standard deviation of the MSCI Europe as reference: The lowest risk group covers the households that completely stay out of risky assets. The cutoffs for the remaining three risk categories are at 0.4 and 0.8 of the MSCI Europe standard deviation. Around 71% of households do not hold any risky assets while 17% of s are categorized into the second lowest risk group. The annual volatility of 5% of the households exceeds 13.3% (i.e. the highest risk category).

2.2.2 The risky choice experiment

The experiment has been described in detail elsewhere (Gaudecker, Soest, and Wengström, 2011; Gaudecker, Soest, and Wengström, 2012) and we limit ourselves to a brief introduction. We make use of an adapted version of the well-established multiple price list format, applied earlier by, for example, Binswanger (1978) and Holt and Laury (2002). Andersen et al. (2006) provide a detailed description.

Each subject faces a sequence of screens with four pairs of lotteries each. An example is shown in Figure 2.C.1. The subject may opt for either lottery 'A' or lottery 'B' in each of the four choice tasks. The payoffs of the 'A'- and 'B'-lotteries do not change, but probabilities vary in such a way that the (riskier) 'B'-lotteries become more favourable as one moves down the screen.

If the choices on the first screen are consistent (i.e. a single switch-point is observed) the subject is routed to a screen containing lotteries with the same payoffs, but a finer probability grid. Andersen, Harrison, Lau, and Rutström (2010) recommend using a closely related method and call it "iterated multiple price list". All subjects were given the seven sets of lotteries listed in Table 2.2.1. For each of these sets, subjects made either eight or four decisions. Our experimental data, therefore, constitute an unbalanced panel of 28 to 56 binary choices for each respondent.

Gaudecker, Soest, and Wengström (2012) compare the online experiment described here to laboratory experiments and find essentially no effects of the im-

Table 2.2.1. Characteristics of the seven sets of lotteries

	Option A		Option B	
Payoff Configuration	Low Payoff	High Payoff	Low Payoff	High Payoff
1	27	33	0	69
2	39	48	9	87
3	12	15	-15	48
4	33	36	6	69
5	18	21	-9	54
6	24	27	-3	60
7	15	18	-12	51

Note: The order was randomised. For each lottery, the subjects made 4 or 8 choices with varying probabilities of obtaining the high outcome.

plementation mode (but substantial differences between students and other socio-economic groups, confirming the added value of a representative sample compared to a student convenience sample). Participants were allocated to one of three different incentive treatments and to one of two randomly determined orderings of the seven sets of lotteries as described by Gaudecker, Soest, and Wengström (2011).

Finally, we note that all payoffs were made three months after the experiment. The outcomes of some lotteries were made known to the subjects immediately, others only just before the payment was made. While we do not model preferences towards the timing of uncertainty resolution in this paper, it is important to note that risk averse choices in late-resolving lotteries provide direct evidence of narrow framing. First-order risk aversion is not enough to explain such behaviour (Barberis, Huang, and Thaler, 2006). As documented in Gaudecker, Soest, and Wengström (2012), the vast majority of subjects in our experiment behaves in such a fashion, which opens up the possibility that risk averse behaviour in the experiment may be related to non-participation in the stock market.

Table 2.2.2 shows the number of observations used in the following analysis and the criteria of exclusion. 2,299 participants were invited to the experiment, 1,928 finished it, and 1,791 took longer than our drop-out time. Our requirements for financial data are fulfilled by 1,457 observations. For 931 individuals both valid financial data with wealth exceeding EUR 1000 and experimental data is available.

Descriptive Statistics for all variables used in the following analysis are shown in Table 2.2.3.

Table 2.2.2. Observations

	(1) sum
Valid Experiment	1791
(Thereof) wealth information available & wealth > €1000	1000
(Thereof) reported risky assets covered > 30 %	931

Note: An experiment is considered valid if the participant finishes the experiment within a time longer than 5.3 minutes, the minimum duration in the parallel laboratory experiment.

Table 2.2.3. Background characteristics

Variable	Percentage
Secondary education or less	56.8
Higher vocational education	28.2
Academic education	14.9
Age 16-34 years	14.8
Age 35-49 years	31.4
Age 50-45 years	33.5
Age 65 and older	20.3
Total wealth below EUR 10,000	15.3
Total wealth between EUR 10,000 and EUR 50,000	16.2
Total wealth between EUR 50,000 and EUR 200,000	30.7
Total wealth above EUR 200,000	37.8
Male	63.8
Female	36.2

2.3 Experimental Preference Parameters and Portfolio Choice

In this section, the connection between preference parameters estimated from experimental choices and the level of risk taken by households is established. This gives first inside how the small-stake parameters relate to large-stake decisions. We first describe the parameters and then move on to explore their connection with portfolio risk.

2.3.1 Preference Parameters

Making use of the risky choice experiments explained above, we estimate the following utility specification which is also an important component of the full model specification introduced later:

$$U(\pi) \;=\; v(\tilde{\pi} - R_\pi) \tag{2.3.1}$$

where

$$v(z) \;=\; \begin{cases} z & \text{for } z \;\geq\; 0 \\ \lambda z & \text{for } z \;<\; 0 \end{cases} \tag{2.3.2}$$

This quasi-linear utility formulation incorporates individual-specific loss aversion λ (first-order risk aversion) relative to the reference point R_π that is set to the lower outcome of the safer lottery. As in Gaudecker, Soest, and Wengström (2011), two types of "errors" are modeled. First, when deciding between two lotteries of corresponding certainty equivalents CE, Fechner errors τ (see, e.g. Loomes (2005)) regulate the probability to choose the lottery with a lower CE:

$$Y_{ij} \;=\; \mathbb{I}\left\{\Delta \mathrm{CE}_{ij} + \tau\,\varepsilon_{ij} \;>\; 0\right\}, \tag{2.3.3}$$

Where the ϵ_{ij} follow a standard logistic distribution and are independent of each other and of the random coefficients in the utility function.

Second, individuals decide with a probability ω at random. While the Fechner errors are assumed to be the same for all individuals, the probability to choose randomly is individual-specific.

Accounting for preference heterogeneity, we allow for observed and unobserved heterogeneity.

$$\eta_i \;=\; g_\eta(X_i^\eta \beta^\eta + \xi_i^\eta), \qquad \eta_i \;\in\; \{\gamma_i, \lambda_i, \omega_i\} \tag{2.3.4}$$

We add regressors for the experimental environment, but not for demographic characteristics since we are controlling for the latter in the ordered probit regressions. Assuming that the unobserved part follows a jointly normal distribution independent of the regressors, we simultaneously estimate the regressors β, the variances of the unobserved heterogeneity components ξ, and the homogeneous parameter τ. In a second step, we calculate for each individual the prior distribution

Table 2.3.1. Estimated Structural Parameters

	N	Mean	Std.Dev.	0.1-Quant.	0.9-Quant.
Loss Aversion	931	13.65	17.33	0.95	43.05
Error Parameter	931	0.25	0.18	0.05	0.50

Note: Descriptive statistics of the individual level estimates of loss aversion and the trembling hand error parameter.

according to observed characteristics and compute the mean of the posterior distribution via Bayesian updating taking into account the actual choices. See Gaudecker, Soest, and Wengström (2011) for more details. The estimates are summarized in Table 2.3.1 and used in the next subsection to explain portfolio risk.

2.3.2 Reduced Form Evidence

In this subsection, the individual-specific structural choice parameters are combined with the survey data set. Table 2.3.2 shows an ordered probit regression of the discretized portfolio risks where the loss aversion and error parameter are standardized.

Without considering control variables (column (1)), an increase in λ by one standard deviation is associated with a decrease in the risky asset share of 15.7%. This effect is stable if several demographic control variables (age, education, wealth, gender) are added. Once a numeracy measure is added, the effect is –10.7% and still significant on the 5%-level. A higher error parameter leads to less risky portfolio choices, as well. This effect is stable on the 5%-significance level where the marginal effect in columns (2) and (3) is –9.83%.

Altogether, a link between structural choice parameters and actual portfolio risk is discovered. Individuals that reveal higher loss aversion and higher error propensity in the experiments, tend to invest less into risky assets. Compared to other household characteristics, the explanatory power of the structural parameters seems to be substantial, but not as high as expected which preempts the difficulties we encounter when fitting the full structural model in the remaining part of the paper.

Table 2.3.2. Discretized Risky Asset Share

	(1)	(2)	(3)
Loss Aversion	-0.157***	-0.129**	-0.107*
	(0.0462)	(0.0494)	(0.0543)
Error Parameter	-0.114*	-0.0983*	-0.0983*
	(0.0445)	(0.0458)	(0.0489)
Vocational edu.		0.226*	0.168
		(0.101)	(0.110)
University edu.		0.453***	0.406**
		(0.116)	(0.125)
Age 35–49		0.417**	0.457**
		(0.161)	(0.163)
Age 50–64		0.437**	0.476**
		(0.164)	(0.166)
Age > 64		0.517**	0.568**
		(0.175)	(0.181)
Wealth 10k–50k		0.418+	0.336
		(0.221)	(0.237)
Wealth 50k–200k		0.757***	0.750***
		(0.195)	(0.209)
Wealth > 200k		1.073***	1.028***
		(0.192)	(0.207)
Female		-0.289**	-0.329**
		(0.0988)	(0.108)
High Numeracy			0.140
			(0.0979)
Observations	931	931	808
Pseudo R^2	0.015	0.092	0.098

Note: Ordered probit regression of the portfolio risk category. The small-stakes parameters are estimated based on the 28 to 56 lottery choices of a household and are standardized. Robust standard errors are used. *** p < 0.001, ** p < 0.01, * p < 0.05, + p < 0.1.

2.4 Theoretical Framework

In this section, we describe the utility specification proposed by BHT and more formally presented in Barberis and Huang (2009) (henceforth BH). We start by outlining the theory regarding consumption and portfolio choices and then describe how agents evaluate small-stake gambles. To a large extent, we follow the specification outlined in BH and make a few changes in order to tailor it to our econometric implementation. We work with discrete time and a recursive utility specification.

Let W_t denote the agent's wealth at the beginning of time period t. The agent's problem consists of choosing the level of period t consumption C_t and allocating the remaining wealth $W_t - C_t$ across the set of available assets $\mathfrak{L}$. Assume that asset $l \in \mathfrak{L}$ pays gross return $\tilde{R}_{l,t+1}$ and that the agent allocates a share $\theta_{l,t}$ of his post-consumption wealth $W_t - C_t$ to it. The the agents' gross wealth at the beginning of period $t+1$ is given by:

$$\tilde{W}_{t+1} \;=\; (W_t - C_t) \sum_{\ell \in \mathfrak{L}} \theta_{\ell,t} \tilde{R}_{\ell,t+1}. \tag{2.4.1}$$

Wealth allocated to asset l can be interpreted as participating in a gamble, which costs $\theta_{l,t}(W_t - C_t)$ at the beginning of period t and yields the uncertain payoffs $\theta_{l,t}(W_t - C_t)\tilde{R}_{l,t+1}$ one time period later. Following BH, we assume that a subset $\mathfrak{M} \subseteq \mathfrak{L}$ of all assets are framed narrowly and that their returns have an impact on the agent's utility that goes beyond their effect through future wealth levels. More specifically, we propose the following slight modification of their recursive utility specification:

$$V_t \;=\; H\left(C_t,\, \mu(\tilde{V}_{t+1}|I_t) + b_0\,(W_t - C_t) \sum_{m \in \mathfrak{M}} \nu(\tilde{G}_{m,t+1}) \right) \tag{2.4.2}$$

where V_t is the utility at time t and the function $H(\cdot)$ aggregates current consumption C_t and future utility. The latter is made up by the certainty equivalent $\mu(\tilde{V}_{t+1}|I_t)$ of the distribution of future utility given the information I_t available at the beginning of time period t and the direct impact of the excess returns on the narrowly framed assets. The excess returns are framed as gambles $\tilde{G}_{m,t+1}$ and defined in relation to a reference return $R_{i,z}$:

$$\tilde{G}_{m,t+1} \;=\; \theta_{m,t}(\tilde{R}_{m,t+1} - R_{i,z}). \tag{2.4.3}$$

Thus, the return of narrowly framed asset m affects current utility both indirectly through its effect on wealth at the beginning of the next time period, $\mu(\tilde{V}_{t+1}|I_t)$, and directly via $b_0(W_t - C_t)\,\nu(\tilde{G}_{m,t+1})$.

The term b_0 indicates the weight assigned to narrow framing. In contrast to BH, who add the expected utility of the narrowly framed assets directly, we work with certainty equivalents $\nu(\cdot)$ also for the narrowly framed part. [2]

Following Epstein and Zin (1989) and much of the subsequent literature, we use the following form for the aggregator function H:

$$H(C,x) = \left((1-\beta)C^{1-\rho} + \beta x^{1-\rho}\right)^{\frac{1}{1-\rho}}, \quad 0 < \beta < 1, \quad 0 < \rho \neq 1. \tag{2.4.4}$$

The next step is to specify the functional forms of the certainty equivalents, $\mu(\cdot)$ and $\nu(\cdot)$. For reasons of tractability and to stay as close as possible to the existing literature, $\mu(\cdot)$ is specified as the certainty equivalent corresponding to a simple power utility function:

$$\mu(\tilde{z}) = \left(\mathbb{E}\left[(\tilde{z})^{1-\gamma}\right]\right)^{\frac{1}{1-\gamma}}, \quad 0 < \gamma \neq 1. \tag{2.4.5}$$

For the narrowly framed part, we follow BH and use a piecewise linear function (with a kink at 0). There are several reasons behind this choice of specification. One reason is that it follows Kahneman and Tversky's (1979) original formulation of prospect theory which is often associated with intuitive thinking and narrow framing. Secondly, it is the simplest form of a utility function featuring first-order risk aversion, which is necessary to explain the rejection of small actuarially fair gambles (see Epstein and Zin (1990) and BHT). The piecewise linear function gives the following certainty equivalent specification for the narrowly framed assets:

$$\nu(\tilde{G}_{\text{risky},t+1}) = v^{-1}\left(\mathbb{E}\left[v(\tilde{G}_{\text{risky},t+1})\right]\right), \tag{2.4.6}$$

where v is given by:

$$v(z) = \begin{cases} z & \text{for } z \geq 0 \\ \lambda z & \text{for } z < 0 \end{cases}, \tag{2.4.7}$$

Note that the way $G_{m,t+1}$ is defined implies that the kink of v at zero implies that returns are coded as gains or losses relative to the return of the risk free asset R_f, the "reference point". Higher returns are considered to be gains and lower returns are considered to be losses.

2. This makes the dimension of b_0 independent of the loss aversion parameter in the narrow framing part (see below), making estimation numerically more stable.

2.4.1 Portfolio Choice and Consumption

In order to solve this model, BH develop an iterative procedure based on the following two equations:

$$B_t^* = \max_{\theta_t \in (0,1)} \left[\mu \left((1-\beta)^{\frac{1}{1-\rho}} \left(\frac{C_t^*}{W_t} \right)^{\frac{\rho}{\rho-1}} \theta_t \tilde{R}_{t+1} \right) + b_0 \sum_{m \in \mathfrak{M}} \nu(\tilde{G}_{m,t+1}) \right] \tag{2.4.8}$$

$$(1-\beta) \left(\frac{C_t^*}{W_t} \right)^{-\rho} = \beta \left(1 - \frac{C_t^*}{W_t} \right)^{-\rho} \left(B_t^* \right)^{1-\rho} \tag{2.4.9}$$

The system is solved by numerically finding the portfolio shares that yield B_t in (2.4.8) for some candidate value C_t, using a bisection method to solve (2.4.9) for an updated value of C_t, and iterating until convergence is achieved.

2.4.2 Choices in small-stake Gambles

We now describe how the small-stake gambles can be evaluated using the utility specifications outlined in the previous section. We follow the first approach in Section 5 of Barberis and Huang (2009)—which goes back to Epstein and Zin (1989)—and assume that agents insert an infinitesimal time step around the gamble and then perform the recursive utility computation. Barberis and Huang (2009) show that the utility when choosing a gamble can be expressed as:

$$V_\pi = H\Big(0,\, A\mu\,(W + \tilde{\pi}) + b_0\,\nu\big(\tilde{G}_\pi\big)\Big), \tag{2.4.10}$$

with:

$$A = (1-\beta)^{\frac{1}{1-\rho}} \left(\frac{C^{*}{}_t}{W_t} \right)^{\frac{\rho}{\rho-1}}, \tag{2.4.11}$$

where:

$$\tilde{G}_\pi = \tilde{\pi} - R_\pi. \tag{2.4.12}$$

Under the functional form assumptions made above, $\mu(\cdot)$ is locally smooth. When the outcomes of gambles π_A and π_B are small relative to lifetime wealth (which is innocuous in our application), $\mu(W+\pi) \approx W + E[\tilde{\pi}]$ and we can express their utility difference as:

$$\begin{aligned}
\Delta V_\pi &\equiv V_{\pi_A} - V_{\pi_B} \\
&= A\big(W + \mathbb{E}[\tilde{\pi}_A]\big) + b_0\ \nu\big(\tilde{G}_{\pi_A}\big) - A\big(W + \mathbb{E}[\tilde{\pi}_B]\big) - b_0\ \nu\big(\tilde{G}_{\pi_B}\big) &(2.4.13)\\
&= A \cdot \mathbb{E}[\tilde{\pi}_A - \tilde{\pi}_B] + b_0\big(\nu\big(\tilde{G}_{\pi_A}\big) - \nu\big(\tilde{G}_{\pi_B}\big)\big), &(2.4.14)
\end{aligned}$$

2.5 Empirical Specification

Our preferred model specification is presented here while alternative specifications are deferred to Appendix 2.A.

First analyses, show that the model as described so far leads to unrealistic stock market choices. Overall subjects tend to be more averse to risk when investing than when making lottery choices. See Appendix 2.A.2 for more details. We, therefore, allow for a different loss aversion parameter in the large-stake and small-stake domain and refine (2.4.7):

$$v(z) = \begin{cases} z & \text{for } z \geq 0 \\ \left(\lambda + \lambda_\ell \cdot \mathbb{I}\{\text{large-scale choice}\}\right) z & \text{for } z < 0 \end{cases}, \tag{2.5.1}$$

Without frictions, the scaling parameter λ_l would be close to 0. Based on the experience described above, we expect it to be larger than 0.

Our set of assets $\mathfrak{L}$ consists of two assets: a safe asset and a narrowly framed risky asset. We discretise the set of possible portfolio choices in four risk categories as described above. Like Barberis and Huang (2009), we assume that the degree of narrow framing for small-stakes gambles is the same as for the risky financial asset. We set maximin reference points: For portfolio choices, it is the return of the safe asset, for gambles the lower return of the safer lottery.

For taking the model to the portfolio data, we assume that individuals maximise a stochastic utility function of the form:

$$\mathscr{V}(\theta, W, \beta, \gamma, \rho, b_0, \lambda, \lambda_l, \tau_\theta) = V(\theta, W, \beta, \gamma, \rho, b_0, \lambda, \lambda_l) + \tau_\theta \cdot \varepsilon_\theta \cdot W \tag{2.5.2}$$

Utility thus consists of the previously described deterministic component V and a stochastic part. Since we do not observe consumption in the data, we assume that consumption is at its optimal level as implied by the model for a given value of the portfolio shares. $\tau_\theta > 0$ is a scaling parameter measuring the relative importance of the deterministic and stochastic components. We assume that the ε_θ follow an extreme value distribution, independent of each other and the individual characteristics and preference parameters in the model. These assumptions imply that choice probabilities for the portfolio shares are given by:

$$\mathbb{P}\left(\theta_i^{\text{obs}}, W, \beta, \gamma, \rho, b_0, \lambda, \lambda_l, \tau_\theta\right) = \frac{\exp\left(\frac{1}{\tau_\theta \cdot W} V(\theta_i^{\text{obs}}, \cdot)\right)}{\sum_{s \in \Theta} \exp\left(\frac{1}{\tau_\theta \cdot W} V(s, \cdot)\right)} \tag{2.5.3}$$

In the estimations, we first estimate (2.5.3) and then evaluate the gambles conditional on the observed portfolio shares, i.e. we assume that investors will not adjust the portfolio allocation policy or consumption choice that they chose in the absence of gambles. This is justified by the small stakes of the gambles compared to

Table 2.5.1. Fixed Parameters

Parameter	Value
β	0.95
γ	3.5
ρ	1.5
b_0	1

Note: The discount factor β, risk aversion in the non-narrowly framed part of utility γ, rate of intertemporal substitution ρ, and narrow framing weight are set to plausible parameter values.

the amounts of wealth invested in the household portfolios. Individuals maximise stochastic utility:

$$\mathscr{V}_\pi(\tilde{\pi}, W, \beta, \gamma, \rho, \lambda, \lambda_l, \tau_\pi) \;=\; V_\pi(\cdot) + \tau_\pi \cdot \varepsilon_\pi \tag{2.5.4}$$

where $V_\pi(\cdot)$ is given by (2.4.10). Each individual faces J_i different choice problems; the set of their indices is denoted by $\mathfrak{J}_i = \{1, 2, \ldots, J_i\}$. Denote by $\tilde{\pi}_{i,j}^{\text{obs}}$ the observed choice by individual i in choice problem $j \in \mathfrak{J}_i$, where $\tilde{\pi}_{i,j}^{\text{obs}} = 1$ if the individual chooses gamble $\tilde{\pi}_{i,j,A}$ and -1 otherwise. As in Section 2.3, we include parameters for both a Fechner error (τ_π) and a trembling hand error (ω). We assume that ε_π is drawn from extreme value distributions. The probability for the observed choice in situation j for a subject i with given preference and error parameters is therefore:

$$\mathbb{P}\left(\tilde{\pi}_{i,j}^{\text{obs}}, W, \beta, \gamma, \rho, b_0, \lambda, \lambda_l, \tau_\pi, \omega\right) \;=\; (1-\omega) \cdot \Lambda\left(\frac{\tilde{\pi}_{i,j}^{\text{obs}}}{\tau_\pi} \Delta V_{\pi,j}(\cdot)\right) + \frac{\omega}{2} \tag{2.5.5}$$

where $\Lambda(\cdot)$ is the standard logistic distribution.

The choice probabilities at the individual level thus depend on a number of preference parameters $(\beta, \gamma, \rho, b_0, \lambda, \lambda_l)$ and error parameters $((\tau_\theta, \tau_\pi, \omega))$. Since we use static data to estimate a dynamic model, not all parameters can be jointly identified. We restrict some of them to plausible values as shown in Table 2.5.1. We are particularly interested in the heterogeneity across individuals in the parameters λ and ω, since this is what our experiment is informative upon. We account for preference heterogeneity with a finite mixture model, allowing for K different types of subjects, indexed by $k \in \mathfrak{K}$. Given these ingredients and dropping the t subscript, the conditional likelihood for subject i's choices of portfolio shares and of his decisions in the experiment given the subject is of type k is:

$$\mathscr{L}_{i,k} \;=\; \mathbb{P}\left(\theta_i^{\text{obs}}, \cdot\right) \prod_{j \in \mathfrak{J}_i} \mathbb{P}\left(\tilde{\pi}_{i,j}^{\text{obs}}, \cdot\right) \tag{2.5.6}$$

where the dots refer to the preference and error parameters for the given type.

The distribution of types may be correlated with observed individual characteristics X, and we assume that the conditional probability (the weight $\boldsymbol{w}_k$) that an individual is of type k given characteristics X and the respective type predictors η_k is given by the multinomial logit probability:

$$\boldsymbol{w}(X_i, \eta_k) = \frac{\exp(X_i \eta_k)}{1 + \sum_{h \in \mathfrak{K}} \exp(X_i \eta_h)} \tag{2.5.7}$$

The (prior) likelihood contribution of a given individual is then given by:

$$\mathcal{L}_i = \sum_{k \in \mathfrak{K}} \boldsymbol{w}(X_i, \eta_k) \cdot \mathcal{L}_{i,k} \tag{2.5.8}$$

After maximising the product of $\mathcal{L}_i$ over the sample of all subjects, we arrive at our parameter estimates. We find that three preference types account for the heterogeneity in our data sufficiently well.

2.6 Results

In this section, we report the results of the estimated finite-mixture model of our preferred model specification. The parameter estimates of the three preference types are presented in Table 2.6.1. While Type 0 is very risk averse, Type 1 is moderately risk averse and has the lowest trembling hand error parameter. Type 2 tends to make risk-seeking lottery choices, but the estimated scaling parameter λ_l is 1.63 such that in the large-stake domain all types make risk averse choices. The average weights in the sample are 48% for Type 0, 29% for Type 1, 23% for Type 2.

Table 2.6.1. Estimated parameters

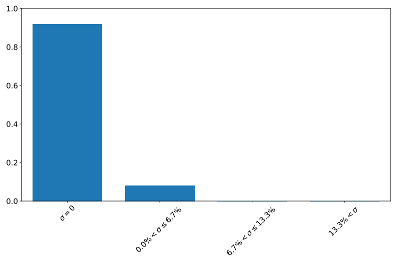
	λ	λ_l	τ_θ	τ_π	ω
Type 0	12.5	1.62	0.00163	1.31	0.287
Type 1	2.88	1.62	0.00163	1.31	0.229
Type 2	0.889	1.62	0.00163	1.31	0.372

The choice probabilities for the portfolio choice are shown in Table 2.6.2. Type 0 individuals barely hold any risky assets (risk category 0). Conversely, households associated with Type 1 invests in no risky assets with 77% probability and in a low-risk portfolio otherwise. Finally, Type 2 individuals invest with a substantial probability in moderate-risk or high-risk portfolios. The last column and Figure 2.6.1 contrast these choice probabilities with the observed portfolio choices. We can fit average behaviour very well.

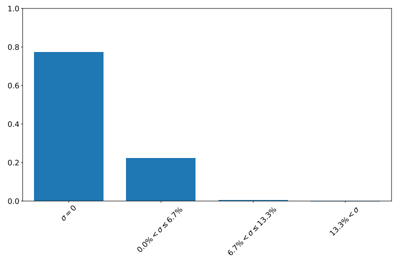
Table 2.6.2. Estimated portfolio choice probabilities

	Type 0	Type 1	Type 2	Total	Observed
Risk Cat 0	0.919	0.773	0.215	0.718	0.712
Risk Cat 1	0.081	0.223	0.258	0.162	0.172
Risk Cat 2	0.000	0.004	0.321	0.074	0.067
Risk Cat 3	0.000	0.000	0.206	0.046	0.049
share	0.482	0.293	0.225	1.000	

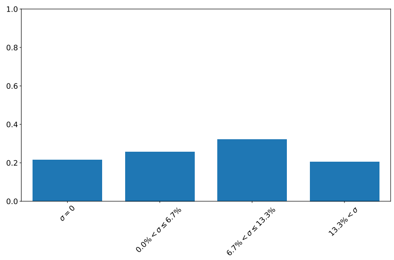
Note: Predicted portfolio risk categories are shown for each type. Risk categories are separated in four groups as described above. The last column shows the observed distribution over those four risk categories. The last row shows the estimated share of each type in the population (type weights).



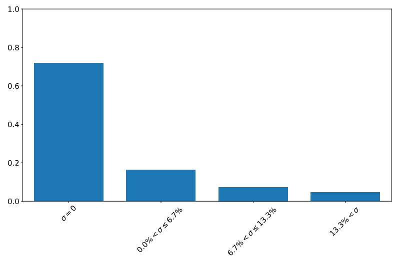
(a) Type 0



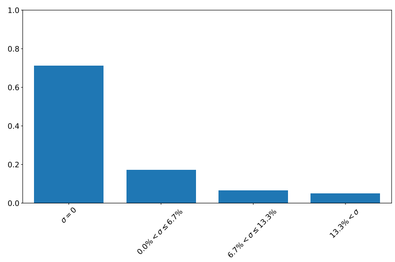
(b) Type 1



(c) Type 2



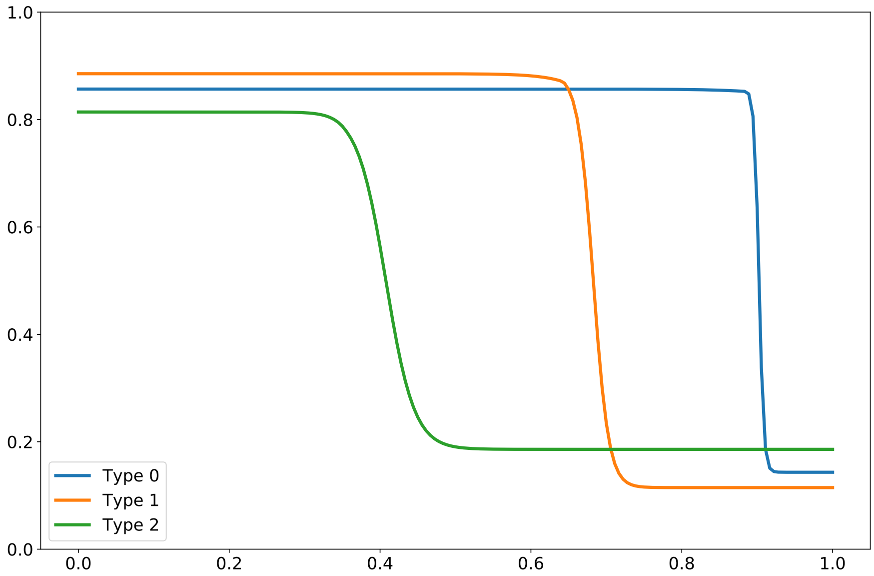
(d) Total



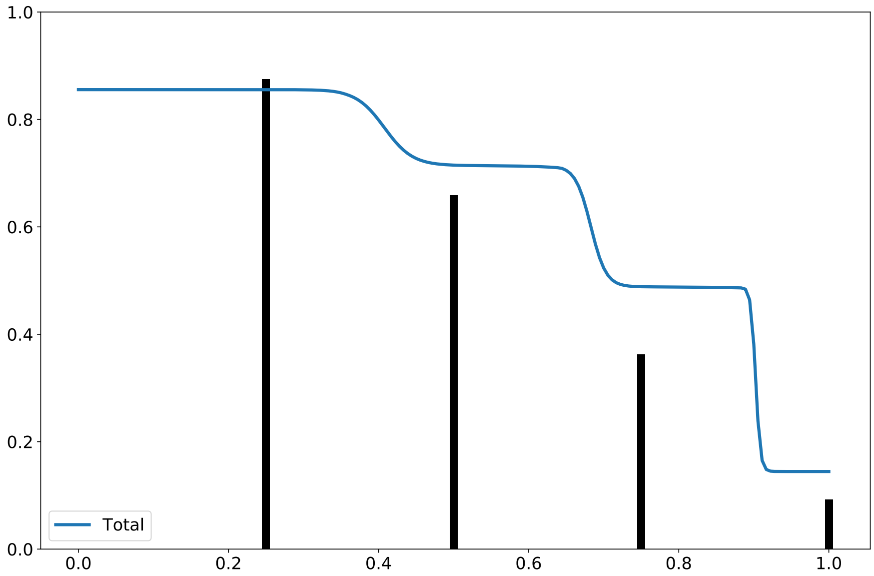
(e) Observed

Figure 2.6.1. Estimated and observed distribution of portfolio choices.

The estimated choice probabilities for gambles are presented in Figure 2.6.3. For specific pay-offs (48, 39) vs (87, 9), it shows the probability to choose the safer gamble (48, 39) depending on the probability of the higher outcome (48 and 87, respectively). As panel (b) reveals, the total (average) choice probabilities fit the observed choice behaviour well.



(a) All types



(b) Observed and Estimated Total

Figure 2.6.3. Choice probabilites for the (48, 39) vs (87, 9) lottery choice for each type in panel (a) and in the aggregate in panel (b) where the bars represent observed choice probabilites.

Table 2.6.3 shows the estimated type predictors η. The results seem very reasonable and align well with previous literature about the distribution of risk preferences. Subjects that are more educated, male or more wealthy are more willing to take risks. These individuals are associated with a higher weight of Type 1 and even more of Type 2. Older subjects, conversely, tend to be more often associated with either Type 0 or Type 2 compared to the sample mean. This is driven by the low error parameter of Type 1.

Table 2.6.3. Estimated type predictors

	Type 1	Type 2
Intercept	-0.367	-1.09
Vocational edu.	0.153	0.305
University edu.	0.519	0.96
Female	-0.778	-1.05
Age 36–50	0.0219	0.226
Age 51–65	-0.413	0.231
Age > 66	-0.462	0.147
Wealth 10k–50k	-0.335	-0.513
Wealth 50–200k	0.289	0.11
Wealth > 200k	0.425	0.497

Note: Estimated predictors for each type are shown. Type 0 is the left out type in the regression.

2.7 Individual-level predictions

One of the central questions of our paper is whether the experimental data help us to predict the preference type of an individual and give meaningful predictions for household portfolio shares. We first present our empirical strategy and show the results afterwards.

2.7.1 Prior and Posterior Distribution of Type Weights

Our benchmark is the choice probabilities that use no information on the type other than X. This is based on the type weights $\boldsymbol{w}(X_i, \hat{\eta}_k)$ implied by the observed covariates X_i and the estimated preference type predictors $\hat{\eta}_k$ and referred to as prior distribution.

Adding the information from the experiment potentially helps us in pinning down the preference type of an individual. It allows us to work with the conditional distribution of the types, given not only the covariates X, but also the observed choices in the experiment, $\tilde{\pi}_i^{obs}$. Using Bayes' Rule, the posterior distribution of preference types is obtained:

$$\boldsymbol{w}^{\text{posterior}}(X_i, \hat{\eta}_k, \tilde{\pi}_i^{\text{obs}}) = \frac{\boldsymbol{w}(X_i, \hat{\eta}_k) \cdot \mathbb{P}\left(\tilde{\pi}_i^{\text{obs}}, \cdot\right)}{\sum_{n \in \mathfrak{K}} \boldsymbol{w}(X_i, \hat{\eta}_n) \cdot \mathbb{P}\left(\tilde{\pi}_i^{\text{obs}}, \cdot\right)}$$

with $\mathbb{P}\left(\tilde{\pi}_i^{\text{obs}}, \cdot\right)$ defined in (2.5.5).

We obtain the predicted portfolio choice probabilities in both cases by multiplying the type weights and the likelihood of portfolio choices conditional on preference type (2.5.3) at the estimated parameter values $\hat{\zeta}$:

$$\mathbb{P}_i(\hat{\zeta}, X_i, \hat{\eta}, \ldots) = \sum_{k \in \mathfrak{K}} \boldsymbol{w}(X_i, \hat{\eta}_k) \cdot \mathbb{P}\left(\hat{\zeta}_k\right) \tag{2.7.1}$$

and

$$\mathbb{P}_i^{\text{posterior}}(\hat{\zeta}, \tilde{\pi}_i^{\text{obs}}, X_i, \hat{\eta}, \ldots) = \sum_{k \in \mathfrak{K}} \boldsymbol{w}^{\text{posterior}}(X_i, \hat{\eta}_k, \tilde{\pi}_i^{\text{obs}}) \cdot \mathbb{P}\left(\hat{\zeta}_k\right) \tag{2.7.2}$$

Figure 2.7.1 shows the prior and posterior distribution of preference types before and after updating. While the weights implied by X_i are all rather close to the population mean, the posterior weights are very precise. In most of the cases the model pins down one type by almost 100%.

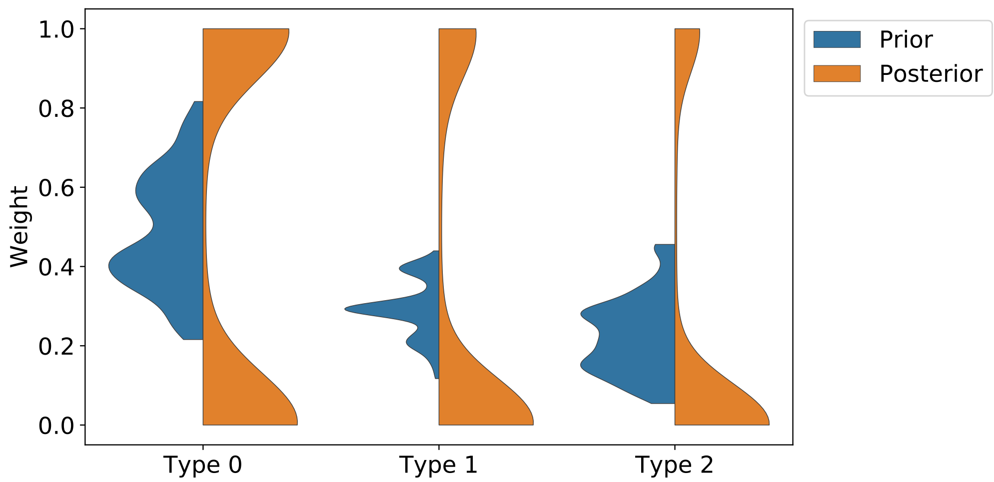


Figure 2.7.1. Prior and posterior distribution of preference type weights

Note: The posterior distribution takes the individual lottery choices into account.

2.7.2 Predicted Portfolio Choice

Making use of these preference type weights, Table 2.A.6 compares the precision for three kind of predictions. The first line uses the unconditional prediction, i.e. the population average for each individual. The second and third line use the prior and posterior distribution as described above. We report three metrics to judge the fit of the predictions. If we take our Likelihood model serious, the log-likelihood presented in the first column is the most relevant one. Columns 2 and 3 present two other commonly used metrics to assess the fit of predictions: the squared and absolute deviation.

Table 2.7.1. Precision of individual level predicitions

Validation Metric	Pf Choice Log-Likelihood	Mean squared deviation	Mean absolute deviation	Gamble Log-Likelihood
Unconditional	-813.168	0.114	0.228	-646.256
Prior	-780.457	0.109	0.220	-500.702
Posterior	-1423.437	0.130	0.218	-444.605

Note: The precision of the prediction of portfolio risk (columns 1 to 3) and a random lottery choice (column 4) are shown for three ways of prediction: first, based on the unconditional distribution, which is based on the observed average. Second, based on the prior distribution of preference weights which takes individual characteristics into account. Third, based on the posterior distribution that, additionally, makes use of the individual lottery choices. The precision of the predictions is evaluated by three different metrics.

The prediction based on the prior distribution performs better than the unconditional distribution according to all metrics. This shows that the structure of our model together with individual demographic characteristics help to explain portfolio choice.

The comparison of the second and third line reveal if the individual level lottery choices improve the prediction further. Although the likelihood contribution improves for 64% of the subjects (not shown), the first column shows that the overall likelihood of the predicted portfolio choices after updating the type weights falls significantly. While the average squared deviation also becomes worse, the average absolute deviation decreases after the updating step which is again driven by the fact that the predictions improve for almost two thirds of the subjects.

The last column confirms that within the small-stake domain, the model helps to predict choices. Predicting one random gamble choice works clearly better when the type weights are updated with the remaining 27 gambles. To summarize our results, by identifying the type of subjects, we are better able to predict choices in the same domain. Too many individuals, however, behave differently across the two domains such that our updated type weights and therefore the prediction based on the posterior distribution, decreases according to two of the three measures we use.

The reason for our overall negative result is that after updating with all gamble choices, the posterior distribution and therefore the portfolio prediction is very precise as shown above. E.g. subjects that make very risk averse lottery choices are given an almost zero probability to hold a medium-risk or high-risk portfolio. However, some of them do invest in any of these categories which strongly decreases the likelihood of our prediction. According to the prior and unconditional distribution all individuals are a true mixture of all three types which is better suitable to fit subjects that make inconsistent choices across domains. In a sense, the data from the gambles are too rich. For lottery choices, we use 28 observations that are all elicited on the same day and therefore quite consistent. The portfolio choice is however summarized by just one choice although it might be the result of several individual choices, as well.[3]

Most importantly, our results imply that the quantitative link we try to establish is too tight to fit observed behaviour in both domains. For a substantial part of the population, modelling attitudes towards risk seems to be insufficient to explain portfolio choice. Richer decision models are necessary that include factors like participation costs or beliefs. For the first, Attanasio and Paiella (2011) shows that plausible levels of participation costs can explain stock market non-participation. For the latter, Hurd and Rohwedder (2011) establishes that households with more optimistic beliefs have a higher likelihood to hold a risky portfolio.

2.8 Conclusion

We establish that preference parameters estimated from experimental lotteries and portfolio choice are related. Second, we estimate a utility specification to explain large-stake portfolio decisions, as well as small-stake lottery choices. The model fits aggregate observed patterns well.

Regarding the individual level prediction of choices, we obtain very mixed results. While we are clearly better able to predict choices in the same domain, we have a much harder time to do so when using individual level lottery choices to infer portfolio choice. On the one hand, the likelihood for two thirds of the households increases and the average deviation decreases. On the other hand, too many subjects behave very different in the two domains and, hence, the likelihood and the average squared deviation of the predictions decreases after making use of the individual lottery choices. The quantitative relationship we tried to establish is too tight to fit observed behaviour.

These results are overall robust to several alternative model specifications. Appendix 2.A reports to of them. Neither removing the scaling parameter nor making

3. An interesting direction of future research could be to make use of multiple elicitations of lottery choices to better understand the stability of risk preferences both within and across domains.

the scaling parameter heterogeneous over types leads to different substantial results: Our model helps to predict within-domain choices, but is not able to fit the full picture of choice behaviour over the two domains.

We discussed explanations for our negative finding. Most importantly, for a substantial part of the population, risk attitudes seem to be of less importance when making portfolio decisions. These results strongly encourage future research about other drivers of portfolio choice. To mind come among other subjective beliefs, participation costs, and cultural factors. One particularly promising area of research is the perceived ambiguity which could explain the results we find. Ambiguity attitudes might drive investment choices, but are not relevant in lottery choices as the winning probabilities are known. A different direction of future research could be to identify subgroups of households for which risk preferences as measured in economic experiments are indeed important and others for which this is not the case. This approach has been followed by Drerup, Enke, and von Gaudecker (2017) for subjective expectations.

Appendix 2.A Alternative Model Specifications

2.A.1 Heterogeneous Scaling Parameter

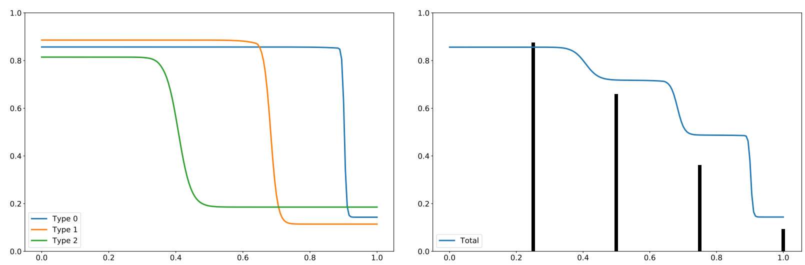
The following specification allows the scaling parameter λ_l to vary over types. The results with respect to predicted lottery portfolio choices and the precision of predictions are very similar.

Table 2.A.1. Results – estimated parameter

	λ	λ_l	τ_θ	τ_π	ω
Type 0	12.5	-2.01	0.00126	1.32	0.286
Type 1	2.88	0.584	0.00126	1.32	0.228
Type 2	0.888	1.62	0.00126	1.32	0.371

Table 2.A.2. Results – simulated and observed portfolio shares

	Type 0	Type 1	Type 2	Total	Observed
Risk Cat 0	0.948	0.710	0.200	0.712	0.712
Risk Cat 1	0.052	0.278	0.255	0.164	0.172
Risk Cat 2	0.000	0.012	0.347	0.080	0.067
Risk Cat 3	0.000	0.000	0.198	0.044	0.049
share	0.482	0.298	0.221	1.000	



(a) All types **(b)** Observed and Estimated Total

Figure 2.A.1. Choice probabilites for the (48, 39) vs (87, 9) lottery choice where the bars represent observed choice probabilites.

Table 2.A.3. Individual Level Predicitions

Validation Metric	Pf Choice Log-Likelihood	Mean squared deviation	Mean absolute deviation	Gamble Log-Likelihood
Unconditional	-813.168	0.114	0.228	-646.256
Prior	-779.200	0.109	0.221	-500.727
Posterior	-1449.232	0.133	0.219	-444.682

2.A.2 No Scaling Parameter (4 Types)

The following specification sets $\lambda_l = 0$. For this specification four types seem to be necessary to fit the observed heterogeneity.

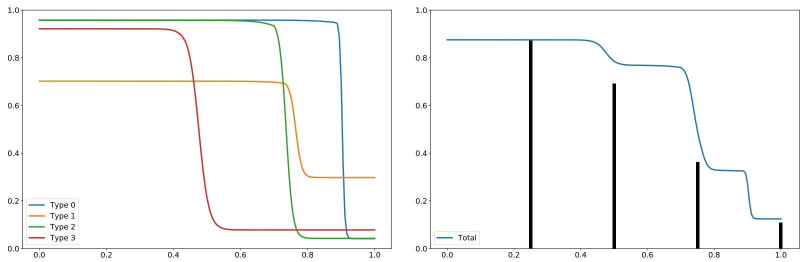
Type 3 is almost risk-neutral and invests only in the highest risk category. The model therefore predicts also in the whole population a too high investment in risk category 4 (0.127 vs the observed 0.049).

Table 2.A.4. Results – estimated parameter

	λ	τ_θ	τ_π	ω
Type 0	12.6	0.0026	1.51	0.0836
Type 1	4.36	0.0026	1.51	0.596
Type 2	3.74	0.0026	1.51	0.0853
Type 3	1.25	0.0026	1.51	0.156

Table 2.A.5. Results – simulated and observed portfolio shares

	Type 0	Type 1	Type 2	Type 3	Total	Observed
Risk Cat 0	0.815	0.659	0.600	0.000	0.590	0.712
Risk Cat 1	0.184	0.312	0.343	0.000	0.255	0.172
Risk Cat 2	0.002	0.028	0.054	0.001	0.028	0.067
Risk Cat 3	0.000	0.001	0.003	0.999	0.127	0.049
share	0.222	0.304	0.347	0.126	1.000	



(a) All types **(b)** Observed and Estimated Total

Choice probabilites for the (48, 39) vs (87, 9) lottery choice. The bars represent observed choice probabilites.

Figure 2.A.3. Choice probabilites for the (48, 39) vs (87, 9) lottery choice

Table 2.A.6. Individual Level Predicitions

Validation Metric	Pf Choice Log-Likelihood	Mean squared deviation	Mean absolute deviation	Gamble Log-Likelihood
Unconditional	-813.168	0.114	0.228	-640.598
Prior	-867.432	0.119	0.259	-471.317
Posterior	-2017.157	0.181	0.278	-383.292

Appendix 2.B Calculating Utility for Non-Optimal Portfolio Shares

In order to calculate the portfolio choice probabilities (2.5.3), we need to calculate the utility at **all** potential portfolio shares, not just the optimal ones. This requires a choice about what agents expect to do in future periods: The two polar cases are sticking to the non-optimal choice forever or expecting to revert to optimal behaviour in $t+1$. We assume the latter for two reasons. First, we find it more appealing intuitively Second, it is more attractive from a computational standpoint. In particular, the first-order condition for consumption (2.4.9) is undefined if B_t becomes negative. This can happen if the narrow framing component has a lot of weight. This is never the case in the optimum, because agents would just avoid investments in narrowly framed assets.

We thus proceed as follows.

1. Using Equations (2.4.8) and (2.4.9) in conjunction with (2.4.2), we calculate $V^*_{t+1}(W_{t+1}=1)$ assuming optimal and stationary choices from period $t+1$ onwards. We thus obtain the optimal long-term choices θ^* and $^{C^*}/_{W}$.
2. We then calculate $V_t(W_t, \theta_i)$ using the formula:

$$V_t(W_t,\theta_i) = \Bigg((1-\beta)\cdot(C^*)^{1-\rho} + \beta\cdot\left(W_t - C^*\right)^{1-\rho} \cdot\left(\mu\left(V^*_{t+1}(W_{t+1} = 1)\cdot\theta_i\cdot\tilde{R}_{t+1}\right) + b_0\cdot\sum_{m\in\mathfrak{M}}\nu(\theta_i\cdot(\tilde{R}_{t+1}-R_f))\right)^{1-\rho} \Bigg)^{\frac{1}{1-\rho}}$$

We would still run into problems if (negative) b_0 …dominates μ, but these should be much more rare than for the previous case of the first order condition. Might still be useful to check for some extreme numbers once we have an idea of what μ looks like. Solution could be to get rid of Epstein-Zin part, as suggested at ECB conference by Michalis.

Table 2.C.1. Portfolio variables, descriptions

Level 0	Level 1	Level 2	Level 3	Level 4
Mutual funds	Mutual and growth funds	Risky financial assets	Total financial assets	Total assets
Growth funds	Mutual and growth funds	Risky financial assets	Total financial assets	Total assets
Shares	Shares	Risky financial assets	Total financial assets	Total assets
Bonds (sovereign, corporate, mortgage)	Bonds and options	Risky financial assets	Total financial assets	Total assets
Options	Bonds and options	Risky financial assets	Total financial assets	Total assets
Checking account with positive balance	Checking and savings accounts	Safe financial assets	Total financial assets	Total assets
Savings and deposit accounts	Checking and savings accounts	Safe financial assets	Total financial assets	Total assets
Bank certificates and deposits	Checking and savings accounts	Safe financial assets	Total financial assets	Total assets
Saving certificates	Checking and savings accounts	Safe financial assets	Total financial assets	Total assets
Saving or endowment insurance policy	Cash value of insurances	Safe financial assets	Total financial assets	Total assets
Mortgage-related life insurance	Cash value of insurances	Safe financial assets	Total financial assets	Total assets
Life-cycle savings plan	Cash value of insurances	Safe financial assets	Total financial assets	Total assets
Single premium annuity insurance policy	Cash value of insurances	Safe financial assets	Total financial assets	Total assets
Boat	Durables	Non-financial assets (excl. real estate)	Total non-financial assets	Total assets
Car	Durables	Non-financial assets (excl. real estate)	Total non-financial assets	Total assets
Caravan	Durables	Non-financial assets (excl. real estate)	Total non-financial assets	Total assets
Motorbike	Durables	Non-financial assets (excl. real estate)	Total non-financial assets	Total assets
Business equity	Other non-financial assets	Non-financial assets (excl. real estate)	Total non-financial assets	Total assets
Money lent to family/friends	Other non-financial assets	Non-financial assets (excl. real estate)	Total non-financial assets	Total assets
Assets not mentioned in other categories	Other non-financial assets	Non-financial assets (excl. real estate)	Total non-financial assets	Total assets
Primary housing	Primary housing	Total real estate	Total non-financial assets	Total assets
Secondary housing	Total secondary real estate	Total real estate	Total non-financial assets	Total assets
Other real estate	Total secondary real estate	Total real estate	Total non-financial assets	Total assets
Credit-card debt	Total consumer credit	Total non-mortgage debt	Total debt	Total debt
Extended lines of credit	Total consumer credit	Total non-mortgage debt	Total debt	Total debt
Other consumer credit	Total consumer credit	Total non-mortgage debt	Total debt	Total debt
Private loan	Total consumer credit	Total non-mortgage debt	Total debt	Total debt
Hire purchase contracts	Total consumer credit	Total non-mortgage debt	Total debt	Total debt
Checking account with negative balance	Total consumer credit	Total non-mortgage debt	Total debt	Total debt
Student loan	Total consumer credit	Total non-mortgage debt	Total debt	Total debt
Borrowed from friends/family	Other debt	Total non-mortgage debt	Total debt	Total debt
Debts not mentioned in other categories	Other debt	Total non-mortgage debt	Total debt	Total debt
Mortgage on primary housing	Mortgage on primary housing	Total mortgage debt	Total debt	Total debt
Mortgage on secondary housing	Total mortgages on secondary real estate	Total mortgage debt	Total debt	Total debt
Mortgage on other real estate	Total mortgages on secondary real estate	Total mortgage debt	Total debt	Total debt

Appendix 2.C Additional Figures and Tables

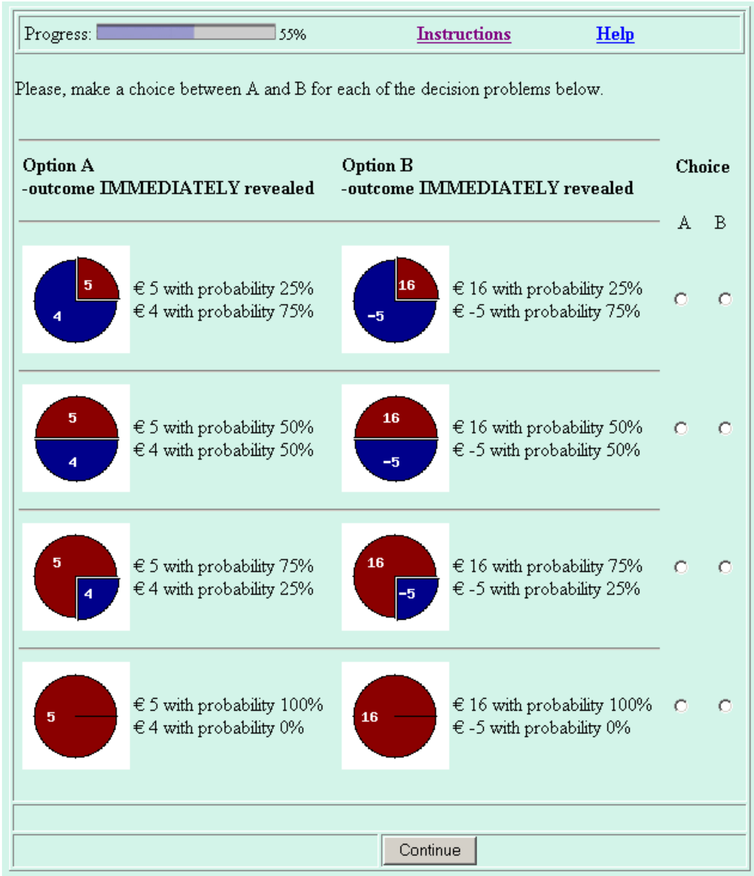


Figure 2.C.1. First screen of a lottery in our experiment (sheet 5).

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Chapter 3

The Distribution of Ambiguity Attitudes

Joint with Hans-Martin von Gaudecker and Axel Wogrolly

3.1 Introduction

Economists typically assume that households have precise knowledge of the relevant probability distribution when taking decisions in non-deterministic contexts. There is mounting evidence that this may not be the case. Elicitations of subjective beliefs regularly reveal violations of the basic axioms of probability theory (e.g. Hurd, 2009) and, when asked, people often express their uncertainty about probability distributions (Bruine de Bruin, Fischhoff, Millstein, and Halpern-Felsher, 2000). Imprecise belief measures translate into low explanatory power of economic models for decisions (Drerup, Enke, and von Gaudecker, 2017). Belief dispersion is high even in contexts where private information should not play a major role (e.g. Manski, 2004).

Consequently, there has been a proliferation of theoretical (Ghirardato and Marinacci, 2001; Klibanoff, Marinacci, and Mukerji, 2005; Chateauneuf, Eichberger, and Grant, 2007) and empirical work ((see, e.g., Butler, Guiso, and Jappelli, 2014; Trautmann and van de Kuilen, 2015; Li, Müller, Wakker, and Wang, 2018)) regarding decisions in situations of ambiguity, i.e., those where subjects are uncertain about the correct probability distribution to employ. Overall, we still know much less about ambiguity preferences than about attitudes towards risk or discounting behaviour. Empirical studies have been largely confined to eliciting ambiguity based on Ellsberg (1961), which involves choices about artificial events of unknown distributions (Dimmock, Kouwenberg, Mitchell, and Peijnenburg, 2015; Dimmock, Kouwenberg, and Wakker, 2015; Dimmock, Kouwenberg, Mitchell, and Peijnenburg, 2016; Bianchi and Tallon, 2018; Delavande, Ganguli, and Mengel, 2019).

We add to a recent literature that aims to measure ambiguity attitudes for natural events (Abdellaoui, Baillon, Placido, and Wakker, 2011; Baillon and Bleichrodt, 2015; Baillon, Bleichrodt, Keskin, l'Haridon, and Li, 2018; Anantanasuwong, Kouwenberg, Mitchell, and Peijnenberg, 2019). Ours is the first study to examine incentivised measures of ambiguity attitudes towards natural events in a representative sample over time and across domains.

To measure ambiguity, we adapt the design of Baillon, Huang, Selim, and Wakker (2018) for use in a representative survey. Using high-powered financial incentives, we elicit four waves of ambiguity attitudes in the context of the stock market over a span of two years; in the fourth wave, we additionally elicit measures from the domain of climate change. Beyond a base payment for survey participation, each individual could earn €20 per wave. Depending on individuals' choices, payment was based on the evolution of a stock market index over the subsequent six month-period or the outcome of a lottery. Expected incentive payments for a rational decision-maker using empirical frequencies for stock returns were €13.5, or an hourly wage of €51.4. On average, we have 92 (minimum: 21, maximum 116) binary decisions at the individual level.

Subjects make several binary decisions between an option whose payoff depends on the development of the stock market and a risky option whose payoff occurs with a known probability. Varying the probabilities of the risky option reveals an individual's *matching probability*; the probability of the lottery at which the subject is indifferent between the two options. We elicit matching probabilities for seven events that depend on the development of the stock market. The distribution of matching probabilities has three salient features. First, the sum of the matching probabilities for an event and its complement is clearly less than one. This indicates that on average, subjects are averse to ambiguity. Second, average matching probabilities are *sub-additive*, the sum of matching probabilities of two mutually exclusive events exceeds the matching probability of their union. This implies individuals are ambiguity-averse for high-probability events and ambiguity-seeking for low-probability events on average (see also Wakker, 2010; Enke and Graeber, 2019). Third, a non-negligible fraction of choice patterns cannot be rationalised by any deterministic theory of choice under uncertainty that we know of. In particular, 57% of subjects at some point assign a higher matching probability to an event that is a strict subset of another.

Based on these observations, we build a model that extracts individual ambiguity attitudes from observed choices whilst accounting for decision errors. Choices depend on three parameters: Ambiguity aversion, which is the average difference between subjective probabilities and matching probabilities. Likelihood insensitivity, which measures how strongly matching probabilities react to underlying changes in subjective probabilities, which can also be interpreted as the perceived level of ambiguity. Finally, the variance of a random component that affects choices for each event. We structurally estimate these three parameters for each respondent using individual-level choices.

Our first conclusion from this exercise is that ambiguity attitudes are very heterogeneous between respondents, each parameter takes on values within its entire domain. Within respondents, parameters are quite stable; wave to wave correlations average 0.25 for ambiguity aversion and 0.31 for likelihood insensitivity. This is comparable to the stability of risk preferences over similar time spans (Chuang and Schechter, 2015). Within-respondent variation in ambiguity attitudes exhibits no systematic trend over time and bears no meaningful relation to observed characteristics. We interpret this variation as being driven by random fluctuations around a stable mean and by measurement error, which is very prevalent in similar tasks (Gillen, Snowberg, and Yariv, 2018).

Across domains, ambiguity attitudes are more stable than previously thought. The panel dimension of our data allows us to adjust for attenuation due to measurement error by instrumenting parameter estimates with those of previous waves. We find that ambiguity aversion is completely transferable between the domains of finance and climate change but that likelihood insensitivity is not. Our results thus suggest that ambiguity aversion is a domain-invariant preference parameter but that likelihood insensitivity consists of both a transferable and a domain-specific component, which aligns well with the interpretation according to which likelihood insensitivity is the perceived level of ambiguity.

To describe between-respondent heterogeneity in the three dimensions of ambiguity aversion, likelihood insensitivity and the variance of decision errors, we re-estimate the model, pooling data across all waves and assign individuals into groups based on the *k*-means algorithm. Four groups suffice to highlight the most important differences in ambiguity attitudes and their correlates. Almost thirty per cent of the subjects are characterised by a high level of perceived ambiguity and ambiguity aversion. Females, individuals with lower numeracy, higher levels of risk aversion, lower wealth and individuals who perceive positive stock market returns to have occurred less frequently are more likely to belong to this group. Nearly a fifth of participants perceive a similar level of ambiguity but are ambiguity-seeking, not averse. They differ from individuals of the first group in that they are less risk-averse and hold more financial assets. The next group, a third of the population, perceives little ambiguity and is neutral towards it, coming close to expected utility maximising behaviour. High probability and financial numeracy, substantial financial assets and thinking historical returns have often been positive are predictive of belonging to this group. The final group, less than a fifth of subjects, makes more erratic decisions, which prevents reliable measurement of their ambiguity attitudes. Individuals in this group tend to be older, male, have lower rates of numeracy and less knowledge of historical stock returns.

In the next section, we describe the data, the design of our survey instrument and we develop stylised facts that motivate our model. We discuss the identification and estimation of our model in Section 3.3. Section 3.4 presents our estimation results; we conclude in Section 3.5.

3.2 Data, design, and stylised facts

Our data originate from the LISS panel (Longitudinal Internet Studies for the Social Sciences), an online household panel representative of the Dutch population. Participants answer questionnaires exclusively reserved for research every week and are financially compensated for all questions they answer. Our sample consists of the financial deciders within each household.

In this section, we first present the available background information in the LISS panel, some of which was tailored to our application. Then, we describe our design and highlight some regularities in the choice data it produces.

3.2.1 Background characteristics

In the LISS panel, a variety of information about the households including detailed background characteristics and wealth data is elicited yearly or bi-yearly. Table 3.2.1 shows the demographics of our sample. The gender split is even. In terms of age, the fraction of 45 to 65-year-olds in our sample is 36 % which is similar to the population-based on aggregate data from Statistics Netherlands (CBS), excluding individuals aged below 20. We have fewer individuals aged 20 to 45 than in the population (25 % compared to 40 %) and more aged 65 to 85 (33 % compared to 18 %). Our sample is also somewhat better educated, with the top two categories of education equalling 13 % and 28 % compared to 11 % and 19 % in the population. These age and education discrepancies with the population are to be expected given that our sample consists of the financial deciders in each household. Income and financial assets are pooled within households. Mean yearly income is close to €28700, mean financial assets are €54800. These are close to the population-wide household numbers in 2018 which were €29500 and €57800 respectively.

During our data collection, as well as in an extra wave in January 2019, we elicited several additional measures to better understand potential drivers of heterogeneity in ambiguity attitudes:

Risk Aversion. One important characteristic that might be related to ambiguity attitudes is risk aversion. We measure households' risk aversion with a preference survey module designed by Falk, Becker, Dohmen, Huffman, and Sunde (2016) which includes a qualitative component, a general risk question, and a quantitative component that is based on elicited certainty equivalents for risky lotteries. We combine the quantitative and qualitative components as suggested in Falk et al. (2016).

Numeracy. The ability to reason quantitatively is particularly important when making decisions under uncertainty. We measure three components of numeracy. First, a basic numeracy component based on the English Longitudinal Study of Ageing (Steptoe, Breeze, Banks, and Nazroo, 2013). Second, a financial numeracy component that involves interest rates and inflation for which we used a subset of the

Table 3.2.1. Summary statistics

	Observations	Mean	Std. dev.	$q_{0.25}$	$q_{0.5}$	$q_{0.75}$
Female	2235	0.5				
Education: High school or less		0.35				
Education: Junior college		0.24				
Education: College		0.28				
Education: University		0.13				
Age: $\in (20, 45]$	2231	0.25				
Age: $\in (45, 65]$		0.37				
Age: $\in (65, 80]$		0.33				
Age: > 80		0.05				
Income (thousands)	1806	2.39	1.49	1.5	2.17	3
Financial assets (thousands)	1838	54.8	157.37	2.38	15	46.69

Notes: Sample restrictions: Individuals with at least two waves of regular choices in the ambiguity tasks. Choices are irregular if they exhibit recurring patterns whilst also being entered quicker than 85 % of subjects. Income and assets are pooled within households, data from 2018.

questions by van Rooij, Lusardi, and Alessie (2011). Third, a probability numeracy component that tests both basic understanding of probabilities and more advanced concepts such as independence and additivity. We use the questions proposed by Hudomiet, Hurd, and Rohwedder (2018) and additionally add two questions that could be particularly informative about the types of errors that can occur when individuals make decisions in our design. We aggregate the three components into a numeracy index, giving equal weight to each component.

Our measures of numeracy and risk aversion are related to socio-demographics characteristics as in the previous literature (e.g., Dohmen, Falk, Huffman, Sunde, Schupp, et al., 2011; van Rooij, Lusardi, and Alessie, 2011; Hudomiet, Hurd, and Rohwedder, 2018): Older, less educated, and female subjects tend to have lower numeracy skills and are more risk-averse (Table 3.A.2).

Judged historical frequencies of past AEX returns. We also asked individuals to judge how frequently the AEX events used in our designs occurred over the last 20 years. Although there is substantial individual heterogeneity, the last column of Table 3.2.2 shows that the average judged frequencies are not too far from the empirical frequencies. Subjects underestimate the frequency of positive returns on average but think returns greater than 10 % occurred more often than they did.

Optimism. Optimism is a potential determinant of ambiguity attitudes. We elicited optimism and pessimism measures based on the revised life orientation test (**scheier1994distinguishing**), combining them into an overall measure of optimism.

Knowledge of and concern about climate change. To help analyse ambiguity attitudes towards climate change, we asked subjects to report (i) their understanding of the causes and implications of climate change on a five-point scale and (ii) whether climate change is a threat to them and their family on a six-point scale.

3.2.2 Measuring ambiguity attitudes

Our goal is to investigate the distribution and stability of ambiguity attitudes in a representative population. In our main application, we choose the stock market as the source of uncertainty, since decisions under ambiguity are very prevalent in this domain. Furthermore, the subjects are unable to influence the outcome in this context which allows for the incentivisation of their choices. As a benchmark for the stock market, we employ the Amsterdam Exchange Index (AEX), the most important stock index in the Netherlands. Individuals make several binary decisions between an option whose payoff depends on the development of the AEX over the next six months and an option whose payoff occurs with a known probability.

When measuring ambiguity attitudes about natural events, the challenge is to control for any subjective beliefs individuals may hold about them. Suppose we observe individuals refrain from tying their payoff to an increase of the AEX index. This could be either because they perceive AEX returns as ambiguous and are averse to such ambiguity, or because they consider positive AEX returns to be unlikely. To disentangle the two explanations based only on observed choices, we use the design of Baillon, Huang, et al. (2018) in which the role of subjective beliefs is neutralised by having individuals make decisions about events and also the complement of events.

One example of a binary choice situation that forms the core of our design is visualized in Figure 3.2.1. Option 1 pays twenty Euros if the performance of a hypothetical €1000 investment in the AEX over the next six months is within a certain range. In this example, twenty Euros will be paid if the investment is worth more than €1100 in six months, i.e. an increase of more than 10 %. Option 2 is a lottery and pays twenty Euros with probability 50 %, visualised by a pie chart.

Multiple choices between such options provide information about the *matching probability* an individual assigns to the AEX event, which is defined as follows:

Definition 1 (Matching probability)**.** The matching probability $m(E)$ of an event E is the probability p that makes a decision-maker indifferent between a pay-out of X if event E occurs and a bet on a lottery that pays X with probability p.

A chained design of 3–4 binary choices is used to identify the matching probability of an event. Compared to a choice list format, we expect this procedure to reduce complexity for the subjects as they can focus on one question at a time. After every choice, the probability of Option 2 changes depending on the previous choice, pinning down the matching probability to within 0.1. The complete decision tree is shown in Figure 3.B.1.

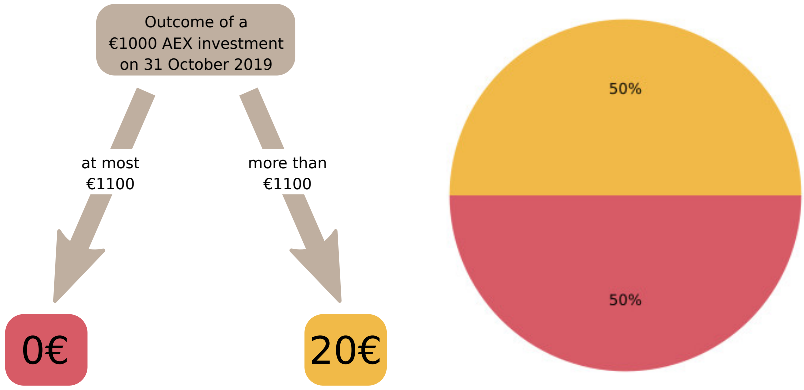

Figure 3.2.1. Exemplary binary choice situation: ambiguous option and risky option

Notes: Labels are translated from Dutch to English.

Following the logic of the design by Baillon, Huang, et al. (2018), we partition the space of possible values the AEX investment can take into three events: $E_1 : Y_{t+6} \in (1100, \infty]$, $E_2 : Y_{t+6} \in (0, 950)$, and $E_3 : Y_{t+6} \in [950, 1100]$. We chose this partition to balance historical 6-month returns of the AEX, for which the respective frequencies were 0.24, 0.28 and 0.48. We elicit matching probabilities for each of these events as well as their complements but initiate respondents by having them first consider the more intuitive event $E_0 : Y_{t+6} \in (1000, \infty]$, i.e. that the value of the investment will increase. The resulting seven events for which we elicit matching probabilities are depicted in Figure 3.2.2.

Because eliciting attitudes about ambiguous events comes with a substantial cognitive burden for participants, we try to make the design as easy to comprehend as possible. We included a tutorial in the design that introduces participants to the choices and their potential consequences.

To analyse stability over time, we repeat the elicitation procedure just described four times. The design was semi-annually rolled out alongside the regular core questionnaires of the LISS panel. We have collected data from waves in May 2018, November 2018, May 2019, and November 2019. Originally, 2773 financial deciders were invited to participate, of which 2146, 2170, 2000, and 1957 completed the questionnaire in the respective waves. One of the binary choices in every wave is played out half a year later, at the start of the next questionnaire, with a possible pay-out of twenty Euros depending on the development of the AEX and chance.[1]

1. Because the choice at each node determines the options at the subsequent node, the design would not be incentive compatible if we selected one of the answered questions for pay-out ex-post. To circumvent this problem, the question that is paid out is selected out of all 91 possible choice situations before the specific subject made any decisions. If the subject did not encounter the selected question during the questionnaire because it was in a different branch of the decision tree, the question is additionally asked at the end of the questionnaire. This mechanism is inspired by Johnson, Baillon,

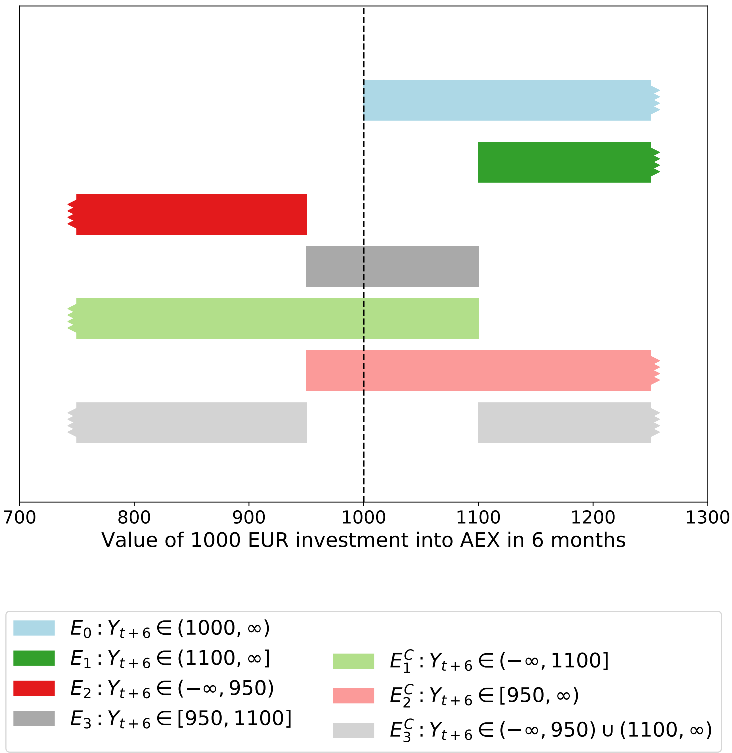

Figure 3.2.2. Events of AEX performance used in the experiment

3.2.3 Matching probabilities and errors

Next, we analyse the distribution of matching probabilities and develop several insides that we use later to build up the empirical model.

Some individuals pick the same option throughout an entire wave, i.e. 28 times in a row. This behaviour could be interpreted as an extreme form of ambiguity aversion or ambiguity seeking but an alternative explanation is that some individuals do not seriously contemplate the choices. As Figure 3.B.2 shows, many of these subjects go through the questionnaire much faster than the rest which points to the latter explanation. We drop subjects if two conditions are met. First, their answers exhibit such patterns and second, their average response time on the first decision for each event is below the 15th percentile of all subjects. We exclude such individuals from the analysis on a wave by wave basis which decreases the sample size by 2.5 %.

As the mean of matching probabilities within events is fairly stable across waves (see Table 3.A.1), Table 3.2.2 depicts summary statistics of the elicited matching

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Bleichrodt, Li, van Dolder, et al. (2015) and has been implemented in a similar fashion by Bardsley (2000). The fact that the choice that is paid out is pre-selected also prevents the subjects from hedging against the encountered ambiguity (Baillon, Halevy, and Li, 2014) probabilities pooled across all waves. The last two columns show the empirical frequencies with which the events occurred and the mean judged historical frequencies reported by the subjects.

Table 3.2.2. Matching probabilities, empirical frequencies and judged historical frequencies

	Mean	Std. dev.	$q_{0.1}$	$q_{0.5}$	$q_{0.9}$	Empirical Frequency	Judged Hist. Frequency
$E_0 : r > 0\%$	0.51	0.28	0.08	0.45	0.92	0.63	0.52
$E_1 : r > 10\%$	0.35	0.25	0.03	0.35	0.75	0.24	0.31
$E_1^C : r \leq 10\%$	0.53	0.29	0.15	0.45	0.97	0.76	
$E_2 : r < -5\%$	0.37	0.27	0.03	0.35	0.75	0.28	0.22
$E_2^C : r \geq -5\%$	0.54	0.30	0.08	0.55	0.97	0.72	
$E_3 : -5\% \leq r \leq 10\%$	0.57	0.29	0.15	0.55	0.97	0.48	0.47
$E_3^C : (r < -5\%) \cup (r > 10\%)$	0.41	0.28	0.03	0.35	0.85	0.52	

Notes: Events were asked about in this order: $E_0 - E_1 - E_2 - E_3 - E_1^C - E_2^C - E_3^C$. Summary statistics for the matching probabilities of the seven events are shown. Matching probabilities are set to the midpoint of the interval identified by the design. Data is pooled across all waves. The last two columns show the empirical frequencies (starting from 1992, own calculation) and the mean judged historical frequencies (reported by the subjects). Sample restrictions: Individuals with at least two waves of regular choices. Choices are irregular if they exhibit recurring patterns whilst also being entered quicker than 85% of subjects.

Three observations can be made. First, the sum of the average matching probabilities of an event and its complement event, e.g. E_1 and E_1^C is less than 1 for all three events E_1, E_2 and E_3. This is an indication that matching probabilities do not equal subjective probabilities, and that individuals experience ambiguity aversion on average. Second, mean matching probabilities are on average *sub-additive*, in the sense that the sum of the matching probabilities of E_1 and E_2 is well above the average matching probability of their union, E_3^C. The same relation is found for the other combinations of two single events. Third, the average matching probability for E_3 is slightly larger than E_1^C or E_2^C. This is surprising because E_3 is a subset of the other two events, and subsets cannot be considered more attractive bets than supersets under any reasonable theory.

If this *set-monotonicity* requirement is violated, it is an indication of a decision error. There are eight pairs of events at which such an error can occur. In total, 57 % of individuals violate set-monotonicity at least once in a given wave. The rate of set-monotonicity violations for a given superset-subset pair depends on the difference of judged historical frequencies of the two events – both in the aggregate (Table 3.A.3) and on the individual level (Table 3.A.4). This is an indication that erroneous answers are not driven by random behaviour alone, but also depend on the events involved. This informs how we specify the error component in our model.

To analyse stability across domains, in the 4th wave we additionally elicit ambiguity attitudes in another domain: climate change. We use the same setup as before, replacing events relating to the AEX with events relating to mean temperature changes during the winter 2019/2020 compared to the previous five winters. The possible temperature changes are partitioned into three events, using cut-offs at +1°C and -0.5°C. We elicit matching probabilities for the three single events, the three complementary events, and the additional event that the temperature change is at least +0°C. Table 3.A.5 shows summary statistics of the matching probabilities.

3.3 Empirical strategy

Based on the observations in the last section, we now introduce the empirical model we use to estimate ambiguity attitudes.

3.3.1 Defining and interpreting ambiguity attitudes

We build upon the bi-separable utility framework of Ghirardato and Marinacci (2001). In that framework, a prospect that pays out X if event E occurs and otherwise nothing is evaluated as $W(E) \cdot V(x)$ where $V(\cdot)$ can be any utility function and $W(\cdot)$ a *decision weight*. W satisfies the following conditions $W(\emptyset) = 0$, $W(\Omega) = 1$, and $B \subseteq A \implies W(B) \leq W(A)$. We assume the decision weight depends on the subjective probability agents assign to the event, where the relation between the two is governed by a *source function* w_S such that $W(E) = w_S(\Pr(E))$ (Abdellaoui et al., 2011).[2] The subscript indicates that the function depends on the source of uncertainty, which is the mechanism that generates it. In this paper, we examine uncertainty about the future development of the AEX and uncertainty about temperature changes.

A subject is ambiguity-averse for an event E if $W(E) < \Pr(E)$, ambiguity-neutral if $W(E) = \Pr(E)$, and otherwise ambiguity-seeking. There is empirical evidence that the degree of ambiguity aversion about an event varies with the subjective probability the decision-maker assigns to it. When individuals stand to gain if an uncertain event occurs, the most common pattern is ambiguity seeking for events individuals regard as long shots and ambiguity aversion for medium or high probability events (Trautmann and van de Kuilen, 2015).

To capture both average ambiguity aversion and its dependence on the subjective probability, we specify $w_S(\Pr(E))$ as the *neoadditive* function introduced by Chateauneuf, Eichberger, and Grant (2007) which has been shown to fit choices very well in settings where both decisions and $\Pr(E)$ are observed (Li et al., 2018).

2. Individuals can be thought of as having subjective probabilities in mind or as making choices that can be rationalized with them.

$$
\begin{aligned}
W(E) &= \tau_0 + \tau_1 \cdot \Pr(E), \text{ for } \Pr(E) \in (0,1) \\
W(\varnothing) &= 0, W(\Omega) = 1 \\
0 &\leq \tau_1 \leq 1, 0 \leq \tau_0 \leq 1 - \tau_1
\end{aligned}
$$

The conditions on the parameters ensure that $W(E)$ equals 0 and 1 only for events agents regard as impossible or certain, unless $\tau_1 = 0$ and subjective probabilities play no role at all. They also rule out that individuals assign a greater weight to events they regard as less probable[3].

In terms of τ_0 and τ_1 we can define two ambiguity parameters:

$$
\begin{aligned}
&\text{Ambiguity aversion} & \alpha &= \frac{1 - 2\tau_0 - \tau_1}{2} & &= E[\Pr(E) - W(E)] & (3.3.1) \\
&\text{Likelihood insensitivity} & \ell &= 1 - \tau_2 & &= 1 - \frac{Cov(W(E), \Pr(E))}{Var(\Pr(E))} & (3.3.2)
\end{aligned}
$$

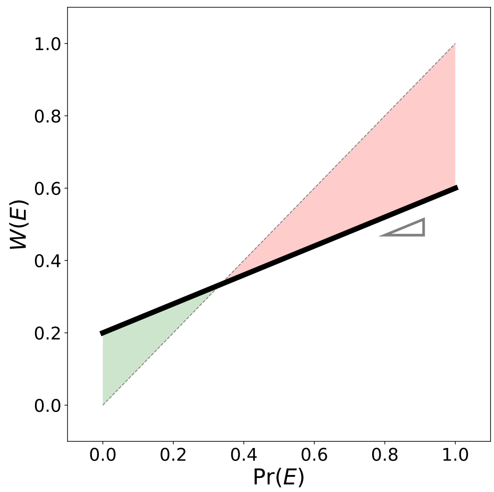

Figure 3.3.1. Ambiguity aversion and likelihood insensitivity with a neoadditive source function

Notes: The figure plots the neoadditive source function $W(E) = \frac{\ell}{2} - \alpha + (1 - \ell) \cdot \Pr(E)$ for $\alpha = 0.1$ and $\ell = 0.6$. Ambiguity aversion α is the red area between $\Pr(E) - W(E)$ where the difference is positive less the green area where the difference is negative. It also equals the distance $Pr(E) - W(E)$ at $\Pr(E) = 0.5$. Likelihood insensitivity is 1 minus the slope of the source function (black line) which is indicated by a grey triangle.

Ambiguity aversion is the average amount by which subjective probabilities exceed decision weights, where we average across all subjective probabilities in the unit interval with equal weight. For the neoadditive function, this is equivalent to

3. In the previous section, we documented that there are set-monotonicity errors for a sizable fraction of individuals, which is an example of giving greater weight to an event that must be less probable. This is one of the reasons we augment the deterministic neoadditive model with a random error component when we estimate it.

$Pr(E) - W(E)$ at $\Pr(E) = 0.5$. Likelihood insensitivity captures the extent to which individuals' decision weights change if the underlying subjective probabilities change. This is 1 minus the slope of the source function, $1 - \tau_1$. Figure 3.3.1 illustrates the concepts for $\alpha = 0.1$ and $\ell = 0.6$. Lower τ_1 and therefore higher ℓ corresponds to a flatter function, i.e. event weights are less responsive to subjective probabilities. An increase of α, on the other hand, corresponds to a downwards shift of $W(E)$ for all subjective probabilities. The range of possible values for α is determined by the level of ℓ. Only for $\ell = 1$, the maximum level of ambiguity aversion ($W(E) = 0$ for all $\Pr(E) \in (0, 1)$) or the maximum level of ambiguity seeking ($W(E) = 1$ for all $\Pr(E) \in (0, 1)$) can be detected. On the other hand, $\ell = 0$ ensures $W(E) = \Pr(E)$, which is the case of expected utility maximisation.

In addition to its interpretation as part of a plain decision weight, ℓ can also be regarded as the perceived level of ambiguity due to the role it plays in multiple prior models (Chateauneuf, Eichberger, and Grant, 2007; Baillon, Bleichrodt, Keskin, et al., 2018). In such a model, individuals evaluate a bet on E with a weighted average of expected utilities calculated with the least and most optimistic belief in an interval of priors. ℓ is the width of the interval and $0.5 + \frac{\alpha}{\ell}$ the weight of the pessimistic expected utility term[4]. This interpretation requires that $\ell \geq 0$ because otherwise the width of the interval would exceed 1, and that $-\frac{\ell}{2} \leq \alpha \leq \frac{\ell}{2}$ for the utility term weights to be in [0, 1].

These conditions are enforced in our main specification and correspond to the conditions on τ_0 and τ_1 stated earlier. While the violation of set-monotonicity ($\ell > 1$) is incompatible with any reasonable model of decision making, the plain decision weight interpretation allows for behaviour such as $\ell \leq 0$ which we might interpret as being hypersensitive to subjective probabilities. In appendix 3.C, we estimate our model keeping only the restriction $\ell \leq 1$, which means that ℓ cannot necessarily be interpreted as the perceived level of ambiguity although the decision weight interpretation remains intact. We find that the estimated ambiguity attitudes of only 12% of individuals fall outside the restrictions of our main specification and that our key results are unaffected.

3.3.2 Estimating ambiguity attitudes

Since matching probabilities find the indifference point $W(E) \cdot V(€20) = p \cdot V(€20)$, they identify the decision weight individuals assign to AEX events when making decisions relating to them: $W(E) = m(E) = p$.[5] The decision weights are identified independently of the functional form of the utility function and, in particular, independently of risk aversion.

4. Except for $\ell = 0$, the expected utility case, when the weights are 0.5

5. We implicitly assume that there is no probability weighting for known probabilities and, hence, $w_{risk}(p) = p$. If this not the case, our results are still informative about ambiguity attitudes in that they measure the difference in weights under uncertainty and risk.

It is easy to see that the neoadditive model, and hence α and ℓ, are identified in terms of the matching probabilities for the events in our design: The difference between $W(E_1) + W(E_2) + W(E_3) = 3\tau_0 + \tau_1$ and $W(E_j) + W(E_j^C) = 2\tau_0 + \tau_1$ identifies τ_0, and then τ_1 is also identified. The subjective probabilities drop whatever they are because the events in the design contain their complements as well.

To capture erratic behaviour as well as systematic behaviour that is not captured well by the deterministic neoadditive model, we augment it with an additive error ϵ_E which we assume is normally distributed with mean zero and a standard deviation of σ_ϵ independently across events. An additive error for events is motivated by the finding documented in Section 3.2.3 that set-monotonicity violations are related to differences in judged historical frequencies of the respective events: Errors are more likely if individuals believe that a pair of events forming a superset and subset have occurred similarly often in the past. Errors that are not specific to events, such as trembling hand errors, cannot generate this pattern.

We estimate the following model

$$\begin{aligned} W(E) &= \tau_0 + \tau_1 \cdot \Pr(E) \\ \epsilon_E &\sim \mathcal{N}\left(0, \sigma_\epsilon^2\right) \\ \Pr(\text{Observed choices for E}) &= \Pr(W(E) + \epsilon_E \in \text{Interval}_E) \end{aligned}$$

by choosing the parameters $\theta := [\tau_0, \tau_1, \Pr(E_0), \Pr(E_1), \Pr(E_2), \sigma_\epsilon]$ to maximise the likelihood

$$\begin{aligned} \mathscr{L}(\theta) &= \prod_{E \in \mathfrak{E}} \Pr(W(E) + \epsilon_E \in \text{Interval}_E; \theta) \\ \text{s.t.} \quad & 0 \leq \tau_1 \leq 1, \; 0 \leq \tau_0 \leq 1 - \tau_1, \\ \Pr(E_1) &\leq Pr(E_0), \; Pr(E_1) + Pr(E_2) \leq 1, \; \Pr(E) \in [0, 1] \end{aligned}$$

for the events E in $\mathscr{E} = \{E_0, E_1, E_2, E_3, E_1^C, E_2^C, E_3^C\}$. Pr(Observed choices for E) is the probability of the sequence of observed choices regarding event E, all of which lead to one of the terminal intervals depicted in Figure 3.B.1.

Baillon, Bleichrodt, Li, and Wakker (2019) propose indices that estimate α and ℓ directly with moments of matching probabilities. Our approach is more difficult to implement because it requires solving constrained optimisation problems for each individual, but it gives us several advantages. First, it ensures that estimated ambiguity parameters obey the theoretical parameter restrictions that rule out irrational behaviour and allow ℓ to be interpreted as the perceived level of ambiguity. Figure 3.E.3 shows the distribution of estimated parameters when the estimation is based on the indices of Baillon, Bleichrodt, Li, et al. (2019). For 25% of subjects, the estimates of ℓ are above 1 which implies they give lower weights to events with higher subjective probabilities. Rather than excluding these individuals or disregarding that such parameter values are not meaningful, we find the best fitting parameters subject to their values being interpretable.

Second, we obtain an extra parameter σ_ϵ. This error parameter informs us about the fit of the model for each subject's choices and therefore the reliability with which α and ℓ are estimated. Individuals that frequently violate set-monotonicity, for instance, will have a high value of σ_ϵ. Third, our approach allows us to use choices for the seventh event E_0 when estimating ambiguity parameters which improves efficiency. These choices could only be included in the indices if choices for the complement event were available as well.

Finally, note that estimating the neoadditive model entails little loss of generality compared to the indices from a theoretical perspective. The indices are invariant to the choice of events in the design only if the neoadditive model is true and ℓ is estimated well if the neoadditive model is a good approximation of the source function (Baillon, Bleichrodt, Li, et al., 2019, Theorem 14 and Proposition 21). Using σ_ϵ, we can quantify the quality of the approximation for each individual. Appendix 3.E repeats our empirical analysis with the indices and comes to broadly similar conclusions, but estimates of ℓ are substantially less stable over time and across domains compared to estimates from our model.

3.4 Results

We now present our results about the estimated ambiguity parameters. First, we examine stability over time, as well as stability across domains. In the last part of this section, we assess the heterogeneity of our three parameters using a discrete classification approach.

3.4.1 Parameter stability over time

To examine the stability of estimated ambiguity attitudes over time, we make use of the panel structure of our data and estimate our model separately for each individual and survey wave. Figure 3.4.1 shows boxplots of the distribution of parameter estimates for each wave. The shapes of the distributions are quite stable wave to wave, particularly those of the ambiguity parameters α and ℓ. The distribution of σ_ε, however, noticeably shifts to the left following the first wave and seems to stabilise thereafter. The reduction of the error parameter likely reflects both a small change in the experimental instructions that made the description more intuitive and a greater familiarity of the respondents with our design.

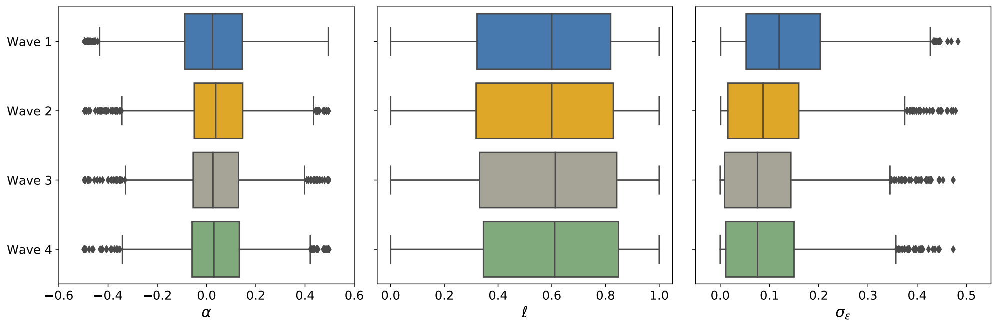

Figure 3.4.1. Distributions of estimated parameters, wave by wave

Notes: Sample restrictions: Individuals with at least two waves of regular choices. Choices are irregular if they exhibit recurring patterns whilst also being entered quicker than 85% of subjects.

To check whether there might be systematic heterogeneity in changes over time that cancels out in the aggregate analysis, we regress changes in estimated parameters across consecutive survey waves on many observables. The results in Table 3.A.6

show that parameter changes are only very weakly related to observable characteristics, with R^2 below 1% for the ambiguity parameters. There is little evidence in our data that ambiguity parameters are systematically changing over the two years.

Figure 3.4.1 also shows that there is substantial variation in all estimated parameters. The ambiguity parameters are spread over the full range of their support. To investigate individual-level parameter stability, we compute correlations between parameter estimates for all pairs of survey waves. Table 3.4.1 shows the results. On average, correlations are 0.25 for ambiguity aversion and 0.31 for likelihood insensitivity though they tend to be higher for consecutive survey waves, which are six months apart, and between survey waves not involving the first wave which was the first exposure of individuals to our design. To interpret the magnitude of these correlations, a comparison with results on risk aversion is instructive. Chuang and Schechter (2015) review the literature on the stability of risk aversion parameters over longer horizons comparable to ours, finding correlations between 0.13 and 0.55 for studies with at least 100 observations. Our results indicate that ambiguity attitudes are of comparable stability to risk attitudes.

Table 3.4.1. Across wave correlations of estimated parameters

	$\hat{\rho}_{1,2}$	$\hat{\rho}_{1,3}$	$\hat{\rho}_{1,4}$	$\hat{\rho}_{2,3}$	$\hat{\rho}_{2,4}$	$\hat{\rho}_{3,4}$	Average $\hat{\rho}$
α	0.25	0.22	0.20	0.26	0.21	0.33	0.25
ℓ	0.24	0.22	0.28	0.35	0.36	0.42	0.31
σ_ε	0.16	0.20	0.21	0.32	0.32	0.36	0.26

Notes: Table shows Pearson correlations of parameter estimates between the survey waves indicated by the subscripts. Parameter estimates are obtained from the model described in Section 3.3.2 separately for each survey wave and individual. Sample restrictions: Observations with regular choices. Choices are irregular if they exhibit recurring patterns whilst also being entered quicker than 85% of subjects.

The moderate magnitude of the correlations means that there is substantial variation in estimated parameters within individuals. As Schildberg-Hörisch (2018) points out regarding risk preferences, this variation likely reflects both measurement error and temporary fluctuations of the underlying parameter around each individual's mean level of the parameter. To address measurement error, we adopt two approaches: When examining stability across domains, we instrument estimated parameters with estimated parameters of other waves. For Section 3.4.3, in which we analyse between-subject heterogeneity, we re-estimate our model, pooling individual choices across survey waves.

3.4.2 Parameter stability across domains

A key question arising for any parameter characterising individual attitudes is how domain-specific it is. Do attitudes towards uncertainty about how the AEX will evolve extend to other, non-financial domains? To address this question, we elicited

α and ℓ not only for events relating to the AEX but also to events relating to how the average temperature in the winter of 2019 compares to the previous five years. Figure 3.4.2 compares the respective distributions of parameters in wave 4. For α and σ_ϵ, the distributions are very similar, but there is notably greater likelihood insensitivity regarding temperature changes. In the following, we examine stability at the individual level.

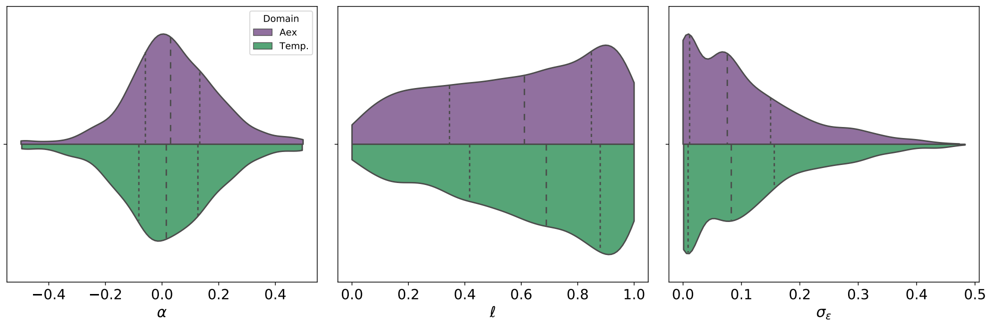

Figure 3.4.2. Distributions of estimated parameters, financial v climate domains

Notes: Estimates for both domains use data from wave 4. The dashed line shows the median, the dotted lines bottom and top quartiles. Sample restrictions: Observations with regular choices. Choices are irregular if they exhibit recurring patterns whilst also being entered quicker than 85% of subjects.

Table 3.4.2 shows regressions for each parameter in the climate domain on parameters from the financial domain elicited in the same wave. The first column of each parameter shows OLS regression with slope coefficients of 0.70, 0.36, and 0.50 for α, ℓ, and σ_ϵ respectively. This suggests a sizable amount of stability across domains, but a much higher stability for ambiguity aversion compared to likelihood insensitivity. The second columns add several controls. For brevity, the coefficients of control variables are shown in the appendix in Table 3.A.8. Our results are unchanged when we control for demographic variables, numeracy, risk aversion, and the extent to which individuals think they understand climate change and deem it a threat. Stability across domains is not driven by these common correlates.

However, the OLS regressions are distorted by estimation error in potentially two ways. First, if estimates of ambiguity attitudes are subject to classical measurement error, the slope coefficients are attenuated to zero and understate the degree to which the parameters are stable across domains. Second, there could be a positive correlation between the estimation errors for estimates across domains, because the parameters were elicited one after another in the 4th wave. This would cause the coefficients to overstate the dependence across domains. To address this, we run two-stage least squares regressions in the third columns for each parameter, instrumenting the AEX related parameters of the 4th wave with those of the previous waves. If estimation errors are uncorrelated across waves, this eliminates both biases.

Table 3.4.2. Dependence of parameters relating to temperature uncertainty on parameters relating to uncertainty about the AEX

Parameter		α			ℓ			σ_ε	
Model	OLS	OLS	2SLS	OLS	OLS	2SLS	OLS	OLS	2SLS
Intercept	-0.01**	0.05*	0.00	0.42***	0.44***	0.20***	0.06***	0.01	-0.03
	(0.00)	(0.03)	(0.03)	(0.02)	(0.06)	(0.07)	(0.00)	(0.02)	(0.02)
AEX param	0.70***	0.70***	1.00***	0.36***	0.34***	0.61***	0.50***	0.48***	1.06***
	(0.03)	(0.03)	(0.09)	(0.03)	(0.03)	(0.06)	(0.03)	(0.03)	(0.11)
Underst. c.c.		-0.01**	-0.01**		-0.02**	-0.02**		0.01**	0.01***
		(0.00)	(0.00)		(0.01)	(0.01)		(0.00)	(0.00)
Threat. by c.c.		0.00	0.00		-0.00	0.01		0.00	-0.00
		(0.00)	(0.00)		(0.01)	(0.01)		(0.00)	(0.00)
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
N	1297	1297	1186	1297	1297	1186	1297	1297	1186
R^2	0.402	0.416	-	0.146	0.170	-	0.216	0.236	-
1st st. F	-	-	79.8	-	-	309.3	-	-	134.7

Notes: Outcomes are estimated parameters in the temperature domain in the 4th wave, regressors are estimated parameters in the AEX domain in the 4th wave. Two-stage least squares models use estimated parameters from the previous three waves as instruments. Controls are age, gender, education, income and assets dummies, risk aversion, basic, financial and probability numeracy and indicators of self-assessed understanding and perceived threat of climate change with a 5 and 6 point scale respectively (see Table 3.A.8). Robust standard errors in parentheses. Sample restrictions: Observations with regular choices. Choices are irregular if they exhibit recurring patterns whilst also being entered quicker than 85% of subjects.

The regressions that adjust for estimation error strikingly show that ambiguity aversion and the magnitude of errors is completely stable across the two domains with point estimates close to 1. This supports the interpretation of ambiguity aversion as stable preference that fully extends across domains. Anantanasuwong et al. (2019) elicit ambiguity attitudes for events from different financial domains: Individual stocks, local and foreign stock indices and crypto funds. They find that ambiguity aversion parameters are very related across these domains with R^2 between 0.4 and 0.54. This is in line with what we find in the OLS regression. A coefficient close to 1 in the 2SLS regression that adjusts for estimation error is likewise in line with the conclusion of Anantanasuwong et al. (2019) who conjecture based on a factor analysis that there is only one underlying ambiguity aversion. Our results indicate that the stability of ambiguity aversion holds not just within financial contexts, but more generally.

We further find that ℓ also has a substantial transferable component, but the slope coefficient of 0.60 is well below 1. Based on the multiple prior interpretation of ℓ as the perceived level of ambiguity, this is expected as perceptions are more likely to differ across domains than preferences. This interpretation is strengthened by the fact that self-reported knowledge of climate change has substantial predictive power for the perceived level of ambiguity in the climate domain, conditional on the perceived level of ambiguity in the financial domain. Anantanasuwong et al. (2019) find a very weak dependence across domains with R^2 ranging from 0.005 to 0.032 which would imply that ℓ is almost completely context-specific. Our analysis shows that a substantial component of likelihood insensitivity is stable across domains. One potential reason our results on the perceived level of ambiguity are at variance with Anantanasuwong et al. (2019) is measurement error. Table 3.4.2 demonstrates that our model-based estimates are subject to sizable measurement error and there is evidence it affects ambiguity attitudes estimated with indices, instead of our model, even more. In Table 3.E.2 we replicate Table 3.4.2 with the index-based estimates that Anantanasuwong et al. (2019) use, and get a comparably small R^2 of 0.028 for ℓ. The 2SLS-measurement-error-adjusted regression slope is, however, in the range of what we find with our model. In line with this explanation, index-based estimates of ℓ are substantially less stable over time (Table 3.E.1).

Our findings suggest that there can be room for external stimuli, such as providing individuals with more information about a source of uncertainty, to change ℓ while this might not be possible for α. This aligns well with the findings by Baillon, Bleichrodt, Keskin, et al. (2018) who conduct such an information experiment.

As with stability over time, the comparison with risk aversion is instructive. Dohmen et al. (2011) examine self-reported assessments of risk aversion in several domains like financial matters, sports, or health and report correlations that correspond to R^2 between 0.16 to 0.36 which is comparable to what we find in the OLS columns of Table 3.4.2. Dohmen et al. (2011) reason that differences in risk attitudes across domains might be more likely to reflects different risk perceptions, rather than differences in actual preferences. This is in line with what we find for ambiguity: A very stable ambiguity aversion component, but that the perception of ambiguity varies across contexts to a certain degree.

3.4.3 Describing heterogeneity in attitudes and error propensities

In this section, we examine heterogeneity in ambiguity attitudes and error propensities and their relation to other individual characteristics. To improve precision, we re-estimate our model, holding ℓ, α, and σ_ϵ fixed but allowing the subjective probabilities to change between waves.

It is crucial to consider the joint distribution of parameters rather than each parameter in isolation for two reasons: First, the error parameter is informative about how reliably the other parameters are estimated, both in terms of statistical precision and fit of the neoadditive model. Second, the magnitude of ambiguity aversion or seeking that can be detected by our design depends on the perceived level of ambiguity. When $\ell = 0$ it must be the case that $W(E) = \Pr(E)$, so there is no scope for ambiguity aversion or seeking.

With this in mind, we classify individuals into one of a discrete set of groups using all three estimated parameters and consider the most striking features of each resulting group. We use the k-means algorithm to do this. For a given number of groups, it assigns individual observations $x_i := [\alpha_i, \ell_i, \sigma_{\epsilon,i}]$ to groups g such that $\sum_i ||x_i - c_{g(i)}||^2$ is minimised for the group means $c_g = \frac{1}{N_g}\sum_{i \in g} x_i$. We scale x_i to mean 0 and standard deviation 1 in the cross section to ensure every component is given equal weight in the optimisation.

We summarise the results of this exercise for $K = 4$ groups, which is the minimum necessary for there to be meaningful group-level differences along the three parameters. In Section 3.D, we double the number of groups and show that the qualitative insights from the $K = 4$ analysis remain intact. We describe the groups in two figures and two tables, with groups sorted by their average ℓ from high to low: Figure 3.4.3 shows the distribution of ambiguity profiles in $(\alpha,\ \ell)$ with the large diamonds indicating group means and the small dots indicating individual profiles. Figure 3.4.4 shows the source function (how decision weights depend on subjective probabilities) for the average ambiguity profile of each group, as well as the average magnitude of the error component. Table 3.4.3 lists means and medians of observable characteristics per group and Table 3.4.4 displays marginal effects of a multinomial logit regression predicting group membership based on the same characteristics.

Group 1: Substantial likelihood insensitivity, on average ambiguity-averse. Almost thirty per cent of individuals in our sample show substantial likelihood insensitivity with ℓ ranging from 0.4 to 1, and are averse to it, with α ranging from 0 to 0.5. Their choices are quite consistent with the neoadditive model, leading to a comparably small error magnitude of 0.14. The blue line in Figure 3.4.4 crosses the 45-degree line just before the subjective probability reaches 0.3 and rises only up to a matching probability of about 0.5. This means on average, individuals in this group are quite ambiguity-averse; they prefer bets on lotteries over bets on AEX events even if they regard them as substantially more likely. In Table 3.4.3 we see that individuals of Group 1 are likely to be somewhat younger than those of other groups, and more likely to be female. They tend to be more risk-averse and hold substantially less financial assets. Besides, group 1 individuals are on average less optimistic than those of groups 2 and 4, both in terms of a personality measure and in terms of how often they think the AEX had a positive return over the last 20 years. Except age and optimism, the characteristics mentioned are also predictive of membership in group 1 in a multinomial logistic regression (Table 3.4.4).

Group 2: Substantial likelihood insensitivity, on average ambiguity-seeking. A smaller group, a fifth of individuals, is associated with a similar ℓ as group 1 and behaves inconsistently at comparably small rate ($\sigma = 0.17$). Unlike group 1 indi-

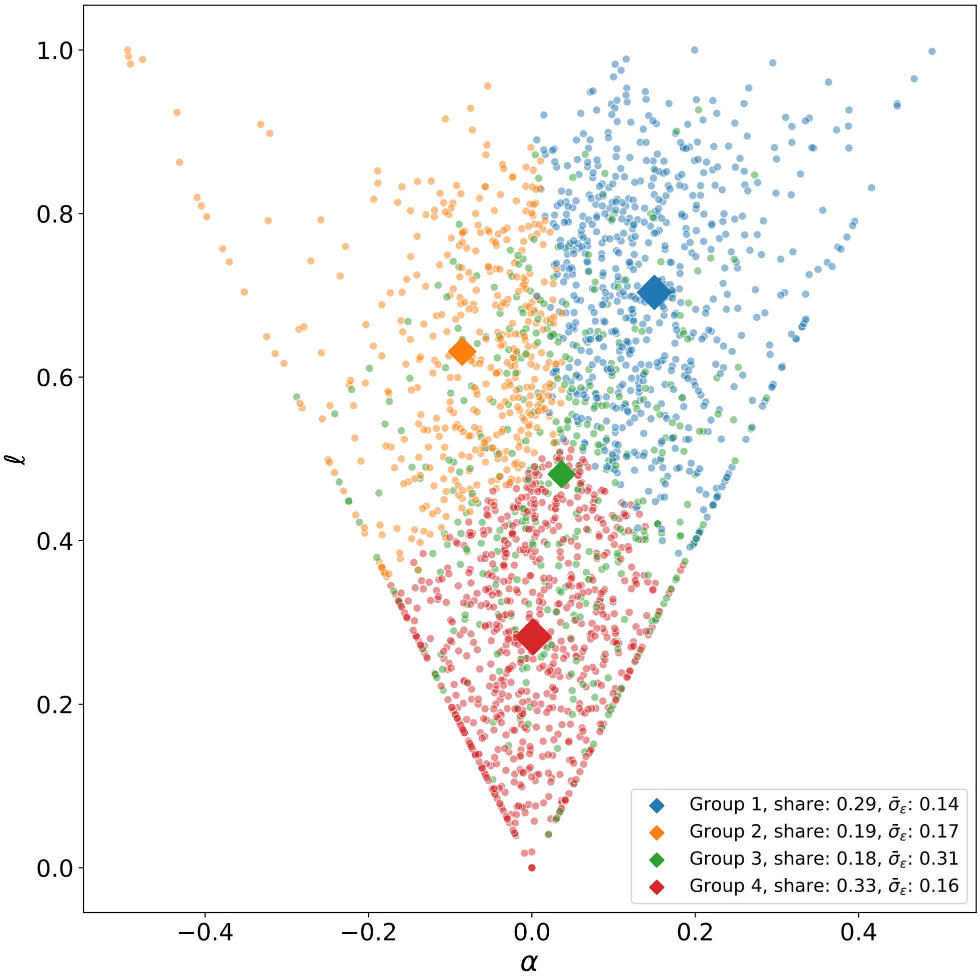

Figure 3.4.3. Summarising heterogeneity in ambiguity profiles with K=4 discrete groups

Notes: The small dots depict individual ambiguity profiles consisting of the aversion parameter α and the likelihood insensitivity parameter ℓ. The large diamonds are group centres resulting from clustering individuals with the k-means algorithm on the parameters α, ℓ and σ_ε. Sample restrictions: Individuals with at least two waves of regular choices. Choices are irregular if they exhibit recurring patterns whilst also being entered quicker than 85% of subjects.

viduals, however, subjects in this group are not averse to the ambiguity that they perceive with α ranging from −0.5 to 0. The orange line in Figure 3.4.4 has a similar slope as the blue line of group 1 due to the comparable ℓ, but is shifted up, crossing the 45-degree line only past the subjective probability of 0.6. This means that individuals in this group exhibit ambiguity seeking behaviour on average, and only become averse to bets on the AEX compared to bets on equally likely lotteries for a high subjective probability of the former. In line with this tendency, the value group 2's financial assets (median) is 73% higher than for individuals of group 1,

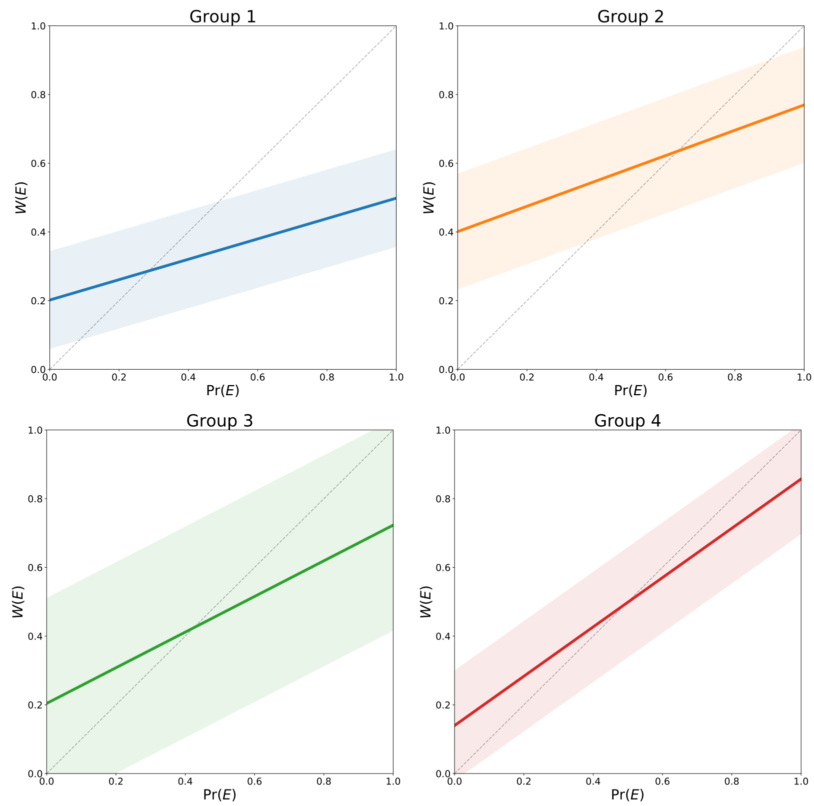

Figure 3.4.4. Decision weights as a function of subjective probabilities, by group (K=4)

Notes: The figure plots the estimated source functions, i.e. the lines $W(E) = \frac{\ell}{2} - \alpha + (1 - \ell) \cdot \mathrm{Pr}(E)$ for the group-average values of α and ℓ. The vertical difference to the 45-degree line measures the extent of ambiguity seeking w.r.t. gains from events whose source of uncertainty is the future development of the AEX. The shaded area around the lines has bandwidth σ_ε, which visualises the imprecision with which observed matching probabilities measure decision events. Sample restrictions: Individuals with at least two waves of regular choices. Choices are irregular if they exhibit recurring patterns whilst also being completed quicker than 85% of subjects.

they tend to be less risk-averse, and there is a more even gender split. Table 3.4.4 shows that almost no characteristics predict an individual is more likely to belong to group 1 in the multinomial logistic regression. This is because their characteristics are close to the average of the sample pool.

Group 3: Decisions less consistent with the model, ambiguity parameters not meaningful. 18 % of individuals are characterised by less consistent choices, with σ_ϵ almost doubling compared to the other groups. The green dots in Figure 3.4.3 are much more spread out, indicating that this group does not form a compact cluster in (α, ℓ) space. A high σ_ϵ can come about through erratic behaviour or because a choice model other than the neoadditive specification we estimated would be appropriate. In line with the former interpretation, individuals in group 3 are characterised by a much lower numeracy than those of other groups. They are less educated, made

Table 3.4.3. Individual characteristics of groups (K=4)

	Group = 1	Group = 2	Group = 3	Group = 4
share	0.29	0.19	0.18	0.33
α	0.15	-0.09	0.04	0.00
ℓ	0.70	0.63	0.48	0.28
σ_{ε}	0.14	0.17	0.31	0.16
Education: University	0.11	0.11	0.06	0.21
Age	55.74	59.56	64.63	53.92
Female	0.58	0.53	0.47	0.42
Income (thousands)	1.63	1.56	1.47	1.75
Financial assets (thousands)	6.47	10.89	8.82	14.71
Risk aversion index	0.13	-0.04	-0.01	-0.08
Numeracy index	-0.14	0.01	-0.69	0.51
Judged hist. freq: positive return	0.48	0.51	0.48	0.59
Judged hist. freq: response error	0.62	0.60	0.76	0.41
Judged hist. freqs: mean absolute deviation	0.19	0.18	0.21	0.19
Optimism	-0.11	0.07	-0.18	0.15

Notes: The first row shows the share of individuals classified to a given group. For each group, the mean of several variables are shown. For income and total assets, the median is reported instead. The variables for risk aversion, numeracy and optimism are standard normalized. Sample restrictions: Individuals with at least two waves of regular choices. Choices are irregular if they exhibit recurring patterns whilst also being completed quicker than 85% of subjects.

more response errors when judging historical stock returns and their judgements differed the most from actual empirical frequencies. They are on average substantially older than individuals in other groups, and more likely to be men.

Group 4: Low likelihood insensitivity, ambiguity neutral. The remaining third of individuals in our sample shows behaviour close to expected utility maximisation. This group is much less insensitive to changes in subjective probabilities, or equivalently, perceives much less ambiguity, with ℓ only 0.26 on average. There is neither a preponderance of ambiguity aversion nor ambiguity seeking, with the mean value of α equal to 0. Individuals of group 4 do not differ from those of group 1 and 2 in terms of how consistent their decisions are with the model. Figure 3.4.4 shows that the estimated source function is close to the 45-degree line that characterises expected utility maximisation - decision weights are within one standard deviation σ_{ϵ} of it over the full range. Individuals of group 4 are more likely to be men and are the youngest on average amongst all four groups, although not much younger than those of group 1. In terms of education, numeracy, as well as the value of financial assets they hold, they score by far the highest. They are also the least risk-averse. Table 3.4.4 shows that numeracy strongly predicts membership of group 4 conditional on everything else. This is in line with expected utility maximisation being a benchmark of rationality, from which individuals in group 4 fall short the least. Similarly, group 4 individuals stand out for accurately believing that AEX returns were positive around 60% of the time in the past. This optimism is also present in terms of a personality measure.

Our analysis shows that taking into account interdependencies of the three parameters is important; the variance of errors renders the other two parameters less reliable and the magnitude of α is constrained by ℓ. To compare our findings to the existing literature, which does not take interdependencies into account, we also regress parameter estimates on characteristics in table 3.E.3. The patterns are broadly in line with the ones just discussed: α is negatively related to age, financial assets, and numeracy while a higher ℓ is associated with being female, as well as lower education, financial assets, and numeracy. Risk aversion is positively related to both indices once we exclude the high error individuals (group 3), which attenuate relationships in regressions.

Earlier studies on the determinants of ambiguity attitudes report relatively weak connections to demographic variables (l'Haridon, Vieider, Aycinena, Bandur, Belianin, et al., 2018) and differ in what connections they find. This is likely because they study ambiguity parameters in different settings, and subject pools of varying demographics are used. As our group-based analysis indicates, the second factor can make a sizable difference. One of our key findings, that ℓ is negatively related to both education and numeracy, is in line with Dimmock, Kouwenberg, and Wakker (2015) and Anantanasuwong et al. (2019) while Dimmock, Kouwenberg, Mitchell, et al. (2015) find a positive relation. There are also opposing findings for the relations of risk aversion and ambiguity attitudes (compare Dimmock, Kouwenberg, Mitchell, et al., 2015; Dimmock, Kouwenberg, and Wakker, 2015; Delavande, Ganguli, and Mengel, 2019). Our results suggest a positive relation to both indices. Contrary to our findings, Butler, Guiso, and Jappelli (2014) find a positive association between wealth and ambiguity aversion.

3.5 Conclusion

This study presented a careful analysis of preferences for decision-making under ambiguity. Motivated by a set of stylised facts, we have set up an empirical model for behaviour in our experiment that features three parameters: ambiguity attitudes, the likelihood insensitivity (or perceived level of ambiguity), and the variance of errors. We have structurally estimated these parameters at the individual level.

Our first main contribution is that we have been able to demonstrate substantial within-person stability of ambiguity attitudes. This holds both over a period of two years and across the domains of financial markets and climate change. In particular, preferences for ambiguity show similar properties as preferences for risk when it comes to stability over time. Across our two contexts, ambiguity aversion is completely stable if we adjust for within-person variability that is due to measurement error, and exhibits stability comparable to risk aversion in measurement error unadjusted comparisons. Likelihood insensitivity, on the other hand, is more variable, strengthening its interpretation as the perceived level of ambiguity, which varies across domains if people are differentially informed. We find some evidence in support of this mechanism; controlling for how much ambiguity individuals perceive in the financial domain, whether they characterise themselves as understanding climate change predicts how much ambiguity they perceive in the climate domain. Nevertheless, there is also a substantial component of this parameter that is stable across contexts.

Our second main contribution has been to describe the patterns of heterogeneity. This has long been done for decisions under risk, but it has proven particularly challenging for decisions under ambiguity. One reason is that all popular models depend on at least two parameters, which are hard to interpret in isolation using parameter-by-parameter regressions. We have instead employed the k-means algorithm to classify individuals into a discrete set of groups. Using four groups, we find that a third of the population comes close to the behaviour subjective expected utility maximisers, almost thirty per cent are very averse to ambiguity while almost twenty per cent seek it. The remaining individuals exhibit erratic behaviour. Individuals of these groups systematically differ in background characteristics with reasonable correlations to ambiguity attitudes.

Our key results depend neither on the specifics of the model we use to estimate ambiguity attitudes, nor on the number of groups we use to analyse their heterogeneity. We also estimate ambiguity attitudes in two alternative ways: A version of our model that relaxes parameter restrictions and keeps only the requirement that rules out set-monotonicity errors, and the indices proposed by Baillon, Bleichrodt, Li, et al. (2019). Both yield broadly similar results, though the perceived level of ambiguity displays much less stability over time when estimated with the indices. When we double the number of groups in the k-means algorithm, the key results of what is predictive of ambiguity attitudes remain as before.

It remains to be learned how ambiguity attitudes evolve over periods longer than the two years we investigate. A further important follow-up question is how ambiguity attitudes affect behaviour, in particular investment decisions in the financial domain and political, as well as personal decisions regarding climate change. Our design elicits ambiguity attitudes over gains but to understand how ambiguity affects real-world behaviour, ambiguity attitudes over losses might play an important role as well. We leave these questions for future research.

Table 3.4.4. Predictors of groups, marginal effects (K=4)

	Group = 1	Group = 2	Group = 3	Group = 4
Age: $\in (35, 50]$	-0.02	0.00	0.02	-0.00
	(0.05)	(0.05)	(0.05)	(0.05)
Age: $\in (50, 65]$	-0.05	0.06	0.04	-0.04
	(0.05)	(0.05)	(0.05)	(0.05)
Age: ≥ 65	-0.08	0.06	0.13**	-0.11**
	(0.05)	(0.05)	(0.05)	(0.05)
Education: Junior college	0.03	-0.01	-0.02	-0.00
	(0.03)	(0.03)	(0.02)	(0.03)
Education: College	0.04	-0.05*	-0.01	0.02
	(0.03)	(0.03)	(0.03)	(0.03)
Education: University	0.01	-0.07*	0.02	0.04
	(0.04)	(0.04)	(0.04)	(0.04)
Income: $\in (1.1, 1.6]$	0.05*	-0.01	-0.03	-0.02
	(0.03)	(0.03)	(0.03)	(0.03)
Income: $\in (1.6, 2.2]$	0.09***	-0.03	-0.04	-0.02
	(0.03)	(0.03)	(0.03)	(0.03)
Income: ≥ 2.2	0.05	-0.03	-0.01	-0.01
	(0.04)	(0.03)	(0.03)	(0.04)
Financial assets: $\in (1.8, 11.2]$	-0.04	0.01	-0.02	0.05
	(0.03)	(0.03)	(0.03)	(0.04)
Financial assets: $\in (11.2, 32]$	-0.09**	-0.03	0.04	0.09**
	(0.04)	(0.03)	(0.03)	(0.04)
Financial assets: ≥ 32	-0.11***	0.00	0.03	0.08**
	(0.04)	(0.03)	(0.03)	(0.04)
Female	0.07***	0.02	-0.07***	-0.02
	(0.02)	(0.02)	(0.02)	(0.02)
Risk aversion index	0.04***	-0.01	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Numeracy index	-0.04**	-0.00	-0.11***	0.15***
	(0.01)	(0.01)	(0.01)	(0.02)
Judged hist. freq: positive return	-0.15***	-0.03	-0.00	0.18***
	(0.04)	(0.04)	(0.04)	(0.04)
Judged hist. freq: response error	-0.03	0.01	0.05**	-0.04
	(0.03)	(0.02)	(0.02)	(0.02)
Judged hist. freqs: mean absolute deviation	-0.23*	-0.23*	0.41***	0.05
	(0.12)	(0.12)	(0.10)	(0.12)
Optimism	-0.02	0.02	-0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
N	1460	1460	1460	1460
Pseudo R^2	0.12	0.12	0.12	0.12

Notes: Multinomial logit regression, robust standard errors in parentheses. For the thresholds of the income and asset quartiles see Table 3.2.1. Income and financial assets are in thousands, pooled within household and adjusted for household size. The variables for risk aversion, numeracy and optimism are standardised. Sample restrictions: Individuals with at least two waves of regular choices. Choices are irregular if they exhibit recurring patterns whilst also being completed quicker than 85% of subjects.

Appendix 3.A Additional tables

Table 3.A.1. Matching probabilities by wave

wave	Wave 1	Wave 2	Wave 3	Wave 4	Pooled
$E_0 : r > 0\%$	0.54	0.51	0.52	0.49	0.51
$E_1 : r > 10\%$	0.32	0.35	0.37	0.36	0.35
$E_1^C : r \leq 10\%$	0.58	0.50	0.52	0.52	0.53
$E_2 : r < -5\%$	0.44	0.35	0.34	0.36	0.37
$E_2^C : r \geq -5\%$	0.50	0.54	0.56	0.56	0.54
$E_3 : -5\% \leq r \leq 10\%$	0.58	0.55	0.58	0.58	0.57
$E_3^C : (r < -5\%) \cup (r > 10\%)$	0.41	0.41	0.41	0.41	0.41

Notes: Events were asked about in this order: $E_0 - E_1 - E_2 - E_3 - E_1^C - E_2^C - E_3^C$. Mean of the matching probabilities of the seven events. Sample restrictions: Individuals with at least two waves of regular choices. Choices are irregular if they exhibit recurring patterns whilst also being completed quicker than 85% of subjects.

Table 3.A.2. Relation of risk aversion and numeracy with characteristics

	Risk aversion index	Numeracy index
Intercept	-0.37***	-0.29***
	(0.11)	(0.11)
Age: $\in (35, 50]$	0.24**	-0.22**
	(0.10)	(0.09)
Age: $\in (50, 65]$	0.32***	-0.23***
	(0.10)	(0.09)
Age: ≥ 65	0.45***	-0.51***
	(0.10)	(0.09)
Female	0.28***	-0.36***
	(0.05)	(0.04)
Education: Junior college	-0.01	0.20***
	(0.07)	(0.06)
Education: College	0.01	0.42***
	(0.06)	(0.06)
Education: University	-0.15**	0.66***
	(0.07)	(0.06)
Income: $\in (1.1, 1.6]$	-0.06	0.07
	(0.07)	(0.07)
Income: $\in (1.6, 2.2]$	-0.04	0.12*
	(0.08)	(0.06)
Income: ≥ 2.2	-0.20**	0.14**
	(0.08)	(0.06)
Financial assets: $\in (1.8, 11.2]$	-0.08	0.53***
	(0.07)	(0.07)
Financial assets: $\in (11.2, 32]$	0.03	0.72***
	(0.08)	(0.07)
Financial assets: ≥ 32	-0.03	0.79***
	(0.08)	(0.07)
N	1614	1614
R^2	0.049	0.291

Notes: Income and financial assets are in thousands, pooled within household and adjusted for household size. OLS regression, robust standard errors in parentheses.

Table 3.A.3. Subset violations by superset-subset pair

	Subset violations	Δ Judged hist. frequencies
$E_0 \supseteq E_1$	0.09	0.21
$E_1^C \supseteq E_2$	0.10	0.47
$E_1^C \supseteq E_3$	0.22	0.22
$E_2^C \supseteq E_0$	0.19	0.26
$E_2^C \supseteq E_1$	0.10	0.47
$E_2^C \supseteq E_3$	0.20	0.31
$E_3^C \supseteq E_1$	0.16	0.22
$E_3^C \supseteq E_2$	0.18	0.31
Any Violation	0.57	-

Notes: The share of subjects that violate the set-monotonicity conditions for each pair of events is reported in column 1. Set-monotonicity is violated if the interval of the elicited matching probability of the subset is strictly larger than the interval of the superset. The last row shows the share of subjects with at least one error in a given wave. Column 2 shows the difference in the historical frequencies of the respective events.

Table 3.A.4. Relation between subset violations and judged historical frequencies of events

	Superset-Subset Error Rate		
Intercept	0.293***	0.159***	0.075***
	(0.004)	(0.005)	(0.006)
|Jud. freq. superset - Jud. freq. subset| (10 pp)	-0.013***	-0.006***	-0.006***
	(0.001)	(0.001)	(0.001)
Superset - Subset fixed effect	No	Yes	Yes
Individual fixed effect	No	No	Yes
N	15632	15632	15632
R^2	0.02	0.09	0.33

Notes: OLS regressions, robust standard errors in parentheses. The outcomes are individual error rates across waves for all superset-subset event pairs. Standard errors are clustered at the individual level. The regressor is the distance in judged historical frequencies for the events of a superset-subset pair, with unit ten percentage points.

Table 3.A.5. Matching probabilities for temperature questions

	Mean	Std. dev.	$q_{0.1}$	$q_{0.5}$	$q_{0.9}$	Empirical Frequency
$E_0 : \Delta T > 0°C$	0.53	0.27	0.15	0.55	0.92	0.55
$E_1 : \Delta T > 1°C$	0.45	0.27	0.08	0.45	0.92	0.26
$E_1^C : \Delta T \leq 1°C$	0.53	0.28	0.15	0.55	0.92	0.74
$E_2 : \Delta T < -0.5°C$	0.40	0.27	0.03	0.35	0.85	0.26
$E_2^C : \Delta T \geq -0.5°C$	0.50	0.29	0.08	0.45	0.92	0.74
$E_3 : -0.5°C \leq \Delta T \leq 1°C$	0.51	0.28	0.15	0.45	0.92	0.48
$E_3^C : (\Delta T < -0.5°C) \cup (\Delta T > 1°C)$	0.47	0.27	0.08	0.45	0.92	0.52

Notes: Events were elicited in the order $E_0 - E_1 - E_2 - E_3 - E_1^C - E_2^C - E_3^C$. Summary statistics for the matching probabilities of the seven events are shown. The last column shows the empirical frequencies (starting from 1990, own calculation)

Table 3.A.6. Relation between estimated parameter changes and characteristics

	Δ Ambiguity aversion (α)	Δ Perc. level of ambiguity (ℓ)	Δ Model error (σ_ε)
Wave 2	0.02*	0.02	-0.02***
	(0.01)	(0.02)	(0.01)
Wave 3	-0.01	0.03	-0.01**
	(0.01)	(0.02)	(0.01)
Wave 4	-0.01	0.02	0.00
	(0.01)	(0.02)	(0.01)
Age: $\in (35, 50]$	-0.01	-0.02	-0.00
	(0.01)	(0.02)	(0.00)
Age: $\in (50, 65]$	0.00	-0.02	0.00
	(0.01)	(0.02)	(0.00)
Age: ≥ 65	0.01	-0.02	0.01**
	(0.01)	(0.02)	(0.00)
Female	-0.01***	0.01	-0.00
	(0.00)	(0.01)	(0.00)
Education: Junior college	0.01	-0.01	-0.00
	(0.01)	(0.01)	(0.00)
Education: College	0.01*	-0.01	-0.00
	(0.01)	(0.01)	(0.00)
Education: University	0.01	-0.01	-0.01*
	(0.01)	(0.01)	(0.00)
Income: $\in (1.1, 1.6]$	-0.00	0.00	0.00
	(0.01)	(0.01)	(0.00)
Income: $\in (1.6, 2.2]$	-0.01	-0.00	0.00
	(0.01)	(0.01)	(0.00)
Income: ≥ 2.2	0.00	0.00	0.00
	(0.01)	(0.01)	(0.00)
Financial assets: $\in (1.8, 11.2]$	0.01	0.00	-0.00
	(0.01)	(0.01)	(0.00)
Financial assets: $\in (11.2, 32]$	-0.00	-0.00	-0.00
	(0.01)	(0.01)	(0.00)
Financial assets: ≥ 32	0.01	-0.00	-0.01
	(0.01)	(0.01)	(0.00)
Risk aversion index	0.00*	0.00	-0.00
	(0.00)	(0.00)	(0.00)
Numeracy index	-0.01**	-0.00	-0.01***
	(0.00)	(0.00)	(0.00)
N	4181	4181	4181
R^2	0.009	0.001	0.016

Notes: Income and financial assets are in thousands, pooled within household and adjusted for household size. OLS regression, robust standard errors in parentheses. Outcomes are within-subject changes in estimated parameters across consecutive waves.

Table 3.A.7. Relation between estimated parameters and characteristics

	α	α	ℓ	ℓ	σ_ε
Intercept	0.06***	0.06***	0.50***	0.52***	0.17***
	(0.01)	(0.02)	(0.03)	(0.03)	(0.01)
Age: $\in (35, 50]$	-0.01	-0.01	-0.00	0.00	0.02**
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)
Age: $\in (50, 65]$	-0.02*	-0.03**	0.01	0.01	0.03***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)
Age: ≥ 65	-0.03**	-0.03**	0.02	0.03	0.05***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)
Female	0.00	0.01	0.03***	0.03***	-0.02***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
Education: Junior college	-0.00	0.00	0.02	0.01	-0.00
	(0.01)	(0.01)	(0.01)	(0.02)	(0.00)
Education: College	-0.01	-0.00	-0.03*	-0.02	-0.01
	(0.01)	(0.01)	(0.01)	(0.02)	(0.00)
Education: University	-0.01	-0.01	-0.04**	-0.04*	-0.00
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)
Income: $\in (1.1, 1.6]$	0.01	0.01	0.01	0.00	-0.01*
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)
Income: $\in (1.6, 2.2]$	0.01	0.02*	0.02	0.02	-0.01*
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)
Income: ≥ 2.2	-0.00	0.00	0.02	0.01	-0.01**
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)
Financial assets: $\in (1.8, 11.2]$	-0.01	-0.01	-0.01	-0.02	-0.00
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)
Financial assets: $\in (11.2, 32]$	-0.01	-0.02*	-0.04**	-0.04**	0.00
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)
Financial assets: ≥ 32	-0.02*	-0.02**	-0.05***	-0.05***	0.00
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)
Risk aversion index	0.00	0.01*	0.01	0.01**	-0.01***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)
Numeracy index	-0.01**	-0.01*	-0.04***	-0.07***	-0.03***
	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)
High σ_ε excluded	No	Yes	No	Yes	No
N	1614	1318	1614	1318	1614
R^2	0.024	0.029	0.084	0.139	0.204

Notes: Income and financial assets are in thousands, pooled within household and adjusted for household size. OLS regressions of the parameters of the pooled model on several individual characteristics. Sample restrictions: Individuals with at least two waves of regular choices. Choices are irregular if they exhibit recurring patterns whilst also being entered quicker than 85% of subjects. In column 2 and column 4, the individuals of the high error group (based on k-means) are excluded. Robust standard errors in parentheses.

Table 3.A.8. Dependence of parameters relating to temperature uncertainty on parameters relating to uncertainty about the AEX

Parameter	α		ℓ		σ_ε	
Model	OLS	2SLS	OLS	2SLS	OLS	2SLS
Intercept	0.05*	0.00	0.44***	0.20***	0.01	-0.03
	(0.03)	(0.03)	(0.06)	(0.07)	(0.02)	(0.02)
AEX param	0.70***	1.00***	0.34***	0.61***	0.48***	1.06***
	(0.03)	(0.09)	(0.03)	(0.06)	(0.03)	(0.11)
Age: $\in (35, 50]$	-0.00	0.00	0.07**	0.10***	0.01	0.01
	(0.01)	(0.01)	(0.03)	(0.04)	(0.01)	(0.01)
Age: $\in (50, 65]$	-0.01	-0.01	0.07**	0.10***	0.01	0.00
	(0.01)	(0.02)	(0.03)	(0.04)	(0.01)	(0.01)
Age: ≥ 65	-0.01	-0.01	0.08**	0.09**	0.01	-0.02*
	(0.01)	(0.01)	(0.03)	(0.04)	(0.01)	(0.01)
Education: Junior college	0.00	0.01	0.02	0.03	-0.00	-0.01
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
Education: College	-0.01	-0.00	0.01	0.02	-0.00	-0.00
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
Education: University	-0.01	0.00	-0.05**	-0.03	0.01	0.01
	(0.01)	(0.01)	(0.03)	(0.03)	(0.01)	(0.01)
Income: $\in (1.1, 1.6]$	-0.00	-0.01	-0.01	-0.01	0.00	0.01
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
Income: $\in (1.6, 2.2]$	-0.00	-0.01	-0.02	-0.02	-0.00	-0.00
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
Income: ≥ 2.2	0.00	0.00	-0.01	-0.00	0.00	0.00
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
Financial assets: $\in (1.8, 11.2]$	-0.01	0.00	-0.01	-0.01	0.01	0.02*
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
Financial assets: $\in (11.2, 32]$	-0.00	0.01	-0.03	-0.00	0.01	-0.00
	(0.01)	(0.01)	(0.02)	(0.03)	(0.01)	(0.01)
Financial assets: ≥ 32	0.01	0.02	-0.04	-0.02	0.01	0.01
	(0.01)	(0.01)	(0.02)	(0.03)	(0.01)	(0.01)
Female	-0.02**	-0.01	0.00	0.00	0.00	0.01**
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
Risk aversion index	-0.01*	-0.01**	-0.00	-0.01	-0.00	0.00
	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)
Numeracy index	0.00	0.01	0.01	0.03**	-0.01***	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)
Judged hist. freq: positive return	-0.03**	-0.02	0.01	0.05*	0.00	0.01
	(0.01)	(0.02)	(0.03)	(0.03)	(0.01)	(0.01)
Judged hist. freq: response error	0.01*	0.02*	0.02	0.02	0.00	-0.00
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
Judged hist. freqs: mean absolute deviation	-0.02	-0.00	-0.06	-0.01	0.02	-0.02
	(0.04)	(0.05)	(0.07)	(0.08)	(0.03)	(0.03)
Optimism	-0.00	0.00	0.01	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)
Underst. c.c.	-0.01**	-0.01**	-0.02**	-0.02**	0.01**	0.01***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)
Threat. by c.c.	0.00	0.00	-0.00	0.01	0.00	-0.00
	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)
N	1297	1186	1297	1186	1297	1186
R^2	0.416	-	0.170	-	0.236	-
1st st. F	-	79.8	-	309.3	-	134.7

Notes: Outcomes are estimated parameters in the temperature domain in the 4th wave, regressors are estimated parameters in the AEX domain in the 4th wave. Two stage least squares models use estimated parameters from the previous three waves as instruments. Robust standard errors in parentheses. Sample restrictions: Observations with regular choices. Choices are irregular if they exhibit recurring patterns whilst also being entered quicker than 85% of subjects.

Appendix 3.B Additional figures

Figure 3.B.1 shows the decision tree we use to elicit the matching probability of one aex event. Suppose for example, a subject answered in the following sequence: LOT, AEX, AEX, AEX. Then we would know that the matching probability lies between 40 % and 50 %. Suppose conversely, a subject answered LOT, LOT, LOT, LOT. Then we would know that the matching probability lies between 0 % and 1 %.

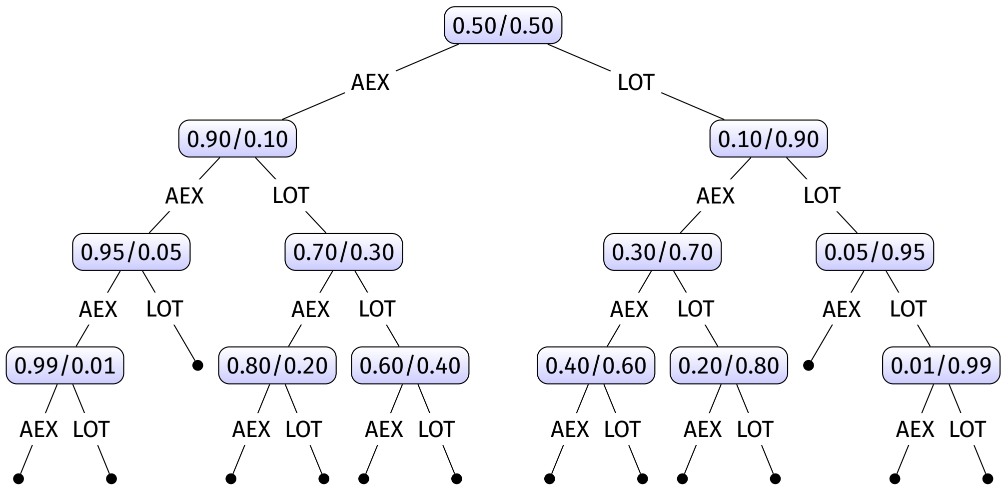

Figure 3.B.1. Iterative sequence of lottery probabilities for one AEX event

Figure 3.B.2 shows the distributions of time taken for the first choice relating to each event, for individuals who used repeating choice patterns for events (always choosing the lottery or always choosing the AEX) and for those who did not.

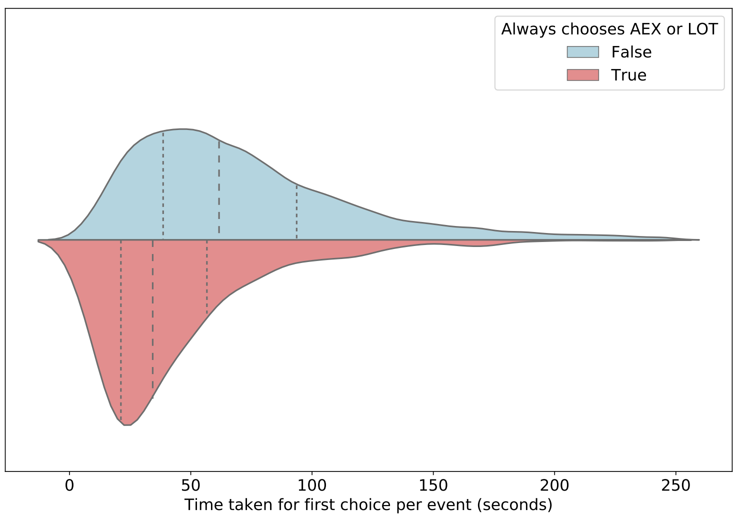

Figure 3.B.2. Time taken for first choice, by choice pattern

Appendix 3.C Relaxing parameter restrictions

We restimate our model but keep only the constraint that $\tau_2 > 0$ and the probability constraints, which means that the only behaviour ruled out in the deterministic part of the model are set-monotonicity violations. We calculate the area between the 45 degree line and $\min(\max(\tau_0 + \tau_1 \Pr(E), 0), 1)$ to obtain α, and 1 minus the average slope of $\min(\max(\tau_0 + \tau_1 \Pr(E), 0), 1)$ over the range $Pr(E) \in [0.05, 0.95]$ to obtain ℓ.

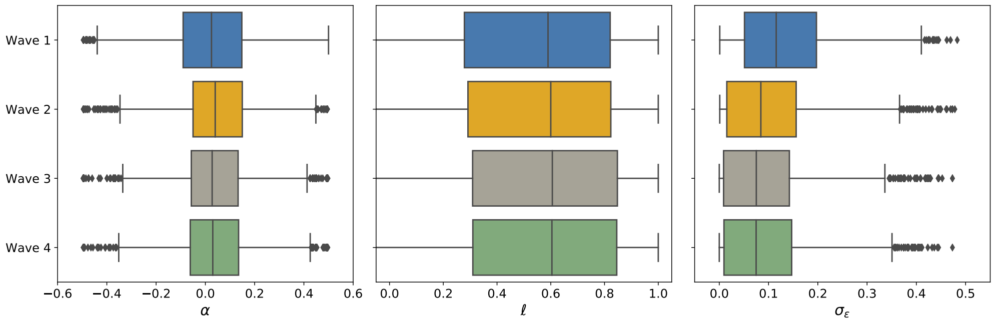

Figure 3.C.1. Distributions of estimated parameters, wave by wave

Notes: Sample restrictions: Observations with regular choices. Choices are irregular if they exhibit recurring patterns whilst also being entered quicker than 85% of subjects

Table 3.C.1. Across wave correlations of estimated parameters

	$\hat{\rho}_{1,2}$	$\hat{\rho}_{1,3}$	$\hat{\rho}_{1,4}$	$\hat{\rho}_{2,3}$	$\hat{\rho}_{2,4}$	$\hat{\rho}_{3,4}$	Average $\hat{\rho}$
α	0.25	0.22	0.20	0.27	0.22	0.33	0.25
ℓ	0.22	0.20	0.24	0.32	0.33	0.39	0.29
σ_ε	0.13	0.17	0.20	0.27	0.28	0.32	0.23

Notes: Table shows Pearson correlations between parameter estimates across waves, with subscripts indicating the waves. Parameter estimates are obtained by the model described in Section 3.3.2 but removing parameter restrictions except $\tau_2 > 0$. The model is estimated separately for each survey wave and individual. Sample restrictions: Observations with regular choices. Choices are irregular if they exhibit recurring patterns whilst also being entered quicker than 85% of subjects.

Table 3.C.2. Dependence of parameters relating to temperature uncertainty on parameters relating to uncertainty about the AEX

Parameter		α			ℓ			σ_ε	
Model	OLS	OLS	2SLS	OLS	OLS	2SLS	OLS	OLS	2SLS
Intercept	-0.01**	0.05*	0.01	0.41***	0.42***	0.16**	0.06***	0.01	-0.03
	(0.00)	(0.03)	(0.03)	(0.02)	(0.06)	(0.08)	(0.00)	(0.02)	(0.02)
AEX param	0.70***	0.70***	1.00***	0.36***	0.35***	0.65***	0.49***	0.46***	1.12***
	(0.03)	(0.03)	(0.09)	(0.03)	(0.03)	(0.07)	(0.03)	(0.03)	(0.12)
Underst. c.c.		-0.01**	-0.01**		-0.02**	-0.02**		0.01**	0.01***
		(0.00)	(0.00)		(0.01)	(0.01)		(0.00)	(0.00)
Threat. by c.c.		0.00	0.00		-0.00	0.01		0.00	0.00
		(0.00)	(0.00)		(0.01)	(0.01)		(0.00)	(0.00)
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
N	1297	1297	1186	1297	1297	1186	1297	1297	1186
R^2	0.400	0.414	-	0.139	0.159	-	0.202	0.223	-
1st st. F	-	-	80.0	-	-	257.1	-	-	81.5

Notes: Sample restrictions: Observations with regular choices. Choices are irregular if they exhibit recurring patterns whilst also being entered quicker than 85% of subjects. Robust standard errors in parentheses. Outcomes are estimated parameters in the temperature domain in the 4th wave, regressors are estimated parameters in the AEX domain in the 4th wave. Two stage least squares models use estimated parameters from the previous three waves as instruments. Controls are age, gender, education, income and assets dummies, risk aversion, basic, financial and probability numeracy and indicators of self-assessed understanding and perceived threat of climate change with a 5 and 6 point scale respectively.

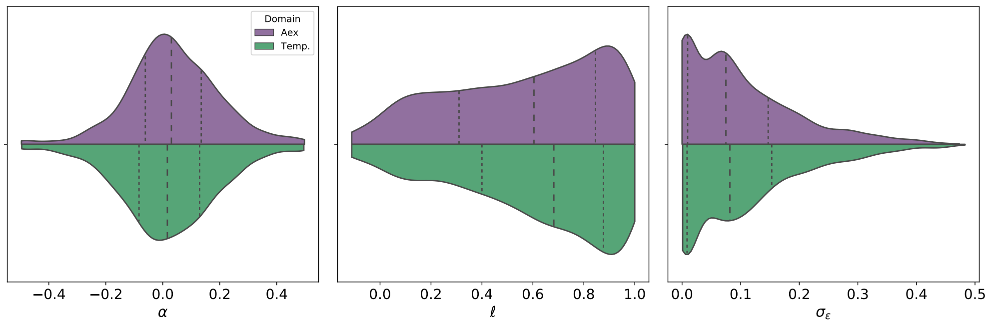

Figure 3.C.2. Distributions of estimated parameters, AEX v Temperature domains

Notes: Sample restrictions: Observations with regular choices. Choices are irregular if they exhibit recurring patterns whilst also being entered quicker than 85% of subjects.

Table 3.C.3. Individual characteristics of groups (K=4)

	Group = 1	Group = 2	Group = 3	Group = 4
share	0.29	0.21	0.18	0.32
α	0.15	-0.07	0.03	0.00
ℓ	0.70	0.62	0.49	0.26
σ_ε	0.14	0.16	0.31	0.16
Education: University	0.11	0.14	0.05	0.20
Age	55.51	58.06	65.05	54.79
Female	0.58	0.53	0.47	0.41
Income (thousands)	1.62	1.58	1.47	1.75
Financial assets (thousands)	6.32	10.95	10.00	14.71
Risk aversion index	0.12	-0.05	-0.02	-0.07
Numeracy index	-0.12	0.05	-0.72	0.48
Judged hist. freq: positive return	0.48	0.53	0.47	0.58
Judged hist. freq: response error	0.62	0.57	0.77	0.43
Judged hist. freqs: mean absolute deviation	0.18	0.18	0.22	0.19
Optimism	-0.11	0.06	-0.18	0.16

Notes: The first row shows the share of individuals classified to a given group. For each group, the mean of several variables are shown. For income and total assets, the median is reported instead. The variables for risk aversion, numeracy and optimism are standard normalized. Sample restrictions: Individuals with at least two waves of regular choices. Choices are irregular if they exhibit recurring patterns whilst also being completed quicker than 85% of subjects.

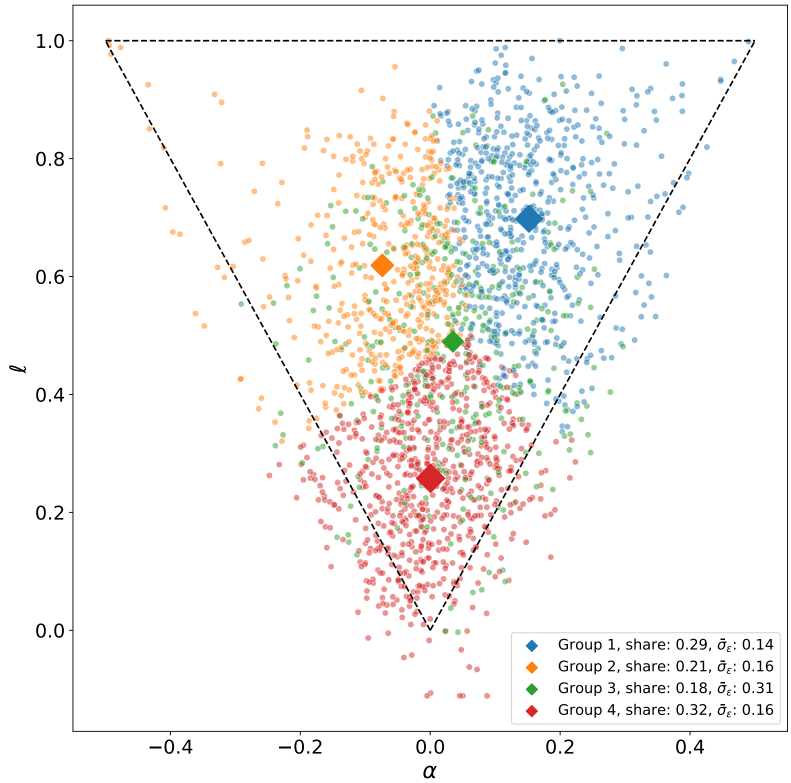

Figure 3.C.3. Summarising heterogeneity in ambiguity profiles with K=4 discrete groups

Notes: The small dots depict individual ambiguity profiles consisting of the aversion parameter α and the likelihood insensitivity parameter ℓ. The large diamonds are group centres resulting from clustering individuals with the k-means algorithm on the parameters α, ℓ and σ_ε. We dashed black triangle shows the region into which we constrain estimates in our main model. Sample restrictions: Individuals with at least two waves of regular choices. Choices are irregular if they exhibit recurring patterns whilst also being entered quicker than 85% of subjects.

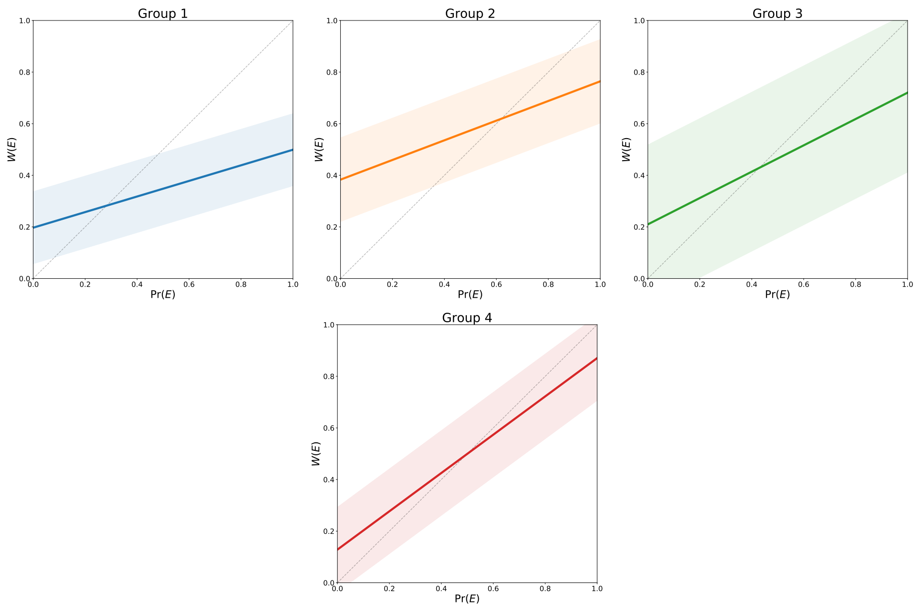

Figure 3.C.4. Event weights as a function of subjective probabilities, by group (K=4)

Notes: Sample restrictions: Individuals with at least two waves of regular choices. Choices are irregular if they exhibit recurring patterns whilst also being completed quicker than 85% of subjects. The figure plots the lines $W(E) = \frac{\ell}{2} - \alpha + (1 - \ell) \cdot \Pr(E)$ for the group-average values of α and ℓ. The vertical difference to the 45 degree line measures the extent of ambiguity seeking w.r.t. gains from events whose source of uncertainty is the future development of the AEX.

Table 3.C.4. Predictors of groups, marginal effects (K=4)

	Group = 1	Group = 2	Group = 3	Group = 4
Age: $\in (35, 50]$	-0.02	-0.03	0.05	-0.00
	(0.05)	(0.05)	(0.06)	(0.05)
Age: $\in (50, 65]$	-0.08	0.02	0.08	-0.02
	(0.05)	(0.05)	(0.06)	(0.05)
Age: ≥ 65	-0.10**	0.01	0.18***	-0.08*
	(0.05)	(0.05)	(0.06)	(0.05)
Education: Junior college	0.02	-0.01	-0.00	-0.01
	(0.03)	(0.03)	(0.02)	(0.03)
Education: College	0.04	-0.05*	-0.00	0.01
	(0.03)	(0.03)	(0.03)	(0.03)
Education: University	-0.01	-0.02	0.01	0.02
	(0.04)	(0.04)	(0.04)	(0.04)
Income: $\in (1.1, 1.6]$	0.06*	-0.01	-0.02	-0.02
	(0.03)	(0.03)	(0.03)	(0.03)
Income: $\in (1.6, 2.2]$	0.09***	-0.04	-0.03	-0.02
	(0.03)	(0.03)	(0.03)	(0.03)
Income: ≥ 2.2	0.06*	-0.04	-0.01	-0.01
	(0.04)	(0.03)	(0.03)	(0.04)
Financial assets: $\in (1.8, 11.2]$	-0.05	0.04	-0.03	0.04
	(0.03)	(0.03)	(0.03)	(0.04)
Financial assets: $\in (11.2, 32]$	-0.09**	-0.00	0.03	0.06*
	(0.03)	(0.04)	(0.03)	(0.04)
Financial assets: ≥ 32	-0.12***	0.02	0.03	0.07*
	(0.04)	(0.04)	(0.03)	(0.04)
Female	0.07***	0.02	-0.07***	-0.01
	(0.02)	(0.02)	(0.02)	(0.02)
Risk aversion index	0.03***	-0.01	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Numeracy index	-0.02*	-0.01	-0.11***	0.15***
	(0.01)	(0.01)	(0.01)	(0.02)
Judged hist. freq: positive return	-0.14***	-0.01	-0.01	0.16***
	(0.04)	(0.04)	(0.03)	(0.04)
Judged hist. freq: response error	-0.01	-0.00	0.05**	-0.03
	(0.03)	(0.02)	(0.02)	(0.02)
Judged hist. freqs: mean absolute deviation	-0.30**	-0.22*	0.42***	0.11
	(0.12)	(0.12)	(0.10)	(0.12)
Optimism	-0.02*	0.02	-0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
N	1460	1460	1460	1460
Pseudo R^2	0.12	0.12	0.12	0.12

Notes: Income and financial assets are in thousands, pooled within household and adjusted for household size. Sample restrictions: Individuals with at least two waves of regular choices. Choices are irregular if they exhibit recurring patterns whilst also being completed quicker than 85% of subjects.

Appendix 3.D Setting the number of groups to K = 8

We double the number of groups from $K = 4$ to $K = 8$ when allocating individuals into groups with the k-means algorithm and reproduce the analyses of Section 3.4.3.

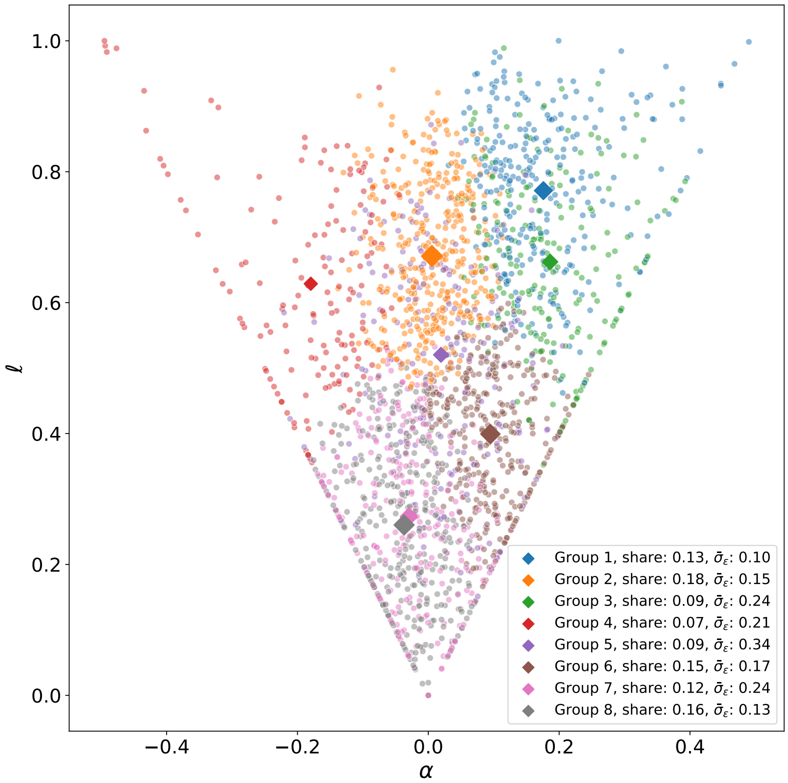

Figure 3.D.1. Summarising heterogeneity in ambiguity profiles with K=8 discrete groups

Notes: The small dots depict individual ambiguity profiles consisting of the aversion parameter α and the likelihood insensitivity parameter ℓ. The large diamonds are group centres resulting from clustering individuals with the k-means algorithm on the parameters α, ℓ and σ_ε. Sample restrictions: Individuals with at least two waves of regular choices. Choices are irregular if they exhibit recurring patterns whilst also being entered quicker than 85% of subjects.

Table 3.D.1. Individual characteristics of groups (K=8)

	G = 1	G = 2	G = 3	G = 4	G = 5	G = 6	G = 7	G = 8
share	0.13	0.18	0.09	0.07	0.09	0.15	0.12	0.16
α	0.18	0.01	0.19	-0.18	0.02	0.09	-0.03	-0.04
ℓ	0.77	0.67	0.66	0.63	0.52	0.40	0.27	0.26
σ_ε	0.10	0.15	0.24	0.21	0.34	0.17	0.24	0.13
Education: University	0.10	0.12	0.07	0.10	0.05	0.12	0.15	0.26
Age	54.72	56.38	61.59	63.47	66.55	54.15	60.88	51.61
Female	0.67	0.56	0.47	0.51	0.49	0.48	0.39	0.40
Income (thousands)	1.58	1.61	1.47	1.54	1.40	1.71	1.73	1.76
Financial assets (thousands)	5.07	9.56	6.40	11.76	9.85	11.76	14.68	14.85
Risk aversion index	0.17	-0.02	0.13	0.08	-0.09	0.00	-0.11	-0.10
Numeracy index	-0.16	0.02	-0.52	-0.20	-0.85	0.35	-0.01	0.66
Judged hist. freq: positive return	0.46	0.50	0.45	0.50	0.50	0.55	0.53	0.62
Judged hist. freq: response error	0.64	0.56	0.73	0.67	0.77	0.51	0.59	0.35
Judged hist. freqs: mean absolute deviation	0.19	0.18	0.21	0.19	0.21	0.19	0.21	0.18
Optimism	-0.10	-0.00	-0.22	0.04	-0.23	0.07	0.08	0.18

Notes: The first row shows the share of individuals classified to a given group. For each group, the mean of several variables are shown. For income and total assets, the median is reported instead. The variables for risk aversion, numeracy and optimism are standard normalized. Sample restrictions: Individuals with at least two waves of regular choices. Choices are irregular if they exhibit recurring patterns whilst also being completed quicker than 85% of subjects.

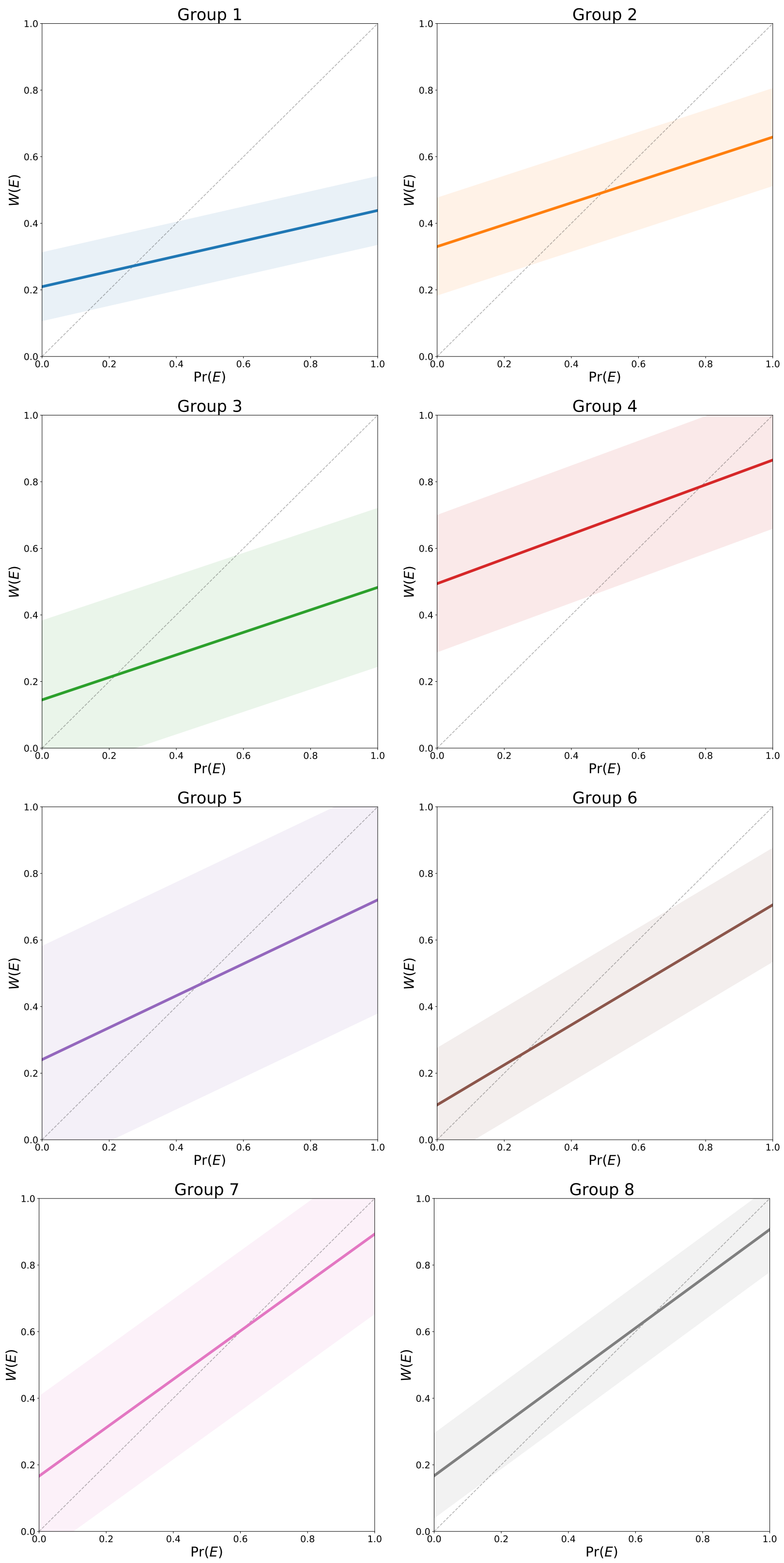

Figure 3.D.2. Event weights as a function of subjective probabilities, by group (K=8)

Notes: The figure plots the estimated source functions, i.e. the lines $W(E) = \frac{\ell}{2} - \alpha + (1-\ell) \cdot \Pr(E)$ for the group-average values of α and ℓ. The vertical difference to the 45 degree line measures the extent of ambiguity seeking w.r.t. gains from events whose source of uncertainty is the future development of the AEX. The shaded area around the lines has bandwith σ_ε, which visualises the imprecision with which observed matching probabilities measure event events. Sample restrictions: Individuals with at least two waves of regular choices. Choices are irregular if they exhibit recurring patterns whilst also being completed quicker than 85% of subjects.

Table 3.D.2. Predictors of groups, marginal effects (K=8)

	G = 1	G = 2	G = 3	G = 4	G = 5	G = 6	G = 7	G = 8
Age: $\in (35, 50]$	-0.01	-0.02	-0.05	0.09	0.02	-0.04	0.04	-0.04
	(0.03)	(0.05)	(0.04)	(0.07)	(0.06)	(0.04)	(0.05)	(0.04)
Age: $\in (50, 65]$	-0.02	-0.02	-0.03	0.10	0.04	-0.11***	0.08	-0.03
	(0.04)	(0.05)	(0.04)	(0.07)	(0.05)	(0.04)	(0.05)	(0.04)
Age: ≥ 65	-0.05	-0.03	-0.01	0.12*	0.10*	-0.09**	0.08	-0.11***
	(0.03)	(0.05)	(0.04)	(0.07)	(0.05)	(0.04)	(0.05)	(0.04)
Education: Junior college	0.01	0.01	-0.01	-0.03*	-0.01	-0.01	0.06**	-0.02
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)
Education: College	0.01	-0.01	-0.00	-0.03*	-0.02	-0.02	0.06**	0.02
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)
Education: University	0.02	-0.01	-0.03	-0.03	0.01	-0.10***	0.10***	0.04
	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Income: $\in (1.1, 1.6]$	0.03	0.02	0.02	-0.03	-0.02	-0.04	-0.01	0.04
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)
Income: $\in (1.6, 2.2]$	0.05*	-0.00	0.01	0.00	-0.02	0.02	-0.02	-0.03
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)
Income: ≥ 2.2	0.04	-0.01	-0.00	-0.00	-0.03	-0.01	0.01	0.01
	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)
Financial assets: $\in (1.8, 11.2]$	-0.04	0.01	-0.03	0.00	-0.03	0.04	-0.03	0.07**
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)
Financial assets: $\in (11.2, 32]$	-0.05**	-0.01	-0.03	-0.01	0.01	0.01	0.03	0.05
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)
Financial assets: ≥ 32	-0.08***	-0.02	-0.04	0.01	0.01	0.01	0.03	0.07*
	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)
Female	0.07***	0.03	-0.03*	-0.00	-0.04**	0.02	-0.04*	-0.00
	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Risk aversion index	0.02***	-0.00	0.00	0.00	-0.01	-0.00	-0.01	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Numeracy index	-0.02*	-0.01	-0.03***	-0.02**	-0.06***	0.05***	-0.04***	0.12***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Judged hist. freq: positive return	-0.08**	-0.10**	-0.04	-0.01	0.02	0.03	0.00	0.18***
	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
Judged hist. freq: response error	-0.01	-0.01	0.01	0.00	0.01	0.01	0.01	-0.02
	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Judged hist. freqs: mean absolute deviation	-0.06	-0.41***	0.14*	0.01	0.14*	-0.03	0.29***	-0.09
	(0.09)	(0.12)	(0.09)	(0.07)	(0.08)	(0.10)	(0.10)	(0.10)
Optimism	-0.01	0.02	-0.01*	0.01	-0.01	-0.00	0.01	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
N	1460	1460	1460	1460	1460	1460	1460	1460
Pseudo R^2	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10

Notes: Multinomial logit regression. Robust standard errors. For the thresholds of the income and asset quartiles see Table 3.2.1. Income and financial assets are in thousands, pooled within household and adjusted for household size. The variables for risk aversion, numeracy and optimism are standard normalized. Sample restrictions: Individuals with at least two waves of regular choices. Choices are irregular if they exhibit recurring patterns whilst also being completed quicker than 85% of subjects.

Appendix 3.E Analysis with indices

We estimate ambiguity attitudes using the indices proposed by Baillon, Bleichrodt, Li, et al. (2019) except that to maintain comparability with our main results, we do not divide the estimate of the ambiguity aversion parameter α by 2.

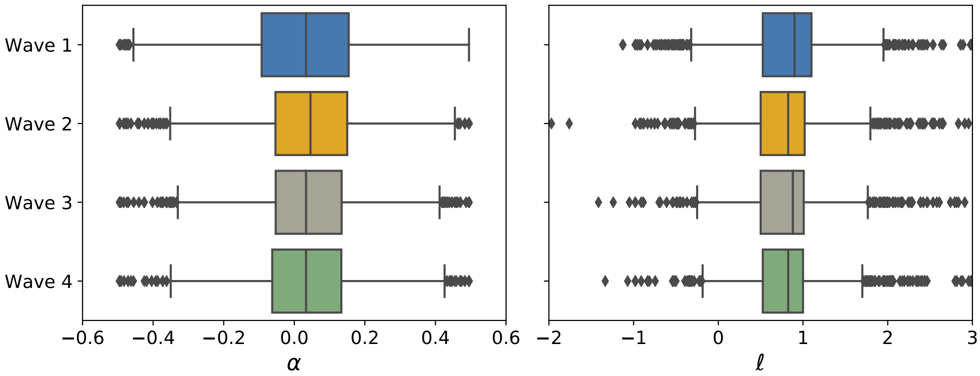

Figure 3.E.1. Distributions of estimated parameters, wave by wave

Notes: Sample restrictions: Observations with regular choices. Choices are irregular if they exhibit recurring patterns whilst also being entered quicker than 85% of subjects. Parameter estimates are the indices proposed by Baillon, Bleichrodt, Li, et al. (2019), calculated for each survey wave and individual.

Table 3.E.1. Across wave correlations of estimated parameters

	$\hat{\rho}_{1,2}$	$\hat{\rho}_{1,3}$	$\hat{\rho}_{1,4}$	$\hat{\rho}_{2,3}$	$\hat{\rho}_{2,4}$	$\hat{\rho}_{3,4}$	Average $\hat{\rho}$
α	0.21	0.18	0.24	0.32	0.25	0.20	0.24
ℓ	-0.02	0.02	0.03	0.19	0.15	0.15	0.09

Notes: Sample restrictions: Observations with regular choices. Choices are irregular if they exhibit recurring patterns whilst also being entered quicker than 85% of subjects. Table shows Pearson correlations between parameter estimates across waves, with subscripts indicating the waves. Parameter estimates are the indices proposed by Baillon, Bleichrodt, Li, et al. (2019), calculated for each survey wave and individual.

Table 3.E.2. Dependence of parameters relating to temperature uncertainty on parameters relating to uncertainty about the AEX

Parameter		α			ℓ	
Model	OLS	OLS	2SLS	OLS	OLS	2SLS
Intercept	-0.00	0.05*	0.01	0.73***	0.64***	0.07
	(0.00)	(0.03)	(0.03)	(0.03)	(0.10)	(0.23)
AEX param	0.69***	0.68***	1.05***	0.16***	0.14***	0.79***
	(0.03)	(0.03)	(0.10)	(0.04)	(0.04)	(0.23)
Underst. c.c.		-0.01**	-0.01**		-0.01	-0.01
		(0.00)	(0.01)		(0.01)	(0.02)
Threat. by c.c.		0.01	0.01		0.01	0.02
		(0.00)	(0.00)		(0.01)	(0.02)
Controls	No	Yes	Yes	No	Yes	Yes
N	1297	1297	1186	1297	1297	1186
R^2	0.386	0.400	-	0.028	0.052	-
1st st. F	-	-	67.1	-	-	24.4

Notes: Sample restrictions: Observations with regular choices. Choices are irregular if they exhibit recurring patterns whilst also being entered quicker than 85% of subjects. Robust standard errors in parentheses. Outcomes are estimated parameters in the temperature domain in the 4th wave, regressors are estimated parameters in the AEX domain in the 4th wave. Two stage least squares models use estimated parameters from the previous three waves as instruments. Controls are age, gender, education, income and assets dummies, risk aversion, basic, financial and probability numeracy and indicators of self-assessed understanding and perceived threat of climate change with a 5 and 6 point scale respectively. Parameter estimates are the indices proposed by Baillon, Bleichrodt, Li, et al. (2019), calculated for each survey wave and individual.

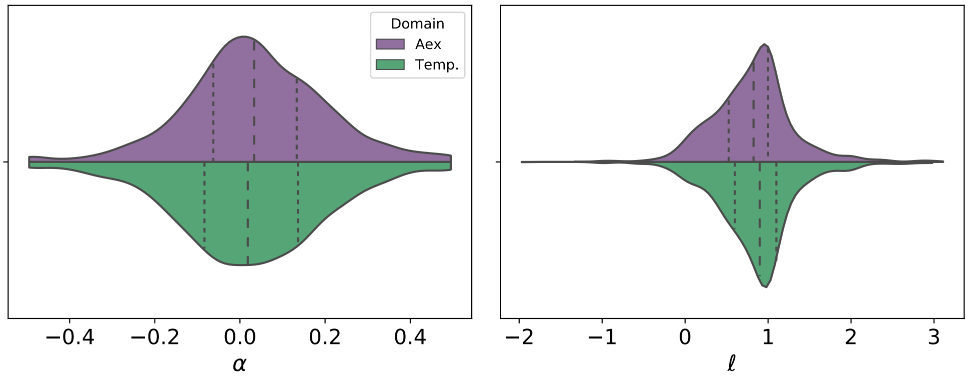

Figure 3.E.2. Distributions of estimated parameters, AEX v Temperature domains

Notes: Sample restrictions: Observations with regular choices. Choices are irregular if they exhibit recurring patterns whilst also being entered quicker than 85% of subjects. Parameter estimates are the indices proposed by Baillon, Bleichrodt, Li, et al. (2019), calculated for each survey wave and individual.

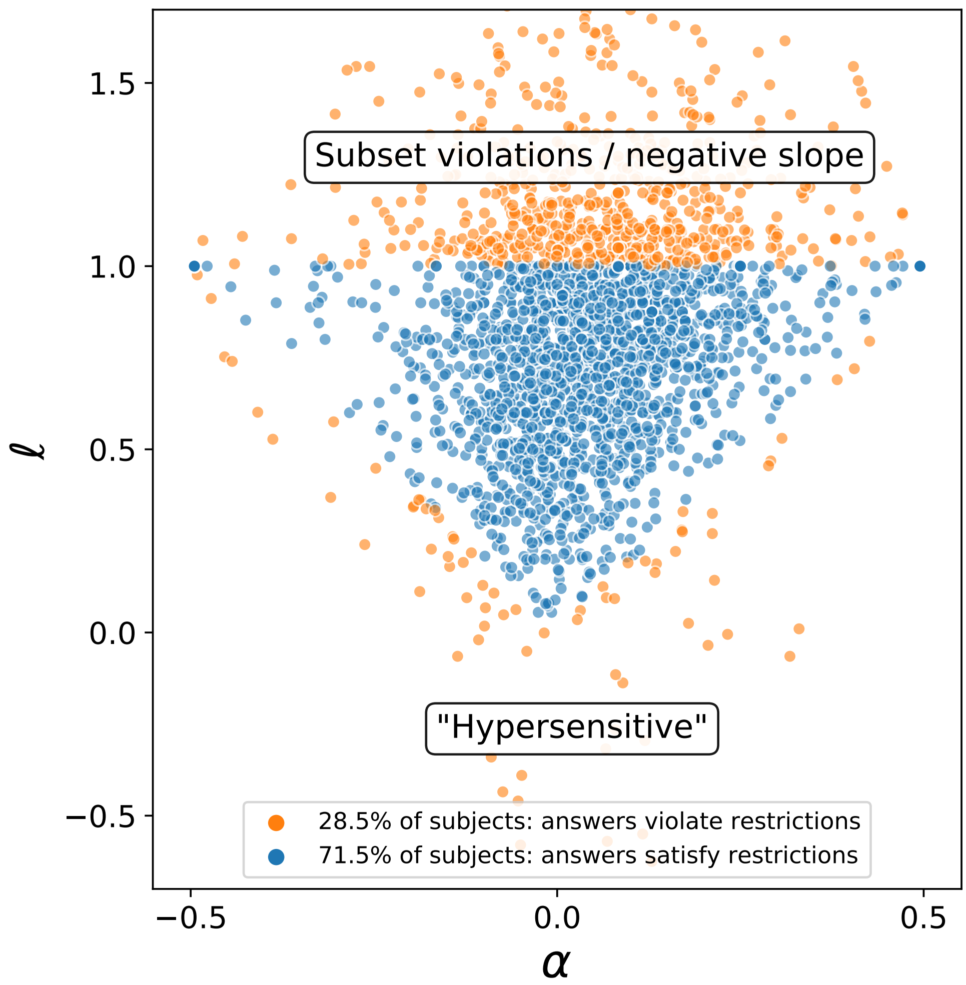

Figure 3.E.3. Summarising heterogeneity in ambiguity profiles, indices

Notes: Sample restrictions: Individuals with at least two waves of regular choices. Choices are irregular if they exhibit recurring patterns whilst also being entered quicker than 85% of subjects. Parameter estimates are across-wave averages of the indices proposed by Baillon, Bleichrodt, Li, et al. (2019). The blue dots are parameter values that satisfy the restrictions we impose in our main model. Values above can only came about through set-monotonicity errors. Values below indicate hypersensitivity.

Table 3.E.3. Relation between estimated indices and characteristics

	α	ℓ
Intercept	0.06***	0.78***
	(0.01)	(0.03)
Age: $\in (35, 50]$	-0.01	0.03
	(0.01)	(0.03)
Age: $\in (50, 65]$	-0.02*	0.04
	(0.01)	(0.03)
Age: ≥ 65	-0.02**	0.08**
	(0.01)	(0.03)
Female	0.01	-0.00
	(0.01)	(0.01)
Education: Junior college	-0.00	0.03
	(0.01)	(0.02)
Education: College	-0.01	-0.06***
	(0.01)	(0.02)
Education: University	-0.01	-0.07**
	(0.01)	(0.03)
Income: $\in (1.1, 1.6]$	0.01	-0.01
	(0.01)	(0.02)
Income: $\in (1.6, 2.2]$	0.01	0.02
	(0.01)	(0.02)
Income: ≥ 2.2	-0.00	0.01
	(0.01)	(0.02)
Financial assets: $\in (1.8, 11.2]$	-0.00	-0.00
	(0.01)	(0.02)
Financial assets: $\in (11.2, 32]$	-0.01	-0.01
	(0.01)	(0.02)
Financial assets: ≥ 32	-0.02*	-0.02
	(0.01)	(0.02)
Risk aversion index	0.00	-0.00
	(0.00)	(0.01)
Numeracy index	-0.01*	-0.07***
	(0.00)	(0.01)
N	1614	1614
R^2	0.021	0.093

Notes: OLS regressions of the ambiguity indices pooled over all waves on several individual characteristics. Income and financial assets are in thousands, pooled within household and adjusted for household size. Sample restrictions: Individuals with at least two waves of regular choices. Choices are irregular if they exhibit recurring patterns whilst also being entered quicker than 85% of subjects. Robust standard errors in parentheses.

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