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The Distribution of Ambiguity Attitudes

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This paper analyzes the stability and distribution of ambiguity attitudes using a broad population sample. Using high-powered incentives, we collected six waves of data on ambiguity attitudes about financial markets—our main application—and climate change. Estimating a structural stochastic choice model, we obtain three individual-level parameters: Ambiguity aversion, likelihood insensitivity, and the magnitude of decision errors. These parameters are very heterogeneous in the population. At the same time, they are stable over time and largely stable across domains. We summarize heterogeneity in these three dimensions using a discrete classification approach with four types. Each group makes up 20-30 % of the sample. One group comes close to the behavior of expected utility maximizers. Two types are characterized by high likelihood insensitivity; one of them is ambiguity averse and the other ambiguity seeking. Members of the final group have large error parameters; robust conclusions about their ambiguity attitudes are difficult. Observed characteristics vary between groups in plausible ways. Ambiguity types predict risky asset holdings in the expected fashion, even after controlling for many covariates.

Keywords: ambiguity attitudes; temporal stability; domain specificity; socio-demographic factors; cluster analysis; household portfolio choice
JEL: D81, G41, C38, D14,

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1 Introduction

People face ambiguity in many domains. How likely is it that the return on a portfolio of stocks is larger than some threshold for a certain horizon? What are the odds that an offered job will be sufficiently better than the current one? Will climate change make living at the current place of residence much harder during one's lifetime? In a large class of models, decisions in the face of ambiguity depend on two core parameters. Ambiguity aversion is the average dislike for ambiguous events compared to risky events with known probabilities. Likelihood insensitivity measures how strongly decisions react to changes in subjective beliefs about the ambiguous event; an alternative interpretation of this parameter is the degree of ambiguity. Decision-making under risk emerges as the special case where both parameters are irrelevant.

To what extent ambiguity aversion and likelihood insensitivity represent fundamental personal traits is, however, largely an open question. How stable are they over time and across domains? Do they vary in expected ways with observable characteristics in broad population samples? What is the connection between ambiguity attitudes and decisions in everyday life? This paper sheds light on these questions. In doing so, we address methodological questions on how to deal with decision errors when eliciting ambiguity attitudes and on how to best describe heterogeneity when traits are interdependent.

Six bi-annual waves of data on ambiguity attitudes in the domain of the stock market form the basis of our analysis. We collected this data in a probability-based sample of the Dutch population using substantial financial incentives (expected hourly compensation corresponded to 51 €). In one wave, we also included the domain of climate change. In total, we analyze data from almost 2,200 individuals or 11,000 person × wave observations.

In each wave, respondents faced a series of choices between receiving a prize with some known probability or receiving it in case an ambiguous event occurred. As an example, one such event consisted of an investment in a stock market index yielding a positive return over the upcoming six months. For seven events like this per wave, our design yields data on individuals' *matching probabilities*. For the matching probability, an individual is indifferent between receiving the prize with that probability and receiving it if the ambiguous event occurs.

Descriptively, five salient features emerge for matching probabilities. First, the sum of average matching probabilities for an event and its complement is less than one. This implies that, on average, subjects are averse to ambiguity. Second, average matching probabilities are *sub-additive* in the sense that the sum of matching probabilities of two mutually exclusive events exceeds the matching probability of their union. This means individuals are ambiguity averse for high-probability events and ambiguity seeking for low-probability events on average. Third, matching probabilities differ widely across subjects. Fourth, a non-negligible fraction of choice patterns violates set-monotonicity; i.e., choices reveal a higher matching probability for an event that is a strict subset of another. Such patterns cannot be rationalized by deterministic theories of choice under uncertainty. Fifth, the rate of set-monotonicity violations is highest for pairs of choices where—based on a separate question on the historical behavior of the stock market—individuals judge the past frequency of the event forming the subset to be large relative to that of the superset.

To account for these facts, we set up a stochastic choice model with three parameters of interest. Ambiguity aversion and likelihood insensitivity control the deterministic part of the model; the third parameter is the relative weight of its stochastic component. In a first step, we structurally estimate the model for each individual × wave observation separately. The stylized facts on matching probabilities are reflected in the marginal parameter distributions. On average, individuals are ambiguity averse. Likelihood insensitivity is quantitatively very important for the majority of observations. All parameters display large heterogeneity. For example, a substantial fraction of subjects display ambiguity seeking behavior on average. Most choice sequences cannot be fully rationalized by the deterministic model and the importance of the stochastic component turns out to be a key feature for describing different individuals' choice sequences.

We show that all three parameters are stable over time and largely stable across domains. Over time, the stability of ambiguity aversion and likelihood insensitivity is comparable to what previous literature finds for risk preferences. When accounting for attenuation due to measurement error, we find that there are no systematic changes in the sense that individuals' parameters in one time period are the best predictors for parameters in another period. Looking across the domains of finance and climate change, ambiguity aversion and the magnitude of decision errors are completely transferable in this sense. Transferability is lower for likelihood insensitivity. These results suggest that ambiguity aversion is a domain-invariant preference parameter but that individuals have different degrees of trust in their probability judgments in different domains (or that they perceive a different level of ambiguity).

Imposing stability of preferences, we find that a clustering approach is a useful way to describe parameter heterogeneity. From an ex-ante perspective, it does not place any restrictions on the joint distribution of the three parameters and thus accounts for the non-separable nature of the model. Empirically, we find that four groups—each of which has a share of 20-30 %—summarize broad choice patterns well. One type is fairly close to the behavior of subjective expected utility maximization; ambiguity aversion and likelihood insensitivity play limited roles. For two groups, likelihood insensitivity is large. They differ in their attitude toward ambiguity. The first of the two displays substantial aversion on average, the other one a slight preference for it. For the three groups described so far, the deterministic part of the model has high explanatory power. The stochastic element plays a much more important role for the last group, which is thus characterized by very noisy decision-making; choice patterns in that group do not reveal much about ambiguity attitudes.

Individual characteristics differ in sensible ways across the four groups. For example, subjects behaving close to subjective expected utility maximization are the most educated, display the highest level of numeracy, and the lowest risk aversion. The groups classified to be ambiguity averse and ambiguity seeking, respectively, are similar in many dimensions of observed characteristics, often assuming intermediate positions. There are exceptions for the ambiguity averse group, which has a high share of females, the lowest financial wealth, and ceteris paribus the highest risk aversion. Finally, the members of the group whose decision-making is noisiest are the oldest, and they have the lowest average levels of education and numeracy.

The preference groups predict portfolio choice behavior. This holds true even after conditioning on a large set of observable characteristics, including financial wealth and risk aversion. We consider two measures of portfolio choice: Whether people hold risky assets and the share invested into these. The group closest to subjective expected utility maximization has the riskiest portfolios according to both measures; the ambiguity averse group takes the least amount of risk.

Our paper is related to various strands of the literature. The importance of distinguishing between uncertainty and risk has been introduced by Keynes (1921) and Knight (1921). Ellsberg (1961) showed deviations from the subjective expected utility paradigm in a controlled empirical setting. Based on those considerations, a burgeoning theoretical literature has produced tractable models of choice under ambiguity (e.g., Gilboa and Schmeidler, 1989; Ghirardato and Marinacci, 2001; Chateauneuf, Eichberger, and Grant, 2007). Our empirical specification is directly based on these models.

Recent advances in measurement techniques (Baillon, Huang, Selim, and Wakker, 2018; Baillon, Bleichrodt, Li, and Wakker, 2021) have made it possible to elicit ambiguity attitudes for domains that go beyond highly stylized settings such as the famous Ellsberg urns. We adapt these methods for use in a broad population survey by simplifying individual decisions, which are all binary choices.

We contribute to the literature examining empirical estimates of ambiguity attitudes. Early papers summarized in Trautmann and van de Kuilen (2015) have mostly focused on working out stylized facts such that on average, behavior is ambiguity seeking for low probability gain events and ambiguity averse for high probability events. More recent studies based on laboratory experiments have focused on limitations to measurement (Baillon, Halevy, and Li, 2022b), the interpretation of parameters (Henkel, 2022), their stability over time (Duersch, Römer, and Roth, 2017) and across domains (Li, Müller, Wakker, and Wang, 2018), or learning (Baillon, Bleichrodt, Keskin, l'Haridon, and Li, 2018). Most directly related to our paper are cross-sectional studies in broader samples. They document large heterogeneity of attitudes (Dimmock, Kouwenberg, Mitchell, and Peijnenburg, 2015; Anantanasuwong, Kouwenberg, Mitchell, and Peijnenburg, 2020) and show connections of ambiguity preferences with portfolio choices (Dimmock, Kouwenberg, Mitchell, and Peijnenburg, 2016; Anantanasuwong et al., 2020). We replicate many of these findings. Based on our unusually large dataset, we are able to estimate the parameters more precisely and unify several conflicting pieces of prior evidence.

We show that one reason for us to be able to do so is that we make use of an explicit stochastic choice model. Doing so has a long tradition in the estimation of risk preferences (e.g., Harless and Camerer, 1994; Hey and Orme, 1994; Loomes and Sugden, 1995; Gaudecker, Soest, and Wengström, 2011; Apesteguia and Ballester, 2021) whereas prior work on ambiguity attitudes has focused on deterministic components of choice.

Another reason is that prior work looking at parameter heterogeneity and behavioral consequence has focused on marginal parameter distributions. This approach has limits because the preference parameters are inherently non-separable. If a decision-maker does not perceive any ambiguity for a given event, her ambiguity aversion does not play a role. Similarly, if the stochastic component is very important, changing the parameters of the deterministic component will hardly alter the power of the model to explain data. Modelling parameter heterogeneity as a discrete distribution in nonlinear models is a common approach in other strands of the literature (e.g., Heckman and Singer, 1984; Keane and Wolpin, 1997). We make use of clustering techniques introduced more recently into econometrics (Bonhomme and Manresa, 2015), which are computationally favorable.

In the next section, we sketch a framework for interpreting decisions under ambiguity and describe our design and the resulting data, including the descriptive facts on matching probabilities. Section 3 presents our structural model and the results for wave-by-wave parameter estimates, establishing the properties for their stability over time and across domains. In Section 4, we classify individual-specific parameters into types and describe these types' relation to personal characteristics and portfolio choice behavior. That section also examines robustness to various specification choices and provides a detailed comparison with the literature. We discuss the findings in Section 5.

2 Ambiguity framework and data

In this section, we first sketch the framework we use to define ambiguity attitudes. We focus on the interpretation of two key parameters. Next, we introduce our version of the paradigm by Baillon, Huang, et al. (2018), which we implemented in the LISS panel. In Section 2.3, we describe some stylized facts in our data on ambiguity attitudes, which include up to six waves for 2,177 respondents, collected over a period of three years. These key facts will guide our empirical strategy in Section 3.1 below. In between those two sections, we briefly describe additional variables that will be important for our analyses in Section 2.4.

2.1 Definition of ambiguity attitudes and parameter interpretation

We focus on prospects—i.e., state-contingent outcomes as in Wakker (2010)—which pay out $x > 0$ if event $E \in \Omega$ occurs and nothing otherwise, denoting such prospects as $x_E 0$. Decision-makers value monetary quantities according to a utility function $u(\cdot)$. We normalize $u(0) = 0$ and assume that $u(x) > 0$. Using the biseparable utility framework of Ghirardato and Marinacci (2001), a decision-maker evaluates the prospect $x_E 0$ as $W(E) \cdot u(x)$. Her event weighting function $W(E)$ satisfies $W(\emptyset) = 0$, $W(\Omega) = 1$, and set-monotonicity in the sense that $B \subseteq A \implies W(B) \leq W(A)$.

Following Abdellaoui, Baillon, Placido, and Wakker (2011), we assume that decision weights depend on subjective probabilities $\Pr_{\text{subj}}(E)$ and the source of uncertainty S (e.g., an urn with an unknown distribution of balls, the future evolution of the stock market, or the path that will be taken by the earth's climate). $W(E)$ then boils down to how decision weights depend on subjective probabilities for a particular source of uncertainty; it is thus called the source function (Wakker, 2010). In this model, Baillon, Huang, et al. (2018) and Baillon, Bleichrodt, Li, et al. (2021) define two parameters describing ambiguity attitudes, both of which are zero for subjective expected utility maximizers:

$$\text{Ambiguity aversion} \qquad \alpha^S = \mathbb{E}[\Pr_{\text{subj}}(E) - W(E)], \tag{1}$$

$$\text{Likelihood insensitivity} \qquad \ell^S = 1 - \frac{Cov(W(E), \Pr_{\text{subj}}(E))}{Var(\Pr_{\text{subj}}(E))}. \tag{2}$$

Ambiguity aversion is the average amount by which subjective probabilities exceed decision weights. Decision-makers with $\alpha^S = 0$ are ambiguity neutral on average; negative values indicate a dominance of ambiguity seeking behavior. Likelihood insensitivity captures the extent to which individuals' decision weights change when the underlying subjective probabilities change. In certain multiple-prior models (Ghirardato, Maccheroni, and Marinacci, 2004; Dimmock, Kouwenberg, Mitchell, et al., 2015; Alon and Gayer, 2016), likelihood insensitivity can be interpreted as the perceived level of ambiguity. See Online Appendix A for more details on the ambiguity framework and different interpretations.

For our main results, we further assume that $W(E)$ is *neo-additive* (Chateauneuf, Eichberger, and Grant, 2007):

$$\begin{aligned} W(E) &= \tau_0^S + \tau_1^S \cdot \Pr_{\text{subj}}(E) \text{ for } \Pr_{\text{subj}}(E) \in (0,1) \\ W(E) &= 0 \text{ for } \Pr_{\text{subj}}(E) = 0 \\ W(E) &= 1 \text{ for } \Pr_{\text{subj}}(E) = 1 \\ 0 &\leq \tau_1^S, 0 \leq \tau_0^S \leq 1 - \tau_1^S \end{aligned} \tag{3}$$

Neo stands for "non-extreme outcome", i.e., weights are zero (one) for events the decision-maker considers impossible (certain); they are linear in $\Pr_{\text{subj}}(E)$ in between. We chose this functional form because of its tractability and good empirical performance (Li et al., 2018). For the neo-additive weighting function, α^S and ℓ^S have very simple representations:

$$\alpha^S = \frac{1 - 2\tau_0^S - \tau_1^S}{2}, \tag{4}$$
$$\ell^S = 1 - \tau_1^S. \tag{5}$$

Alternatively, Baillon, Huang, et al. (2018) and Baillon, Bleichrodt, Li, et al. (2021) show that α and ℓ can be estimated under different assumptions using the empirical analogues of the moments in Equations (1)-(2). We will pursue that as a robustness check and comment on the relative merits in Section 3.1, after having introduced the structure of our data.

2.2 Measuring ambiguity attitudes

In order to measure ambiguity attitudes, we adapt the method developed by Baillon, Huang, et al. (2018) and Baillon, Bleichrodt, Li, et al. (2021) for use in a general population. Our main source of uncertainty is the Amsterdam Exchange Index (AEX), the most widely known stock market index in the Netherlands. We expect individuals to differ in their perception of the AEX. For some, probabilities may be close to objective. Others might perceive substantial uncertainty regarding its evolution.

Eliciting attitudes about ambiguous events is cognitively demanding for participants. To keep this burden low, we confront subjects with binary choices only. Going through a tutorial introducing the choice situations and potential payoff consequences was mandatory in the initial survey round. In later waves, the tutorial was optional, but advertised prominently. Compared to a choice list format as in Baillon, Huang, et al. (2018), we expect this procedure to reduce complexity as subjects can focus on one question at a time.

Individuals make a series of choices, all of which share the structure shown in Figure 1. Each decision is between a bet on an event relating to the performance of the AEX over the subsequent six months and a lottery with known probabilities. In the example in Figure 1, Option 1 pays out € 20 if a hypothetical € 1,000 investment in the AEX is worth more than € 1,100 six months in the future. Option 2 is a lottery and pays € 20 with probability 50 %. The lottery is introduced as a wheel of fortune during the tutorial and it is spun when determining payoffs.

Depending on her choice between the AEX event and the lottery, a subject is presented with another choice with the same AEX event and a different lottery. If the subject choose the AEX event, we increase the winning probability of the lottery and vice versa. For each event, subjects make three to four binary choices (see Online Appendix Figure B.1 for the entire decision tree). Our data identify an interval for the *matching probability* where the length of the interval will be between 0.01 and 0.1, depending on the path taken in the decision tree.

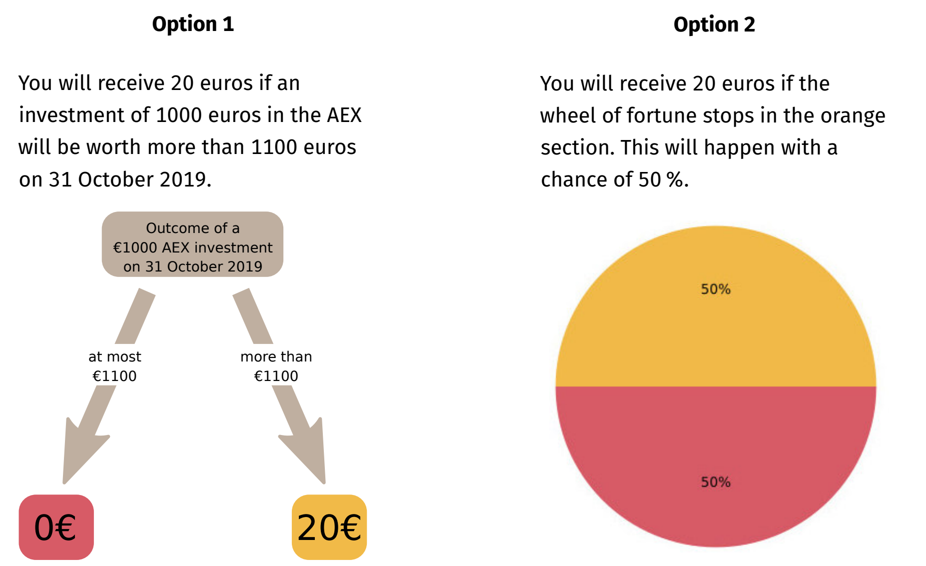


Figure 1. Exemplary binary choice situation

Notes: Labels are translated from Dutch to English. The date refers to the data collection during the month of May 2019.

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 and zero otherwise.

For the ambiguity model sketched in the previous section and many others, Dimmock, Kouwenberg, and Wakker (2016) show that matching probabilities are useful for analyzing ambiguity attitudes because they are independent of utility function parameters and any weighting of probabilities.

The remainder of our design closely follows Baillon, Huang, et al. (2018). We partition the space of possible values the AEX investment can take into three events: $E_1^{AEX} : Y_{t+6} \in (1100, \infty]$, $E_2^{AEX} : Y_{t+6} \in [0, 950)$, and $E_3^{AEX} : Y_{t+6} \in [950, 1100]$, see Figure 2. This partition leads to balanced historical 6-month returns of the AEX with empirical frequencies in the 1999-2019 period of 0.24, 0.28, and 0.48, respectively. We elicit matching probabilities for each of these events along with their complements. Additionally, we include the event $E_0^{AEX} : Y_{t+6} \in (1000, \infty]$. As it comprises all outcomes for which the AEX is not declining, it is arguably the most intuitive event and should ease the entry for participants.

If we selected one of the answered questions for pay-out ex-post, the chained design would not be incentive compatible. Inspired by Bardsley (2000) and Johnson, Baillon, Bleichrodt, Li, van Dolder, et al. (2021), we let subjects start a random number generator to select the question to be paid out before they make any deci-

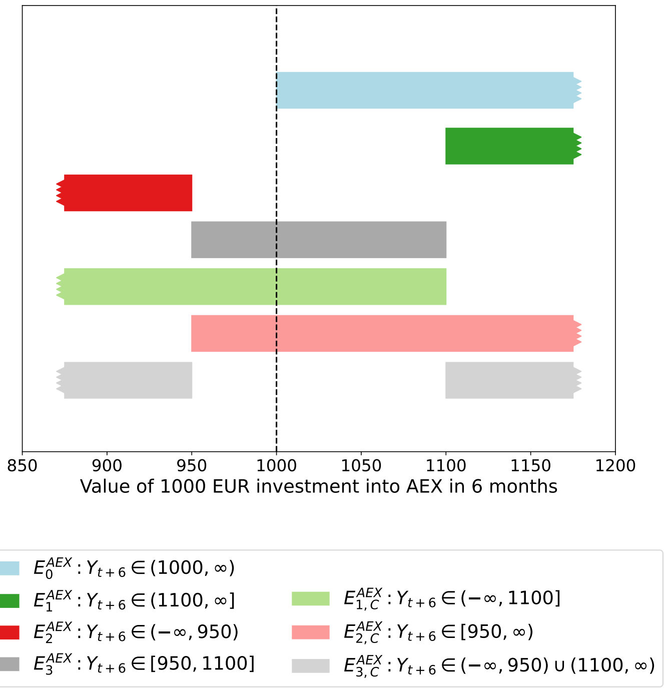


Figure 2. Events of AEX performance used in the experiment

sions. The selected question was displayed as a meaningless sequence of characters. If the subject did not encounter the selected choice situation during the questionnaire—i.e., she took a different branch in the decision tree—we presented it after all other decisions had been made. Pre-selection of the choice to be paid out makes it difficult for subjects to hedge against the encountered ambiguity (Baillon, Halevy, and Li, 2022a).[1] For every subject in our experiment, we either played out a lottery or checked the evolution of the AEX after six months, i.e., no additional randomness was introduced by paying only a fraction of subjects. Expected incentive payments for a expected utility decision-maker using empirical frequencies for stock returns were € 13.50. At the median response time, this amounts to an hourly wage of € 51.

1. Baillon, Halevy, and Li (2022b) showed that measuring ambiguity attitudes might not be possible at all for when paying out one choice at random. In their data, some subjects appear to integrate all decisions, creating a hedge against ambiguity. We do not think that this is much of a concern in our data because there is no direct hedge for the event E_0^{AEX}, described just below. Any strategy integrating the seven different events in a way that would yield a perfect hedge against ambiguity would require substantial cognitive effort. Furthermore, individuals did not have the required information on the structure of the design in the first wave and we do not see a sharp decline in ambiguity aversion in the subsequent wave (see Table 4 below). Hence, we feel comfortable with the assumption that respondents isolated their decisions across events.

We implement the elicitation in the LISS (Longitudinal Internet studies for the Social Sciences) panel administered by CentERdata (Tilburg University, The Netherlands). The LISS panel is a representative sample of Dutch individuals who participate in monthly Internet surveys. The panel is based on a true probability sample of households drawn from the population register. Households that could not otherwise participate are provided with a computer and Internet connection. A longitudinal survey is fielded in the panel every year, covering a large variety of domains. Respondents are financially compensated for all questions they answer. On top of that, every respondent had the chance of earning an additional € 20 in our experiment.

We collected six waves of data from November 2018 to May 2021. In November 2019, we additionally included a similar design where the source of uncertainty was the climate in the Netherlands over the subsequent winter. For example, $E_1^{climate}$ referred to the average temperature over the months of December, January, and February being at least 1° Celsius higher than the average temperature over the previous five winters. We chose the evaluation dates for the AEX (and the temperature) such that we could determine payoffs at the start of the subsequent wave. For the example in Figure 1, the subsequent questionnaire in November 2019 would start by showing that screen. We then revealed the value of an AEX investment made on the date somebody took the questionnaire (or the temperature) and played out the lottery (by spinning the "wheel of fortune" on the right). Each participant whose choice turned out to be winning received € 20.

2.3 Data on ambiguity attitudes

In line with the domain of our application, we invited the financial deciders of households to participate. Initial invitations went out to 2,773 individuals, 2,407 of whom completed the questionnaire in at least one wave. Unless they dropped out of the LISS panel altogether, we invited respondents for each new wave regardless of their participation status in prior waves. We exclude subjects who seemingly did not spend time with the contents of the questionnaire. In particular, we drop a subject's data for one wave if she chose the same option (AEX or lottery) in all choices and her response time was below the 15th percentile. This condition affects 2 % of person × wave observations. To keep a similar sample for all our analyses—including those geared at stability over time—we require two waves with choice data meeting our inclusion criteria. Our final sample consists of 2,177 unique subjects, with 1,702–1,991 responses per wave; see Online Appendix Table D.1 for more details.

Since event-specific average matching probabilities are fairly stable across waves (see Online Appendix D.2, where we provide detailed statistics on matching probabilities), Table 1 pools all waves for summary statistics at the event-level. Table 2 shows statistics on set-monotonicity violations. We observe five salient features.

Table 1. Matching probabilities, empirical frequencies, and judged historical frequencies

	Mean	Std. Dev.	$q_{0.1}$	$q_{0.5}$	$q_{0.9}$	Empir. Freq. '99-'19	Judged Freq., '99-'19
$E_0^{AEX}: Y_{t+6} \in (1000, \infty)$	0.49	0.27	0.075	0.45	0.93	0.63	0.52
$E_1^{AEX}: Y_{t+6} \in (1100, \infty]$	0.35	0.25	0.03	0.35	0.65	0.24	0.31
$E_{1,C}^{AEX}: Y_{t+6} \in (-\infty, 1100]$	0.51	0.29	0.075	0.45	0.97	0.76	
$E_2^{AEX}: Y_{t+6} \in (-\infty, 950)$	0.37	0.26	0.03	0.35	0.75	0.28	0.22
$E_{2,C}^{AEX}: Y_{t+6} \in [950, \infty)$	0.55	0.29	0.15	0.55	0.97	0.72	
$E_3^{AEX}: Y_{t+6} \in [950, 1100]$	0.56	0.28	0.15	0.55	0.97	0.48	0.47
$E_{3,C}^{AEX}: Y_{t+6} \in (-\infty, 950) \cup (1100, \infty)$	0.42	0.27	0.075	0.45	0.85	0.52	

Notes: Events were asked about in the order $E_0^{AEX} \cdot E_1^{AEX} \cdot E_2^{AEX} \cdot E_3^{AEX} \cdot E_{1,C}^{AEX} \cdot E_{2,C}^{AEX} \cdot E_{3,C}^{AEX}$, see Figure 2. Matching probabilities are set to the midpoint of the interval identified by the design. Data for 2,177 subjects are pooled across all waves. The next-to-last column shows the frequency of each event over half-year horizons in the 1999-2019 period. The last column contains subjects' average estimates thereof, which were elicited in May 2019 (see Section 2.4). Judged frequencies are available for 1952 subjects in our sample. Online Appendix D.2 provides more statistics on matching probabilities including variation across waves.

First, the sum of the average matching probabilities of an event and its complement is less than 1. Similar to findings for Ellsberg (1961) urns, this pattern indicates that matching probabilities are not equal to subjective probabilities; individuals are ambiguity averse on average. This is in line with findings in Dimmock, Kouwenberg, and Wakker (2016) and Anantanasuwong et al. (2020, both studies are also based on broad population samples) while Baillon, Huang, et al. (2018) observe ambiguity seeking choices on average in a time pressure task among students.

Second, mean matching probabilities are sub-additive for composite events. E.g., the sum of the matching probabilities of E_1^{AEX} and E_2^{AEX} is well above the average matching probability of their union, $E_{3,C}^{AEX}$. Sub-additivity implies that on average, subjects are likelihood-insensitive. This is a very robust finding in studies based on Ellsberg urns (e.g. Dimmock, Kouwenberg, and Wakker, 2016), as well as natural events (e.g. Li, 2017; Baillon, Bleichrodt, Keskin, et al., 2018).

Third, there is large variation across individuals for all matching probabilities. Interdecile ranges vary between 0.57 and 0.82, with an average of 0.74. This fact reveals large heterogeneity in response patterns. Standard deviations in our sample line up with related designs in Dimmock, Kouwenberg, and Wakker (2016) and Li (2017), who report values between 0.24 and 0.33.

Fourth, violations of set-monotonicity are prevalent. From Figure 2, it is easy to see that eight pairs of events bear the potential of such violations.[2] The first

2. The superset-subset pairs are $E_0^{AEX} \supset E_1^{AEX}$, $E_{1,C}^{AEX} \supset E_2^{AEX}$, $E_{1,C}^{AEX} \supset E_3^{AEX}$, $E_{2,C}^{AEX} \supset E_0^{AEX}$, $E_{2,C}^{AEX} \supset E_1^{AEX}$, $E_{2,C}^{AEX} \supset E_3^{AEX}$, $E_{3,C}^{AEX} \supset E_1^{AEX}$, and $E_{3,C}^{AEX} \supset E_2^{AEX}$.

column of Table 2 shows that the set-monotonicity violation rate over all waves and superset-subset pairs is 14 %. Slicing the data in a different way, for each wave, 55 % of individuals violate set-monotonicity at least once (see Table D.4 in the Online Appendix). While substantial, such frequencies are anything but uncommon in general subject pools (see, for example Gaudecker, Soest, and Wengström (2011) for risky choices or Dimmock, Kouwenberg, and Wakker (2016) and Anantanasuwong et al. (2020) for ambiguity attitudes). We view violations of set-monotonicity as prima-facie evidence for decision errors. That is, they are unlikely to reflect preferences but rather carelessness or difficulties in understanding the tasks.

Table 2. Judged historical frequencies and set-monotonicity violations

	Dependent variable: Set-monotonicity violation			
	(1)	(2)	(3)	(4)
Intercept	0.14^{***}	0.17^{***}		
	(0.0024)	(0.003)		
Judged frequencies (superset - subset)		-0.076^{***}	-0.044^{***}	-0.037^{***}
		(0.0055)	(0.0054)	(0.006)
Superset-subset pair fixed effects	No	No	Yes	Yes
Individual fixed effects	No	No	No	Yes
Observations	15616	15616	15616	15616

Notes: This table reports OLS regressions on the subject × superset-subset pair level. The dependent variable is the rate of set-monotonicity violations, averaged across waves. Set-monotonicity is violated if the lower bound of the interval elicited for the matching probability of the subset is strictly larger than the upper bound of the corresponding interval of the superset. The first column reports the average set-monotonicity violation rate. The remaining columns include the distance in judged historical frequencies over the 1999-2019 period for the two events in a superset-subset pair (elicited in May 2019, see Table 1 and Section 2.4 below). Column 3 adds superset-subset pair fixed effects and column 4 additionally adds individual fixed effects. Standard errors are clustered at the individual level. Sample: All waves meeting our inclusion criteria (i.e., there is variation across options and/or completion time is outside the fastest 15 %, see Section 2.3) for individuals with at least two such waves, who completed the May 2019 survey.
$* - p < 0.1, ** - p < 0.05, *** - p < 0.01.$

Fifth, set-monotonicity errors occur more often when individuals judge the past frequency of the event that forms the the subset to be large relative to that of the superset. In May 2019, we asked individuals to state the empirical frequency of the events we also use during elicitation of ambiguity attitudes. The remaining columns of Table 2 add the difference in judged historical frequencies between superset-subset pairs as an explanatory variable. The relation is clearly negative, no matter whether we add fixed effects for superset-subset pairs and individuals. The negative coefficients imply that for superset-subset pairs where the difference between the judged frequency of the superset and the subset is large, the likelihood of set-monotonicity errors tends to be low. For example, from Table 1 we see the average frequencies $E_{1,C}^{AEX} = 0.69$, $E_2^{AEX} = 0.22$, and $E_3^{AEX} = 0.47$. The resulting average set-monotonicity violations are 0.1 for $E_{1,C}^{AEX} \supset E_2^{AEX}$ and 0.24 for $E_{1,C}^{AEX} \supset E_3^{AEX}$ (see

Table 3. Descriptive statistics on key variables

	N Subj.	Mean	Std. Dev.	$q_{0.25}$	$q_{0.5}$	$q_{0.75}$
Female	2177	0.5				
Education: Lower secondary and below	2177	0.26				
Education: Upper secondary	2177	0.34				
Education: Tertiary	2177	0.4				
Age	2177	57	16	45	59	69
Monthly hh net income (equiv., thousands)	2110	2.2	1	1.6	2.1	2.8
Total hh financial assets (equiv., thousands)	1727	39	120	2.6	12	34
Owns risky financial assets	1727	0.2				
Share risky financial assets (if any)	338	0.35	0.26	0.12	0.29	0.52
Risk aversion index	2121	0	1	−0.68	−0.026	0.67
Numeracy index	2064	0	1	−0.55	0.27	0.78
Understands climate change	1936	0.54	0.21	0.5	0.5	0.75
Threatened by climate change	1936	0.55	0.22	0.4	0.6	0.6

Notes: Sample: Individuals with at least two waves meeting our inclusion criteria (i.e., there is variation across options and/or completion time is outside the fastest 15 %, see Section 2.3). Net income and assets are pooled within partners and equivalized, data from 2018. Risk aversion and numeracy are normalized to have mean zero and unit variance. The variables concerning climate change are normalized such that they vary between 0 and 1.

Online Appendix Table D.4). Hence, if two events are rather similar in subjects' memory, set-monotonicity violations are more likely to occur.

The first four stylized facts are also present in the data collected with climate change as the source of uncertainty (see Online Appendix Table D.3). We cannot check the fifth stylized fact because we did not ask about historical frequencies. Mean matching probabilities of complementary events add up to less than 1. Matching probabilities are sub-additive for composite events on average. Interdecile ranges are even larger than for the AEX, with an average of 0.85. Set-monotonicity violations are just as prevalent as in the case for the AEX (see Online Appendix Table D.4).

2.4 Background characteristics

The LISS panel allows individual-level linkage of our choice data with a variety of information collected about the LISS panel members. This includes background information from regular surveys and additional questionnaires we ran ourselves. Table 3 shows the socio-demographic composition of our sample, variables relating to personal finances, and additional measures we collected. More detailed statistics can be found in Online Appendix D; our questionnaires are documented in Online Appendix B.

Socio-economic characteristics. The gender split is even. The average age is close to 57 years with ample variation. The share of subjects with tertiary education is 40 %; another 34 % hold an upper secondary degree. Net household income—pooled within households and equivalized using the square root of adults in the household—amounts to € 2,200 per month. Financial assets are equivalized in the same way. Our measure includes assets kept in joint accounts and assets assigned to the respondent (i.e., the person identifying as being most familiar with the household's finances); it does not include assets solely owned by the partner.

Risky asset holdings. 20 % of our sample directly hold risky assets which include among others individual stocks, funds, and bonds (we provide more detail in Online Appendix D.4). Conditional on owning risky assets, the average share is 35 %.

Judged historical frequencies of past AEX returns. In May 2019, we asked individuals to judge how frequently the AEX events used in our designs ($E_0^{AEX}, E_1^{AEX}, E_2^{AEX}, E_3^{AEX}$) occurred over the previous 20 years. Although there is substantial individual heterogeneity, the last column of Table 1 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 that returns greater than 10 % occurred more often than they did.

Risk Aversion. We measure households' risk aversion using the preference survey module developed by Falk, Becker, Dohmen, Huffman, and Sunde (2016). The module includes a general risk question and a quantitative component that is based on elicited certainty equivalents for risky lotteries. We combine the qualitative and quantitative components as suggested in Falk et al. (2016). Risk aversion bears the same relation to observed characteristics as in prior literature (e.g., Dohmen, Falk, Huffman, Sunde, Schupp, et al., 2011; Gaudecker, Soest, and Wengström, 2011): Older, lower income, and female subjects tend to be more risk averse (see Online Appendix Table D.5).

Numeracy. We measure three dimensions of numeracy: First, a basic numeracy component that is, e.g., used in the English Longitudinal Study of Ageing (Steptoe, Breeze, Banks, and Nazroo, 2013); second, a financial numeracy component that involves interest rates and inflation (a subset of the questions of van Rooij, Lusardi, and Alessie (2011)); third, a probability numeracy component proposed by Hudomiet, Hurd, and Rohwedder (2018), which tests both basic understanding of probabilities and more advanced concepts such as independence and additivity. We aggregate the three components into a numeracy index, giving equal weight to each component. Our aggregated measure of numeracy is related to socio-demographics in similar ways as has been shown for its components in other settings (e.g., van Rooij, Lusardi, and Alessie, 2011; Hudomiet, Hurd, and Rohwedder, 2018, also see Table D.5)

Knowledge of and concern about climate change. To help analyze ambiguity attitudes toward climate change, we asked subjects to report (i) their perceived understanding of the causes and implications of climate change and (ii) whether climate change is a threat to them and their family on Likert scales. We normalize the variables such that they vary between 0 and 1.

3 Estimation strategy, marginal parameter distributions, and stability

The stylized facts in Section 2.3 showed that on aggregate, behavior is indicative both of ambiguity aversion and likelihood insensitivity. At the same time, heterogeneity in matching probabilities is large. Decision errors are frequent and more likely for events that people judge to have been closely related in the past. Our empirical strategy, described next, takes these features into account in a stochastic model of choice. Its key parameters are ambiguity aversion, likelihood insensitivity, and the variance of decision errors.

Section 3.2 describes the distributions of wave-by-wave estimates of these parameters. We find that all of them are important in determining behavior and that they are very heterogeneous across subjects. Section 3.3 shows that there are no systematic changes within individuals over time.

Section 3.4 adds the survey using climate change and asks to what extent the estimated parameters are stable across completely different sources of uncertainty. Ambiguity aversion turns out to be transportable directly and this is largely true for decision errors, too. In contrast, likelihood insensitivity is more specific to a particular source of uncertainty.

3.1 Empirical strategy

We estimate the neo-additive model at the individual level, which allows us to match average levels of ambiguity aversion and likelihood insensitivity while respecting the large heterogeneity in the data. Because frequent set-monotonicity violations increase in the perceived similarity of two events in the past, we augment the deterministic model with an additive error term, also known as a Fechner error (e.g. Loomes and Sugden, 1995). Assuming this error term to be normally distributed, we have

$$m(E) = W(E) + \varepsilon_E \quad \text{with} \quad \varepsilon_E \sim \mathcal{N}\left(0, \left(\sigma^S\right)^2\right), \tag{6}$$

where $W(E)$ is given by (3). Let $m_{\text{lb}}^{\text{ub}}(E) := \{m(E) \,|\, \text{lb}(E) \leq m(E) \leq \text{ub}(E)\}$ be the interval identified by the choice sequence. The likelihood that the actual matching probability falls into the interval becomes

$$\Pr\left(m(E) \in m_{\text{lb}}^{\text{ub}}(E)\right) = \Pr(m(E) \leq \text{ub}(E)) - \Pr(m(E) \leq \text{lb}(E)) \tag{7}$$

We use θ to group the parameters of (3) and (6) for all events in one wave of data:

$$\theta := [\tau_0^S, \tau_1^S, \sigma^S, \Pr_{\text{subj}}(E_0), \Pr_{\text{subj}}(E_1), \Pr_{\text{subj}}(E_2)].$$

The likelihood of observing individual i's data in wave t becomes

$$\mathscr{L}(\theta_{i,t}) = \prod_{E\in\{E_0^S,\ldots,E_{3,C}^S\}} \Pr\Big(m(E;\,\theta_{i,t}) \in \big(m_{\text{lb}}^{\text{ub}}(E)\big)_{i,t}\Big), \tag{8}$$

which we estimate subject to the constraints on τ_0^S and τ_1^S given in (3) and $\Pr_{\text{subj}}(\cdot)$ being proper probabilities (including the cross-event constraints $\Pr_{\text{subj}}(E_0) > \Pr_{\text{subj}}(E_1)$ and $\Pr_{\text{subj}}(E_0) + \Pr_{\text{subj}}(E_2) \leq 1$). When maximizing the sum of the log-likelihoods over events, the objective function is not globally concave due to complex interactions of the parameters (e.g. for a poorly parameterized model the likelihood increases when σ goes to infinity). We, therefore, employ global optimization techniques. See Online Appendix C for further details.

It is easy to see that the neo-additive model, and hence α^S and ℓ^S, are identified in terms of the matching probabilities for the events in our design. $W(E_1) + W(E_2) + W(E_3) = 3\tau_0^S + \tau_1^S$ and $W(E_j) + W(E_j^C) = 2\tau_0^S + \tau_1^S, j \in \{1,2\}$ give three equations with two unknowns. The subjective probabilities drop because the events in the design contain their complements as well. The general reasoning does not depend on the functional form. In fact, Baillon, Huang, et al. (2018) and Baillon, Bleichrodt, Li, et al. (2021) propose indices that estimate α and ℓ directly with moments of matching probabilities (also see Section 2.2).[3]

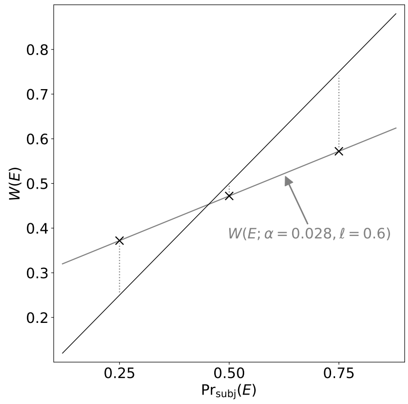
When decision errors are prevalent, however, our estimation strategy adds clarity. Our procedure enforces the theoretical restrictions on the parameters, attributing deviations from the best-fitting deterministic model to the random component of the matching probability in (6). Since there is no random component in the indices approach, researchers are left with the choice between restricting themselves to individuals with valid (α,ℓ)-pairs (e.g., Anantanasuwong et al., 2020) and keeping all observations regardless of whether the estimated parameters make sense (e.g., Dimmock, Kouwenberg, Mitchell, et al., 2015; Dimmock, Kouwenberg, and Wakker, 2016).

When panel data are available and one is willing to impose stability of parameters, it is even more helpful to explicitly account for randomness. In our approach, a large discrepancy between the parameters estimated for two waves will lead to a large variance of the random component. In an approach based on indices, the

3. From a theoretical perspective, imposition of the neo-additive model comes with little loss of generality in our design. Baillon, Bleichrodt, Li, et al. (2021, Theorem 14 and Proposition 21) show that the indices are invariant to the choice of events only under the neo-additive model and ℓ is estimated well only if the neo-additive model is a good approximation of the source function. Using σ^S, we can quantify the quality of the approximation for each individual – while we shall think of it as measuring truly inconsistent behavior, part of it could be due to a nonlinear source function.

	α^{AEX}	ℓ^{AEX}	σ^{AEX}
Mean	0.034	0.58	0.1
Std. dev.	0.16	0.29	0.1
$q_{0.05}$	−0.22	0.084	0.001
$q_{0.25}$	−0.057	0.34	0.009
$q_{0.5}$	0.028	0.6	0.076
$q_{0.75}$	0.13	0.84	0.15
$q_{0.95}$	0.3	0.98	0.3

(a) Statistics



(b) Illustration of median parameters

Notes: Parameters are estimated separately for each of 2,407 individuals × up to 6 waves; all 11,502 estimates are used to produce the statistics in Panel a. See Table E.1 and Figure 5 for the same statistics broken down by wave. Panel b illustrates $W(E)$ at the median parameter estimates from Panel a with subjective probabilities fixed at 0.25, 0.5, and 0.75. The dotted vertical lines depict the difference between $W(E)$ and a bet on a lottery with the same entry probability of the good outcome. The gray line shows the neo-additive source function $W(E) = W\left(\mathrm{Pr}_{\text{subj}}(E); \alpha, \ell\right)$ evaluated at the median parameter estimates from Panel a. Sample: All waves meeting our inclusion criteria (i.e., there is variation across options and/or completion time is outside the fastest 15 %, see Section 2.3) for individuals with at least two such waves.

Figure 3. Marginal distributions of estimated parameters

closest one can do is to average the data across waves. However, with this approach it is impossible to tell apart an individual with perfectly stable preference parameters from someone whose behavior changes erratically from one wave to the next, so long as their mean values for α and ℓ are the same.[4]

3.2 Marginal parameter distributions

Panel a of Figure 3 shows the marginal distribution of our parameters of interest, focusing for now on the AEX waves. There is substantial variation in all estimated parameters. The ambiguity parameters are spread over a large part of their support. Ambiguity aversion prevails at both the mean and at the median; we estimate ambiguity seeking behavior at the first quartile. Likelihood insensitivity is substantial with mean and median values around 0.6. The standard deviation of the distribution of the Fechner errors varies from tiny values at the fifth and twenty-fifth percentiles to 0.3 at the 95$^{\text{th}}$ percentile.

We illustrate these numbers with choice behavior in an environment similar to a task in our design, fixing subjective probabilities. A decision maker decides between

4. Where possible, we have repeated our analyses using the indices from Baillon, Bleichrodt, Li, et al. (2021). We will discuss the results in Section 4.3 among other robustness checks and to connect directly to prior literature.

a lottery yielding €x with probability p and a prospect $x_E 0$ with $\Pr_{\text{subj}}(E) = p$. In our model, behavior is characterized by the difference $W(E) - p$, which yield the probability to choose the prospect $x_E 0$ when plugged into the cumulative distribution function of $\mathcal{N}\left(0, \left(\sigma^{AEX}\right)^2\right)$. Figure 4b illustrates this for the median parameter estimates from Figure 4a and $\Pr_{\text{subj}}(E) = p \in \{0.25, 0.5, 0.75\}$. The decision weights $W(E) = W\left(\Pr_{\text{subj}}(E); \alpha, \ell\right)$ are shown as crosses. $W(E) - p$ is the vertical distance between the crosses and the 45°-line.[5]

For $p = \Pr_{\text{subj}} = 0.5$, likelihood insensitivity does not impact choices because $W(E) - p = -\alpha^{AEX}$. At the median value of σ^{AEX}, the probability to choose the prospect $x_E 0$ would be 36 %, which is substantially below 50 %. Hence, the seemingly small value $\alpha^{AEX} = 0.028$ can lead to sizable deviations from subjective expected utility maximization, even at the point where likelihood insensitivity does not play a role. At the 75$^{\text{th}}$ percentile of σ^{AEX}, the choice probability still is 42 %. Changing α^{AEX} shifts the line $W(\Pr_{\text{subj}}(E); \alpha^{AEX}, \ell^{AEX})$; the value at the first quartile of α^{AEX} implies ambiguity seeking behavior for $p = \Pr_{\text{subj}} = 0.5$.

For the other two choices depicted in Figure 4b, the probabilities to choose $x_E 0$ amount to 0.95 (for $p = 0.25$) and 0.01 (for $p = 0.75$). When likelihood insensitivity changes, the line for $W(\Pr_{\text{subj}}(E); \alpha^{AEX}, \ell^{AEX})$ rotates in the point $(0.5, W\left(0.5; \alpha^{AEX}, \ell^{AEX}\right))$. Increasing it thus makes both choice probabilities even more extreme; decreasing it brings $W(E) - p$ closer to the 45°-line. At the first quartile of ℓ^{AEX}, the choice probability for $p = 0.25$ ($p = 0.75$) is 0.77 (0.07) when holding the other two parameters at their median values. If ℓ^{AEX} was at its fifth percentile, the decision-maker would exhibit ambiguity aversion for $p = 0.25$ as well and choose $x_E 0$ with probability 0.46.

This analysis has shown that there is rich heterogeneity, but the model makes sharp predictions for a wide range of estimated values of σ^{AEX}. One limitation of the analysis in this section is that the marginal distributions naturally do not capture the co-variation of the three parameters.[6] We will address this in Section 4 below, where we also place our results in the literature. To lend credibility to our approach in Section 4, however, we first establish that there is no systematic variation in individual parameters over time.

3.3 Parameter stability over time

Figure 5 depicts the same quantiles of the parameter estimates' distributions as in Figure 4a, but separately for each wave (the corresponding numbers are listed in

5. Tables E.3–E.5 in Online Appendix E.1 show the values of $W(E) - p$ and the corresponding choice probabilities, varying α^{AEX}, ℓ^{AEX}, and σ^{AEX} along the five quantiles shown in Panel 4a of Figure 3 (for brevity, we do not show choice probabilities for the fifth and twenty-fifth percentile of σ^{AEX} because virtually all of them are zero or one).

6. It does not make sense to consider correlations or other linear measures of co-variation in this setting because the constraints in (3) imply that $|\alpha| \leq \ell/2$, causing a highly nonlinear relationship unless α always has the same sign, which clearly is not the case.

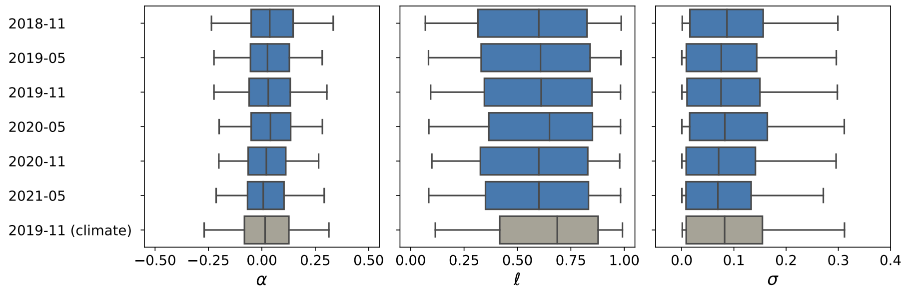


Figure 5. Marginal distributions of estimated parameters, wave by wave

Notes: This figure reports box plots for the distributions of α (left column), ℓ (middle column), and σ. Parameter estimates are obtained from the model described in Section 3.1 separately for each survey wave and individual. Parameters are reported separately for each AEX elicitation and the elicitation on climate change (last row). The boxplots depict the quartiles as well as, indicated by the whiskers, the 5 %/95 % percentiles of each distribution. Sample: All waves meeting our inclusion criteria (i.e., there is variation across options and/or completion time is outside the fastest 15 %, see Section 2.3) for individuals with at least two such waves.

Table E.1 along with means and standard deviations). The shapes of all three parameters' distributions look broadly similar for the AEX waves. Statistical methods reveal some differences, however.[7] Regressing each of the three parameters on wave dummies shows that on average, ambiguity aversion was largest in the first wave and decreased by about 0.025 until the last wave. This is equivalent to a change from the 54th percentile to the 48th percentile in the pooled data. There are no significant changes in average likelihood insensitivity between the early and the late waves. For the standard deviation of Fechner error, we again find a slight downward trend. The decrease is about 0.015 between the first and the last wave; equivalent to a change from moving from the 64th percentile to the 57th percentile in the pooled data. For all three parameters, there is one salient feature: In May 2020, all three parameters are significantly higher than predictions based on a linear trend. That data collection took place shortly after a huge increase in volatility of the AEX, associated with the onset of the Covid-19 pandemic. The overall pattern is consistent with a moderate amount of learning—except for likelihood insensitivity—and a transitory shock associated with the uncertainty during the initial phase of the pandemic. Economically speaking, the changes are limited.

The more interesting question is whether the three parameters are stable at the individual level, i.e., whether systematic changes alter the ranking of individuals over time. In a first pass to address this question, we regress the estimates of the last three waves on the respective parameter values of the first three waves.[8] The

7. See Table E.2 and Figure E.1 in Online Appendix E.1 for the full set of results backing the remainder of this paragraph.

8. In practice, we stack the data so that each combination of dependent and independent variables enters as one row of data. Standard errors are clustered at the individual level. Alternatively, Table E.7

first column in Table 4 shows that the OLS coefficients are 0.25 for α^{AEX}, 0.36 for ℓ^{AEX}, and 0.32 for σ^{AEX}. To interpret the magnitude of these coefficients—which can be interpreted as correlations since the variance of the parameters does not change much over time—a comparison with results on risk aversion is instructive. Chuang and Schechter (2015) review the literature on the stability of risk aversion parameters. They report that studies with at least 100 observations and at least one month between elicitations find correlations between 0.13 and 0.48. Our results fall in this range which indicates that measures of ambiguity attitudes are of comparable stability to measures of risk attitudes.

However, it is well known that estimated risk aversion parameters are subject to large measurement error (e.g. Friedman, Isaac, James, and Sunder, 2014; Frey, Pedroni, Mata, Rieskamp, and Hertwig, 2017; Schildberg-Hörisch, 2018; Gillen, Snowberg, and Yariv, 2019). There is no reason to expect this to be different for our parameters. We thus follow Gillen, Snowberg, and Yariv (2019) and run ORIV (obviously related instrumental variables) regressions. In our setting, this amounts to instrumenting one wave's parameter estimates with parameter estimates from a second wave to predict parameters in a third wave. The core assumption is that measurement error is uncorrelated across waves. We partition the data so that we predict parameters in waves 4-6 with parameters from waves 1-3.[9] Regressions are run in a stacked dataset using all permutations of selecting the endogenous regressor and the instrument from waves 1–3 and the dependent variable from waves 4–6. Standard errors are clustered on the individual level.

The last two columns in Table 4 show the results of accounting for measurement error in this way. The difference between the columns is that in Column (2), there are no additional regressors. In Column (3), we control for a large set of control variables; coefficients are reported in Online Appendix Table E.8. All F-statistics for the first stage regressions exceed 100. All coefficients of interest are between 0.95 and 0.99; none of them is statistically different from 1. The results indicate that once measurement error is accounted for, the underlying individual-level parameters do not vary systematically over time.

3.4 Parameter stability across domains

A key question arising for any parameter characterizing individual attitudes is how domain-specific it is (see, e.g. Dohmen et al., 2011, for risk attitudes). We address this question using the design with climate as the source of uncertainty, described in the last paragraph of Section 2.2. We noted that the stylized facts for the matching probabilities are broadly similar to those for the AEX at the end of Section 2.3.

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in Online Appendix E.2 reports correlations between parameter estimates for all pairs of survey waves. Naturally, they are very similar to the regression coefficients on average.

9. As demonstrated by Tables E.9–E.11 in Online Appendix E.2, where we split our data is immaterial for the results.

Table 4. Predicting last three waves of ambiguity parameters with first three waves

		OLS	ORIV	
		(1)	(2)	(3)
$\alpha^{AEX}_{\text{last 3 waves}}$	Intercept	0.017^{***}	-0.0097^{**}	
		(0.0025)	(0.0038)	
	$\alpha^{AEX}_{\text{first 3 waves}}$	0.25^{***}	0.95^{***}	0.98^{***}
		(0.01)	(0.07)	(0.09)
	Adj. R^2	0.07		
	1st st. F		148	101
$\ell^{AEX}_{\text{last 3 waves}}$	Intercept	0.37^{***}	0.024	
		(0.0087)	(0.022)	
	$\ell^{AEX}_{\text{first 3 waves}}$	0.36^{***}	0.97^{***}	0.95^{***}
		(0.01)	(0.04)	(0.05)
	Adj. R^2	0.14		
	1st st. F		512	292
$\sigma^{AEX}_{\text{last 3 waves}}$	Intercept	0.066^{***}	-0.0012	
		(0.0019)	(0.0054)	
	$\sigma^{AEX}_{\text{first 3 waves}}$	0.32^{***}	0.99^{***}	0.97^{***}
		(0.01)	(0.05)	(0.08)
	Adj. R^2	0.082		
	1st st. F		250	129
Controls		No	No	Yes
N Subjects		1859	1859	1452

Notes: Table shows OLS and ORIV regressions with the parameter estimates of the May 2020, November 2020, and May 2021 waves as dependent variables and the parameter estimates of the three earlier waves as potential independent variables and instruments. The table is split vertically, such that the first set of rows reports the regressions based on α^{AEX} as dependent and independent variables. The middle set of rows shows the results for ℓ^{AEX} and the last part of the table those for σ^{AEX}. Parameter estimates are obtained from the model described in Section 3.1 separately for each survey wave and individual. In line with the ORIV approach, we use a stacked data set in which all respective combinations of dependent, independent, and (for the ORIV regressions) instrumental variables enter as a separate observation. In all regressions, standard errors are clustered on the individual level and reported in parentheses. Controls are age dummies, gender, education, income and assets dummies, risk aversion, and numeracy. Full regression results reported in Online Appendix Table E.8. Sample: All waves meeting our inclusion criteria (i.e., there is variation across options and/or completion time is outside the fastest 15 %, see Section 2.3) for individuals with at least two such waves in 2018/2019 and at least one such wave in 2020/2021 (This is required for ORIV regressions and we impose the same restriction for the OLS regression). * $- p < 0.1$, ** $- p < 0.05$, *** $- p < 0.01$.

We estimate our model for the climate data in the same way as we do for one wave of the AEX data. The last row in Figure 5 shows the distribution of the estimated parameters. For α and σ, the distributions are visually similar, although ambiguity aversion is lower in the climate data than its average across the AEX waves (see Table E.6). Likelihood insensitivity regarding temperature changes is notably greater than for the AEX data; the average difference amounts to 0.05.

Parameter stability at the individual level is the more interesting question once more. Table 5 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 0.69, 0.35, and 0.51 for α, ℓ, and σ respectively. This suggests sizable stability across domains, particularly for ambiguity aversion.

Again, there is reason to believe the OLS estimates may be biased. Classical measurement continues to be the same concern as before. However, one may also suspect spurious *positive* correlation because the two elicitations were separated only by a short introduction to the climate change questions. To address this issue, we run two-stage least squares regressions, instrumenting the endogenous regressor from the November 2019 wave with the same parameter from other waves. As in the case of temporal stability, the bias is eliminated if estimation errors are uncorrelated across waves. As in Table 4, the second column of Table 5 reports on a specification without controls and the third column on a specification controlling for many covariates (the full list of coefficients can be found in Online Appendix Table E.12). The coefficients of interest are very similar in both specifications.

The coefficient for ambiguity aversion is precisely estimated and statistically indistinguishable from 1. This supports the interpretation of ambiguity aversion as a stable preference that extends across domains. Anantanasuwong et al. (2020) elicit ambiguity attitudes in a sample of households holding risky assets 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 a correlation coefficient around 0.7, which is very close to what we find in the OLS regression. More closely related to our 2SLS regression, Anantanasuwong et al. (2020) conduct a factor analysis and conclude that ambiguity aversion can be described by one underlying trait. 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 (0.63 when controls are added) 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. Anantanasuwong et al. (2020) also find weaker dependence across domains for ℓ with correlation coefficients ranging of 0.16 or 0.45, depending on whether they keep subjects with set-monotonicity violations in the sample (their results for α were

Table 5. Predicting climate ambiguity parameters with AEX parameters

		OLS	2SLS	
		(1)	(2)	(3)
$\alpha^{climate}_{2019-11}$	Intercept	-0.003	-0.016^{***}	
		(0.0033)	(0.0039)	
	$\alpha^{AEX}_{2019-11}$	0.69^{***}	1.04^{***}	1.06^{***}
		(0.03)	(0.05)	(0.07)
	Adj. R^2	0.39		
	1st st. F		215	148
$\ell^{climate}_{2019-11}$	Intercept	0.43^{***}	0.28^{***}	
		(0.015)	(0.024)	
	$\ell^{AEX}_{2019-11}$	0.35^{***}	0.60^{***}	0.63^{***}
		(0.02)	(0.04)	(0.05)
	Adj. R^2	0.13		
	1st st. F		735	406
$\sigma^{climate}_{2019-11}$	Intercept	0.053^{***}	0.022^{***}	
		(0.0027)	(0.005)	
	$\sigma^{AEX}_{2019-11}$	0.51^{***}	0.83^{***}	0.88^{***}
		(0.03)	(0.05)	(0.07)
	Adj. R^2	0.23		
	1st st. F		92	51
Controls		No	No	Yes
N Subjects		1843	1843	1411

Notes: This table shows OLS and 2SLS regressions with the parameter estimates for the decisions about changes in climate (elicited in November 2019) as the dependent variable and the parameter estimates for the decisions about the AEX elicited in November 2019 as independent variable. For the 2SLS regressions, the parameters of all other AEX waves are used as instruments. Parameter estimates are obtained from the model described in Section 3.1 separately for each survey wave and individual. For 2SLS, we use a stacked data set in which all instrumental variables enter as a separate observation and we cluster standard errors on the individual level. Controls are age dummies, gender, education, income and assets dummies, risk aversion, numeracy, and indicators of self-assessed understanding and perceived threat of climate change. The latter two vary between 0 and 1. Full regression results reported in Online Appendix Table E.12. Sample: All waves meeting our inclusion criteria (i.e., there is variation across options and/or completion time is outside the fastest 15 %, see Section 2.3) for individuals with at least two such waves.
$* - p < 0.1, ** - p < 0.05, *** - p < 0.01$.

unaffected by this choice). Correcting for measurement error, we find a substantially higher common component.[10] Turning to the third panel in Table 5, the stability of the standard deviation of the Fechner error is around 0.85 and, thus, in between the values for the other two parameters.

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 5. Dohmen et al. (2011) reason that differences in risky behavior across domains might be more likely to reflect different risk perceptions, rather than differences in actual preferences. This fits well with our results: Ambiguity aversion is very stable, but the perception of ambiguity varies across contexts to a certain degree. One interpretation of our findings is 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 affect α much, unless it is on a constraint implied by ℓ. This aligns well with the findings by Baillon, Bleichrodt, Keskin, et al. (2018) who conduct such an information experiment.

4 Ambiguity types and financial behavior

The previous section has established that each of our three parameters of interest is very heterogeneous across individuals, but remarkably stable over time. The first finding, however, is of limited importance for describing decision behavior and heterogeneity therein. This is due to the non-separable nature of the choice model. The argument might be clearest for the relation between ambiguity aversion α and likelihood insensitivity (or the perceived level of ambiguity) ℓ. For example, individuals who fully trust their probability judgments (who do not perceive any ambiguity) necessarily have an ambiguity aversion parameter of zero. In general, the constraints in (3) imply that $|\alpha| \leq {}^{\ell}/_{2}$, so ambiguity aversion is bounded by the degree of likelihood insensitivity (the perceived level of ambiguity). In a similar vein, the two preference parameters hardly matter if σ takes on very high values.

In the first part of this section, we thus classify individuals into a discrete set of types, which are characterized by our three parameters of interest. The procedure

10. One potential reason our results on the perceived level of ambiguity are at variance with the results of Anantanasuwong et al. (2020) for their full sample is that they use the indices proposed by Baillon, Bleichrodt, Li, et al. (2021) directly. Table 5 demonstrates that our model-based estimates are likely to be subject to sizable measurement error. In our robustness checks, we show that measurement error affects ambiguity attitudes estimated with BBLW-indices in an even stronger fashion. When replicating Table 5 with index-based estimates, we get an OLS coefficient for ℓ of 0.14, almost the same as that Anantanasuwong et al. (2020, see Table H.4). Unsurprisingly, the 2SLS-measurement-error-adjusted regression slope for the BBLW-indices is in the range of what we find with our model.

does not place any restrictions on the dependence between α, ℓ, and σ. This is one of the reasons discrete types are very widely used in nonlinear economic models (e.g., Keane and Wolpin, 1997). We establish that four types capture a large degree of the observed heterogeneity. In Section 4.2, we show these types are related to socio-demographic characteristics and whether they help predict real-world financial behavior. In Section 4.3, we compare our results to alternative specifications and to the previous literature.

4.1 Describing heterogeneity in attitudes and error propensities

In a first step, we re-estimate (8), imposing that $\tau_{0,i}^{AEX}$, $\tau_{1,i}^{AEX}$, and σ_i^{AEX} do not vary across waves. Hence, there is no subscript t to the parameters anymore. Doing so changes the interpretation of σ_i^{AEX} because, in addition to the previous types of inconsistencies, it will also capture behavior that is erratic only across waves. Estimates of σ_i^{AEX} will thus be substantially larger than our previously-reported estimates of $\sigma_{i,t}^{AEX}$. We then apply the k-means algorithm (e.g., Bonhomme and Manresa, 2015; see Gaudecker and Wogrolly, 2022, for a related application) to classify individuals into a discrete set of groups. The algorithm assigns individual observations $x_i := [\alpha_i^{AEX}, \ell_i^{AEX}, \sigma_i^{AEX}]$ to groups g such that $\sum_i ||x_i - c_{g(i)}||^2$ is minimized for the group means $c_g = \frac{1}{N_g} \sum_{i \in g} x_i$. We follow common practice and scale each component of x_i to mean 0 and standard deviation 1 in the cross-section to ensure all of them are given equal weight in the optimization. The problem is NP-hard, but several heuristic algorithms exist that work well in practice. The method is widely used in machine learning; we use the implementation in the Python library *scikit-learn* (Pedregosa, Varoquaux, Gramfort, Michel, Thirion, et al., 2011).

In the paper, we report results for $k = 4$ types, striking a balance between qualifying as a "summary" and not merging types that display economically meaningful differences in choice behavior. We provide empirical details and a hint at results for alternative choices of k at the very end of this Section 4.1. Figure 6 shows the distribution of ambiguity profiles in the (α, ℓ)-space with large diamonds indicating group means and small dots indicating individual profiles. We do not visualize the standard deviation of errors σ, but list it in the legend along with the share of each type.

At 30%, the largest share of all subjects is estimated to have an ambiguity aversion parameter $\alpha^{AEX} = -0.0002$, likelihood insensitivity $\ell^{AEX} = 0.28$, and a standard deviation of the Fechner errors $\sigma^{AEX} = 0.14$. For all three parameters, the distance to zero is closest in this group, although the error variance is very similar for three out of the four types. Since subjective expected utility maximizers who do not make any errors would have a zero for each parameter, we label it the "near SEU" type. For the example decisions we used in the previous section—binary choices between a lottery yielding €x with probability p and a prospect $x_E 0$ with

$\Pr_{\text{subj}}(E) = p \in \{0.25, 0.5, 0.75\}$—we obtain choice probabilities for the AEX of 0.7, 0.5, and 0.31.[11]

We label the second-largest group, comprising 27 % of the sample, the "Ambiguity averse". This group is estimated to have an ambiguity aversion parameter $\alpha^{AEX} = 0.15$, likelihood insensitivity $\ell^{AEX} = 0.71$, and a standard deviation of the Fechner errors $\sigma^{AEX} = 0.14$. For our example choices, this group has a slight preference for the ambiguous option if $\Pr_{\text{subj}}(E) = p = 0.25$, choosing the ambiguous prospect with 58 % probability. For probabilities $p = 0.5$ ($p = 0.75$), these choice probabilities are 15 % (1.2 %).

A third group is associated with a likelihood insensitivity parameter $\ell^{AEX} = 0.64$, slightly below the value of the ambiguity averse. The standard deviation of the Fechner errors is also very similar to the previous two groups. The defining feature of this group is $\alpha^{AEX} = -0.054$, implying ambiguity seeking behavior on average. This is how we label them, too. For the example decisions, the choice probability for the ambiguous prospect would be 93 % (64 %, 24 %) at $p = 0.25$ ($p = 0.5$, $p = 0.75$).

For all three groups discussed so far, the error variances are estimated to be very close to each other. So it is no surprise that they partition the $(\alpha,\ \ell)$-space in Figure 6 almost perfectly. This is very different for the last group, members of which are scattered almost all over the triangle with valid ambiguity parameters in Figure 6. Twenty percent of individuals are classified to be in this group; what stands out among the parameters is the large standard deviation of the errors with $\sigma^{AEX} = 0.29$. We thus label it the "High noise" type.

This group is special in a few respects. First, the choice probabilities for the three example probabilities move least in this group. This is not due to the source function being particularly close to the 45°-line, but because the random component in (6) is much more important than in the other groups. Viewed from a different angle, no matter what $\Pr_{\text{subj}}(E)$ is, almost any matching probability (systematic plus random component) would occur with some probability substantially larger than zero. Second, we find the largest fraction of set-monotonicity errors in this group (at 25 % of superset-subset pairs, about twice as often as for the other groups). Third, when we go back to the wave-by-wave estimates from Section 3.2, we find them to be most volatile among the high noise types (see Online Appendix Table F.3). This implies that the large error parameters are due both to erratic behavior within and across waves.

With these types at hand, we are now in a position to describe in detail why we picked $k = 4$, referring to results for $k \in \{3, 5, 8\}$. Tables and figures are relegated to the Online Appendix, Sections F.2–F.4. Reducing k to 3 distributes the group we classified as ambiguity seeking across the other three groups. Most individuals go into the near-SEU group, which comprises almost 40 % of the sample. It covers a very

11. See Table F.1 in Online Appendix F.1; Figure F.1 visualizes the source function including the uncertainty introduced by the Fechner errors.

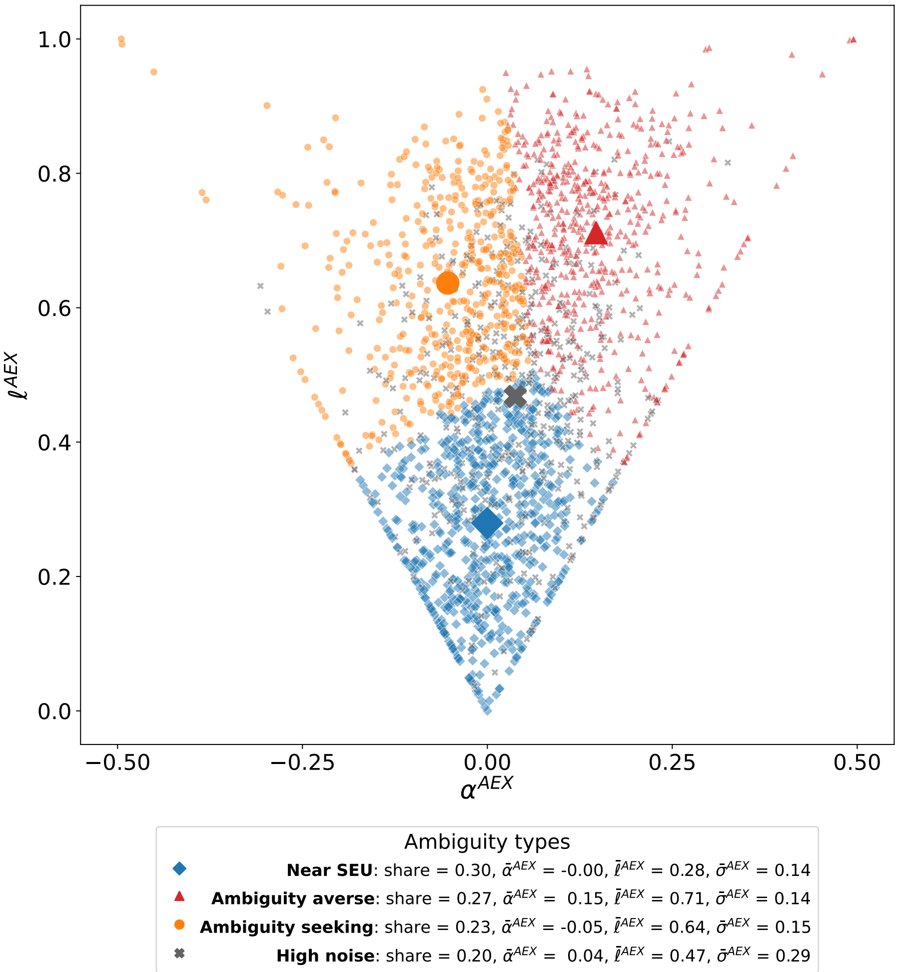

Figure 6. Summarizing heterogeneity in ambiguity profiles with $k = 4$ discrete groups

Notes: The small symbols depict individual preference parameter estimates $(\alpha_i^{AEX}, \ell_i^{AEX})$ obtained from estimating (8) under the assumption that these two parameters and σ_i^{AEX} do not vary across waves. The large symbols are group centers resulting from clustering individuals with the k-means algorithm on the three parameters into four groups. Sample: All waves meeting our inclusion criteria (i.e., there is variation across options and/or completion time is outside the fastest 15 %, see Section 2.3) for individuals with at least two such waves.

	Mean	Std. dev.	$q_{0.05}$	$q_{0.25}$	$q_{0.5}$	$q_{0.75}$	$q_{0.95}$
α^{AEX}	0.035	0.11	−0.13	−0.031	0.032	0.1	0.22
ℓ^{AEX}	0.52	0.22	0.15	0.35	0.53	0.69	0.85
σ^{AEX}	0.17	0.079	0.066	0.12	0.16	0.22	0.33

wide range of behavior – both individuals whose behavior is indistinguishable from SEU-maximization and the subjects at the top left tip of the triangle in Figure 6, i.e., behavior that is most distant from SEU-maximization while consistent, are put in this group. This is not a grouping that makes much sense from a behavioral perspective.

Increasing k to 5 leaves the near SEU and the ambiguity seeking types unchanged. The ambiguity averse and high noise types are split up. The parameters of the original types become slightly more extreme, the parameters of the type in between are all weighted averages of the original types' parameters. Decision behavior is fairly close to the near SEU-type with $k = 4$, but somewhat more erratic. Even when doubling k to 8, there are no groups with clearly different choice behavior from the four types considered in this main text. The four original groups do move somewhat more toward the respective extremes. E.g., in our example decisions, the ambiguity seeking type has choice probabilities for the ambiguous prospect of 94 % / 76 % / 45 % instead of 93 % / 64 % / 24 %. The original labels based on $k = 4$ continue to work for the extreme types and the four additional types are convex combinations thereof.

We conclude that the four types describe overall heterogeneity in choice behavior well, keeping in mind that each group mean summarizes a large volume in $(\alpha^{AEX}, \ell^{AEX}, \sigma^{AEX})$-space. Hence, actual heterogeneity in choice behavior goes well beyond the four types, as is visually clear from Figure 6. Different applications may want to work with much larger k. However, our goal is to have a low-dimensional summary of heterogeneity and $k = 4$ is best suited for this purpose. We now ask how these groups are related to observable characteristics and whether they help explain portfolio choice behavior.

4.2 Ambiguity types: Predictors and consequences

Table 6 describes the groups and their characteristics. There is one column per group. The first two panels repeat the shares and preference parameter estimates from the legend of Figure 6, adding the (very small) standard errors. The lower panel contains average characteristics of groups, including standard errors of these means. We describe the groups without explicitly mentioning the statistical significance of differences, focusing on comparisons where this clearly is the case. As an alternative, we predict group membership in a multinomial regression to partial out the effects of other covariates. Results generally line up, so we relegate the marginal effects to Online Appendix Table F.2.

Near SEU subjects have the highest prevalence of advanced formal education; more than half of them have obtained a tertiary degree and only 13 % are found in the lowest education category. They are among the youngest and somewhat more likely to be male. Monthly income and total financial assets are the highest among all groups, whereas the risk aversion index is the lowest. The numeracy index is 0.63 on average, which is much higher than in any other group and corresponds to

Table 6. Average characteristics of group members

	Ambiguity types			
	Near SEU	Ambiguity averse	Ambiguity seeking	High noise
Share	0.3	0.27	0.23	0.2
α^{AEX}	−0.0002	0.15	−0.054	0.038
	(0.0024)	(0.0031)	(0.0038)	(0.0043)
ℓ^{AEX}	0.28	0.71	0.64	0.47
	(0.0045)	(0.0054)	(0.0056)	(0.0079)
σ^{AEX}	0.14	0.14	0.15	0.29
	(0.0018)	(0.0023)	(0.0024)	(0.0025)
Education: Lower secondary and below	0.13	0.29	0.26	0.42
	(0.013)	(0.019)	(0.02)	(0.024)
Education: Upper secondary	0.31	0.37	0.36	0.29
	(0.018)	(0.02)	(0.022)	(0.022)
Education: Tertiary	0.56	0.33	0.38	0.28
	(0.019)	(0.019)	(0.022)	(0.022)
Age	54	55	57	65
	(0.64)	(0.65)	(0.68)	(0.66)
Female	0.4	0.61	0.52	0.47
	(0.019)	(0.02)	(0.022)	(0.024)
Monthly hh net income (equiv., thousands)	2.5	2.1	2.2	2
	(0.04)	(0.039)	(0.05)	(0.042)
Total hh financial assets (equiv., thousands)	55	23	39	34
	(6.9)	(2.6)	(5.9)	(4.4)
Risk aversion index	−0.1	0.093	0.017	0.0098
	(0.035)	(0.041)	(0.048)	(0.053)
Numeracy index	0.63	−0.2	0.049	−0.72
	(0.024)	(0.038)	(0.042)	(0.056)

Notes: The first row shows the share of individuals classified into a given group. For each group, the mean of several variables are shown. Income and financial assets are in thousands and equivalized for couples. We consider the income of both partners. Total assets include assets kept in joint accounts and those assigned to the respondent (i.e., the person identifying as being most familiar with the household's finances). Risk aversion and numeracy are normalized to have mean zero and unit variance. Sample: All waves meeting our inclusion criteria (i.e., there is variation across options and/or completion time is outside the fastest 15 %, see Section 2.3) for individuals with at least two such waves.

the second tercile in the entire sample. Many of these characteristics point toward this group being the most sophisticated one in statistical and financial matters. This is consistent with subjected expected utility maximization being a benchmark of rationality, from which near SEU subjects fall short the least.

The ambiguity averse and the ambiguity seeking groups are similar in their educational attainment, assuming a position in between the extremes. The average age is 55-57 years and similar to that of the near SEU type. Among all groups, the ambiguity averse group has the highest share of women, which is just about average for the ambiguity seeking type. Both groups find themselves in between the near SEU and high noise types for income, although the difference between the ambiguity averse and high noise groups is not significantly different from zero. Total financial asset holdings are the lowest among the ambiguity averse. In terms of risk aversion, the two groups are indistinguishable in statistical terms. If we control for other characteristics in the multinomial logit model, risk aversion is, however, a significant predictor of the ambiguity averse group. The numeracy index is lower among the ambiguity averse than the ambiguity seeking.

Finally, subjects classified to be of the high noise type are the least educated and oldest on average. The female share is similar to the overall mean. Income is among the lowest, financial assets are in between those of the other groups. The numeracy index is -0.72 on average, which corresponds to the 22$^{\text{nd}}$ percentile in the overall sample. Remember that a high σ may come about through erratic behavior or because the neo-additive function is a bad approximation. The structure of the covariates lends support to the former interpretation in that high noise subjects score lower on dimensions that predict behavior in cognitively demanding tasks.

Next, we show that our estimated preference types help predict financial decisions. Table 7 contains the results of regressing risky asset holdings on the ambiguity types (Columns 1 and 3) and additionally on control variables, including other potential determinants of financial decisions like risk aversion and numeracy (Columns 2 and 4). In the first two columns, the dependent variable is risky asset ownership and we use a Probit model. The last two columns employ a Tobit model to explain the share of risky assets.

Near SEU-type individuals have the highest propensity to own risky assets; they invest the largest share of their wealth into these. In both dimensions, they are followed by individuals classified to be ambiguity seeking and then by the high-noise types. The ambiguity averse have the lowest propensity to own risky assets and the smallest share invested in them. Differences between groups are significant in the unconditional specifications, the exception being that we cannot statistically tell apart shares invested in risky assets of the ambiguity averse and high noise types in column (3). Once we control for a large number of covariates in columns (2) and (4), coefficients drop everywhere while preserving the ranking of point estimates. Many gaps remain large in economic terms. For example, we estimate an 8 percentage point difference in risky asset participation between the near SEU and ambiguity

Table 7. Ambiguity attitudes and portfolio choice: Marginal effects

	Owns risky assets (Probit)		Share risky assets (Tobit)	
	(1)	(2)	(3)	(4)
Ambiguity averse type	-0.23^{***}	-0.084^{***}	-0.44^{***}	-0.17^{***}
	(0.024)	(0.023)	(0.059)	(0.055)
Ambiguity seeking type	-0.1^{***}	-0.018	-0.15^{***}	-0.028
	(0.028)	(0.024)	(0.05)	(0.046)
High noise type	-0.18^{***}	-0.053^{*}	-0.24^{***}	-0.083
	(0.027)	(0.027)	(0.059)	(0.059)
Controls	No	Yes	No	Yes
Observations	1727	1624	1584	1502
Pseudo R^2	0.054	0.3	0.042	0.28
p-values for differences between				
Ambiguity averse, Ambiguity seeking	0	0.0086	0	0.012
Ambiguity averse, High noise	0.034	0.25	0.0041	0.18
Ambiguity seeking, High noise	0.0079	0.22	0.19	0.36

Notes: The first two columns display Probit regressions where the dependent variable is a dummy indicating whether the subject holds any risky financial assets. In the last two columns, we run Tobit regressions with the share of risky financial assets of all financial assets as the dependent variable. The table reports average marginal effects of a change from the left-out type (near SEU) to the respective type. Controls in columns (2) and (4) are age groups, gender, education, income and assets groups, risk aversion, and numeracy. Full regression results reported in Online Appendix Table F.5. Sample: All waves meeting our inclusion criteria (i.e., there is variation across options and/or completion time is outside the fastest 15 %, see Section 2.3) for individuals with at least two such waves. * $- p < 0.1$, ** $- p < 0.05$, *** $- p < 0.01$

averse types. Differences between the ambiguity averse on the one hand and near SEU or ambiguity seeking types on the other hand always remain significant. This is not true for most other comparisons.

Our results on portfolio choice behavior are robust to using an alternative measure of risky assets. We obtain this measure by merging our survey data with administrative records at the individual level (see Zimpelmann, 2021, for an extensive comparison of the measures) due to well-known measurement issues with survey reports of household financial assets. The results, shown in Online Appendix Table F.7 look very similar to those reported in Table 7.[12] In particular, the same conclusions hold for unconditional and conditional differences between the ambiguity averse on the one hand, and near SEU or ambiguity seeking types on the other hand. One difference is that the high noise type looks closer to the ambiguity seeking type when using the administrative assets data. One reason could be that erratic response behavior in our survey is correlated with underreporting of assets.

12. We ran the regressions using the administrative assets data in a remote computing environment at Statistics Netherlands, which is why Table F.7 reports OLS regression results. Comparing Table 7 with OLS regressions using the survey data in Table F.6 shows that this should not affect our conclusions.

In summary, our results show that ambiguity preferences obtained from small-scale controlled choices help explain an important dimension of real-world financial behavior. Importantly, such strong predictive power of our preference parameter estimates should not be taken for granted. For the case of risk aversion, Charness, Garcia, Offerman, and Villeval (2020) show that measures based on designs comparable to ours often fail to explain anything outside of controlled environments.

4.3 Alternative specifications and relation to the literature

Our results are remarkably robust to various decisions we have made in our main analysis.[13] Including all data instead of requiring two waves meeting minimal quality standards increases the number of individuals by 10 %, but does not lead to any substantive changes in the parameter distributions or the clustering outcomes. The coefficients for portfolio choice behavior attenuate slightly toward zero, but all comparisons we have highlighted in the previous section remain significant. The opposite strategy of requiring a balanced panel—i.e., six waves of reasonable data—leads to a drop in the number of individuals by more than 40%. Most statistics remain very close to the values we reported in the main text. One exception is that the average values for ambiguity aversion drop somewhat. In the clustering approach, this is reflected in a lower value of ambiguity aversion for the ambiguity averse type only ($\alpha^{AEX} = 0.12$ instead of 0.15). The long time series per individual lead to more sharply identified differences in types' portfolio choice behavior – most point estimates remain similar, but p-values for the comparisons between groups drop even further.

Another specification choice that is interesting from a modeling perspective concerns the restrictions of the parameters. While the multiple-prior interpretation of our parameters requires $0 \leq \tau_0^S \leq 1 - \tau_1^S$ in (3), an alternative is to take a more descriptive approach, which allows matching probabilities to be hypersensitive to subjective probabilities. Graphically, this means that in the analog to Figure 6, points can now fall below the triangle with valid parameters. Throughout all analysis, the only noticeable change is a drop in the estimated value of ℓ by about 0.02. In the clustering approach, the types have the same average characteristics as before and for 97.5 % of the sample, the assigned groups are identical. This is reflected in the absence of meaningful differences in the group compositions or portfolio choice regressions.

To connect directly with prior literature, we re-run most of our analyses using the indices developed in Baillon, Bleichrodt, Li, et al. (2021). We discussed some a priori considerations in Section 3.1; Online Appendix H has all the tables and figures we refer to in what follows and Section I contains a more detailed comparison

13. For the three alternative specifications that we describe in the following, we provide longer descriptions and repeat all relevant tables and figures in Online Appendices G.1–G.3.

with the literature. Closest to our data are other studies estimating ambiguity attitudes in broad population samples (Dimmock, Kouwenberg, Mitchell, et al., 2015; Dimmock, Kouwenberg, and Wakker, 2016; Anantanasuwong et al., 2020). The first two studies use urns as the source of uncertainty; the last considers four different financial assets, among them the development of the AEX. An important difference is that ours is the only data with a panel dimension. The most direct comparison is thus for the wave-by-wave estimates from Section 3.

Using an index-based approach leaves the wave-by-wave estimates of α^{AEX} mostly unaffected. The median rises from 0.028 to 0.033, the change in the mean is similar, and the distribution is spread out slightly more with a standard deviation of 0.18 instead of 0.16. These values are very much in line with the three studies mentioned in the previous paragraph. As prior literature we also regress the ambiguity aversion parameter on potential determinants. The most interesting relation concerns the relation between risk aversion and ambiguity attitudes. The mixed results of previous papers (Dimmock, Kouwenberg, and Wakker, 2016, and Delavande, Ganguli, and Mengel, 2019 find a negative relation; Dimmock, Kouwenberg, Mitchell, et al., 2015, and Anantanasuwong et al., 2020, a positive one) find their reflection in a zero conditional correlation in our data. In contrast, we found risk aversion to be a strong predictor of the ambiguity types in the previous subsection. In terms of ambiguity aversion the implied relationship is nonlinear: The near-SEU types (α^{AEX} near zero) are clearly less risk averse on average than all other types, whose average α is larger (ambiguity averse and high noise types) or smaller (the ambiguity seeking). This result underscores the importance of considering the multidimensional nature of heterogeneity explicitly.

Along several dimensions, likelihood insensitivity is much more volatile than ambiguity aversion. It is more sensitive to the estimation approach we apply in our data and varies more across different studies – this applies to the source of uncertainty, the co-variation with socio-demographic characteristics, and the relation with portfolio choice.

When moving from our wave-by-wave estimates in Section 3 to an index-based approach, ℓ^{AEX} rises substantially. For example, the median increases from 0.6 to 0.88. This rise is a consequence of the fact that set-monotonicity errors are reflected in a more important random component when estimating (6) whereas they lead to $\ell^{AEX} > 1$ under the indices approach. When partitioning the sample into valid and invalid values of the indices, the mean of σ^{AEX} is 0.07 in the former and 0.16 in the latter. The stochastic component picks up other types of imprecisions as well – in the subsample with valid values of $(\alpha^{AEX}, \ell^{AEX})$, the index-based median estimate of ℓ^{AEX} is 0.8.

The values we estimate using indices are larger than urn-based estimates (both Dimmock, Kouwenberg, and Wakker (2016) and Dimmock, Kouwenberg, Mitchell, et al. (2015) find average values of ℓ^{urn} close to 0.4) and slightly below others for the stock market (Anantanasuwong et al., 2020, estimate the median of ℓ^{AEX} to be 1 when including all observations and 0.89 when conditioning on valid indices).

Looking at the correlates of marginal parameter estimates, ℓ falls in both education and numeracy, which is in line with Dimmock, Kouwenberg, and Wakker (2016) and Anantanasuwong et al. (2020) while Dimmock, Kouwenberg, Mitchell, et al. (2015) find a positive relation. While this holds regardless of whether we use our model or the indices-based approach, the latter masks some interesting patterns. For example, the large positive correlation between ℓ^{AEX} and the oldest age group in the indices-based approach seems to be driven in equal parts by likelihood insensitivity and imprecisions. Furthermore, based on our model estimates, women have a larger ℓ^{AEX}, but a smaller stochastic component. Those relations cancel out for the indices-based approach where likelihood insensitivity is unrelated to gender.

While we are not aware of any studies estimating deviations from a benchmark model in the context of choice under ambiguity, several papers estimate parameters related to the standard deviation of σ^{AEX} in the context of choice under risk. The results line up well with ours. Gaudecker, Soest, and Wengström (2011) find higher age, lower wealth, and lower education levels to be associated with a large influence of the random component of utility. In Choi, Kariv, Müller, and Silverman (2014) high age, low education, low income, and low wealth predict deviations from utility maximizing behavior. Echenique, Imai, and Saito (2021) find younger and cognitively able subjects to come closer to expected utility maximization.

Our larger sample size helps add precision to suggestive prior findings on a negative relation of both α and ℓ on the one hand, and portfolio risk on the other hand. Dimmock, Kouwenberg, and Wakker (2016) find some evidence that both parameters predict low stock market participation rates, but statistical significance depends on the precise specification. Similar statements hold for Anantanasuwong et al. (2020) when it comes to predicting risky investment shares in a sample of investors. In our data, the corresponding regressions show clearly negative coefficients for the indices-based approaches, both for ownership of and for shares invested in risky assets. These findings line up well with our prior analysis based on types.

5 Discussion

We have analyzed a large panel dataset containing incentivized choices between lotteries with known probabilities on the one hand and events relating to the stock market or climate change on the other hand. While the vast majority of economic research has dealt with such real-world events in an expected utility framework, our results have demonstrated that nearly all subjects perceive some degree of ambiguity with respect to these events. Even though there is a large common component, the extent of the perceived ambiguity typically differs across the two domains of financial markets and temperature changes. At the same time, the attitude toward ambiguity is remarkably stable across these two sources of uncertainty.

We have argued that it is useful to explicitly estimate a stochastic choice model because random behavior would otherwise be subsumed in the parameters supposedly characterizing ambiguity attitudes. While there is a long tradition of such models in other strands of the literature, to the best of our knowledge we have provided the first application in the context of ambiguity attitudes. Structural estimates at the individual × wave level have yielded a triplet of ambiguity aversion, likelihood insensitivity (or the perceived level of ambiguity), and the propensity to choose at random as opposed to the best-fitting model.

The properties of these parameters are comparable to parameters relating to risk preferences, which have received much more attention in the literature. In particular, all parameters are highly heterogeneous in the population. At the same time, they are fairly stable over time, with similar properties for risk preferences and ambiguity attitudes. Our IV approach has shown the absence of any systematic changes.

Our core analysis has thus focused on estimating the parameters at the individual level by imposing their stability over time. This means that the random choice component will also pick up variation across waves in addition to within-wave behavior that cannot be explained by the best-fitting deterministic part of the model. We have argued that the most promising way to describe the three-dimensional distribution of parameters—which are inherently non-separable in our choice model—using clustering techniques recently popularized in the econometric literature.

We found that four ambiguity types are a good way to balance parsimony and capture all economically interesting choice patterns. Predictions for choices differ sharply across these groups. The way the groups differ in both a large set of observed characteristics and portfolio choice behavior makes intuitive sense.

Our results suggest that ambiguity attitudes should be treated on par with risk preferences when it comes to their measurement and their importance in explaining behavior. For example, our results demonstrate much higher explanatory power for portfolio choices than similar studies for risk preferences (see the sobering survey in Charness et al., 2020). We view our applications to portfolio choice as highly suggestive. However, more careful modeling is needed in that respect as well as extending the domains – other relevant areas where ambiguity may play an important role are the labor market, lifestyle decisions in relation to climate change, individual health, or housing choices.

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Online Appendix Accompanying: The Distribution of Ambiguity Attitudes*

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Contents

Appendix A Interpretation of the ambiguity framework

In this section, we discuss two possible interpretations of our measured ambiguity attitudes: as parameters of a source function mapping subjective probabilities into decision weights or as parameters of a multiple prior model. The discussion of the latter closely follows Baillon, Bleichrodt, Li, and Wakker (2021) who also sketch how the measured ambiguity attitudes are related to outcome-based ambiguity models like the smooth model Klibanoff, Marinacci, and Mukerji (2005).

A.1 Decision weight interpretation

Based on the decision weight interpretation (Baillon, Bleichrodt, Keskin, l'Haridon, and Li, 2018), ambiguity attitudes are reflected in the event weighting function which relates subjective probabilities to non-additive decision weights. Our definition of ambiguity attitudes in Section 2.1 was based on this conceptualization.

Figure A.1 illustrates the two ambiguity parameters for a neo-additive event weighting function and $\alpha = 0.1$ and $\ell = 0.6$. Likelihood insensitivity ℓ equals 1 minus the slope of the weighting function. Lower τ_1 and therefore higher ℓ corresponds to a flatter function, i.e. event weights and, hence, measured matching probabilities are less responsive to subjective probabilities.

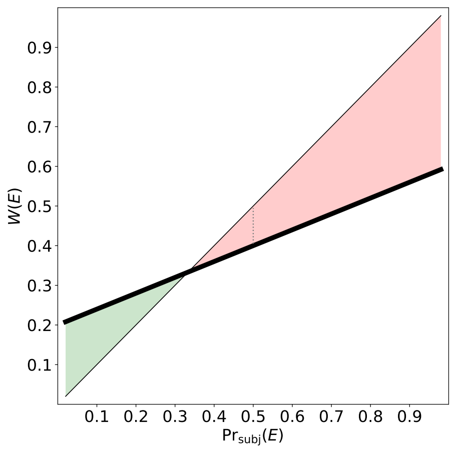


Figure A.1. Ambiguity aversion and likelihood insensitivity with a neo-additive source function

Notes: The thick black line plots the neo-additive source function $W(E) = \tau_0^S + \tau_1^S \cdot \mathrm{Pr}_{\mathrm{subj}}(E)$ for $\alpha = 0.1$ and $\ell = 0.6$. Ambiguity aversion α is the difference between the red area and the green area. In the neo-additive specification, it also equals the distance $\mathrm{Pr}_{\mathrm{subj}}(E) - W(E)$ at $\mathrm{Pr}_{\mathrm{subj}}(E) = 0.5$, indicated by the dotted vertical line. Likelihood insensitivity is 1 minus the slope of the source function.

Ambiguity aversion α, on the other hand, equals the red area minus the green area in the figure or, equally, the distance $\mathrm{Pr}_{\mathrm{subj}}(E) - W(E)$ at $\mathrm{Pr}_{\mathrm{subj}}(E) = 0.5$. An increase of α corresponds to a downward shift of $W(E)$ for all subjective probabilities.

The range of possible values for α is determined by the level of ℓ. Only for $\ell = 1$, α can reach its minimum and maximum.

A.2 Multiple prior models

In multiple prior models, an agent's subjective beliefs are represented by a a convex set C of prior probabilities over events $\pi \in C$. In the α-*max-min*-model (Ghirardato, Maccheroni, and Marinacci, 2004), the decision maker maximizes a weighted average of the expected utilities with respect to the most and least optimistic belief in the prior set:

$$x_E 0 \;\mapsto\; \gamma \min_{\pi \in C} (\pi(E) \cdot V(x)) + (1-\gamma) \max_{\pi \in C} (\pi(E) \cdot V(x))$$

Here, γ represents the weighting of the most pessimistic belief relative to the most optimistic belief and is a measure of ambiguity aversion. The specification is reduced to the *max-min*-model for $\gamma = 1$ and to the *max-max*-model for $\gamma = 0$.

To map this in our framework, we need to parameterize the set of priors. Following Chateauneuf, Eichberger, and Grant (2007), we specify the priors as a type of ϵ-contamination. This specification assumes that the prior set is associated with a reference probability distribution P, but the decision maker is uncertain about the probability distribution and considers the larger prior set C_δ:

$$C_\delta \;=\; \{\pi \;\in\; \Gamma \;:\; \pi(E) \;\geq\; (1-\delta)P(E), \forall E \;\in\; \Theta\}$$

Since the complementary event is restricted in the same way, the considered probability measures are restricted as follows:

$$(1-\delta)P(E) \;\leq\; \pi(E) \;\leq\; (1-\delta)P(E) + \delta, \forall E \;\in\; \Theta$$

Hence, δ indicates the length of the interval of considered probabilities and is used as a measure of the perceived level of ambiguity

In our framework, setting $P(E) = \mathrm{Pr}_{\mathrm{subj}}(E)$ the decision weight reduces to

$$\begin{aligned} W(E) \;&=\; \gamma \cdot (1-\delta)\mathrm{Pr}_{\mathrm{subj}}(E) + (1-\gamma)\big((1-\delta)\mathrm{Pr}_{\mathrm{subj}}(E) + \delta\big) \\ &=\; (1-\gamma)\delta + (1-\delta)\mathrm{Pr}_{\mathrm{subj}}(E) \end{aligned}$$

It is easy to see that δ equals our measure of likelihood insensitivity ℓ. Furthermore, α corresponds to $(\gamma - 0.5) \times \delta$. It is instructive to compare the interpretation of γ and α. The former is a measure of relative ambiguity aversion indicating ambiguity aversion per unit of perceived ambiguity and varies between 0 and 1. Conversely, α measures absolute ambiguity aversion and its range depends on ℓ.

Appendix B Questionnaire

This section documents the questionnaires we used. A typical questionnaire consisted of the following parts which are described in more detail below:

1. Payout for wave 6 months before
2. (Optional) tutorial
3. Draw code of question that is payed out
4. Core ambiguity module (21 to 28 binary choices)
5. Answer pay-out question if not answered before
6. Additional questions (varies between waves)

We collected six waves of data in November 2018, May 2019, November 2019, May 2020, November 2020, and May 2021. In April 2018, we conducted a pilot in the CentERpanel and in May 2018 a pilot in the LISS panel – both with a slightly different design. We also ran an additional survey in January 2019 which did not contain the core ambiguity module but elicited several preference measures and personal characteristics.

B.1 Payout for the prior wave

We chose the evaluation dates for the AEX such that we could determine payoffs at the start of the subsequent wave. By starting the questionnaire with the payout of the last wave, subjects are reminded that their choices are incentivized.

One exemplary payout sequence could look as follows:

> *You participated in a survey six months ago. In this survey, you had the chance to earn 20 euros. This depended on your choices and on chance. Just one of these choices would be chosen. This choice will be played out now and you might earn 20€.*
>
> *Code XAZMG was chosen and is shown on the next screen. [Show graphics for option 1 and option 2 for this question]*
>
> *An investment of 1000 euros in the AEX on the day you completed the questionnaire (November 2, 2018) is worth 1203 euros on April 30, 2019.*
>
> *If you chose option 1, you would have earned 20 euros. If you chose option 2, you had a 50 % chance of winning.*
>
> *On the next screen, spin the wheel of fortune and see if you win or not if you chose option 2.*
>
> *After spinning the wheel of fortune you will see whether you have chosen option 1 or option 2 and you will see whether or not you have won 20 euros.*

On the next screen, the subject spins the wheel of fortune by clicking a button. The wheel of fortune spins around a few times and then stops either in the red or orange part. The following text is shown:

> *The wheel of fortune stops in the red/orange section: you therefore win (no) 20 euros if you chose option 2.*
>
> *On the next screen we show which option you have chosen and whether you have won 20 euros or not.*

On the next screen, we would then show:

> *[Show graphics for option 1 and option 2 for this question] If you chose option 1, you win 20 euros, because an investment of 1000 euros in the AEX is worth 1203 euros on April 30, 2019, as we showed earlier.*
>
> *If you chose option 2, you will win (no) 20 euros, because the wheel of fortune stopped in the red/orange section.*
>
> *You chose option 1 and win 20 euros./ You chose option 2 and do not win 20 euros./ You chose option 2 and win 20 euros.*

Each participant whose choice turned out to be winning received 20 euros.

B.2 Tutorial

Going through a tutorial introducing the choice situations and potential payoff consequences was mandatory when subjects participated for the first time. For subjects who have participated before, we just give a short overview and make the tutorial optional as follows:

> *Now you will be given another set of choices just like you were given in the survey six months ago. Then you will be asked a few more questions. It again depends on your choices and on chance whether you can earn 20 euros in the next survey in this series in November 2019. Then you will be asked a few more questions. It again depends on your choices and on chance whether you can earn 20 euros in the next survey in this series in November 2019.*
>
> *The first option always assumes how the AEX index is doing between now and October 31, 2019. The second option always assumes a spin of the wheel of fortune. Out of all your choices, one is chosen at random. Of course, whether you earn anything also depends on whether you participate in the same questionnaire in six months' time. The following screens explain how these choices work and show an example.*
>
> *Would you like to receive this explanation? yes/no*

The tutorial is based on options that are similar to the options used in the later basic module, but the exact parameters are different (AEX investment worth less than 1050 euros; lottery with winning probability of 25 %). We present the options and let the subject make a choice.

> *Below you will see an example. Then you will be asked two questions to see if you understood how it works. [Show graphics for option 1 and option 2] Option 1: You will receive 20 euros if an investment of 1000 euros in the AEX is worth less than 1050 euros on 31 October 2019. Option 2: You will receive 20 euros if the wheel of fortune stops in the orange section. This happens with a 25 % chance.*

The payout of option 1 depends on the value that an investment of 1000 euros in the AEX index will have on 31 October 2019. You will receive 20 euros if the value is less than 1050 euros, otherwise you will receive nothing.

If you choose option 2, you have a 25 % chance of earning 20 euros. In six months' time, chance (the wheel of fortune) will then determine whether this is so, when you complete the next questionnaire. If your choice falls into the orange section (which is 25 % of the total), you win. If your choice falls into the red section (which is 75 % of the total), you get nothing.

Now you choose: option 1/option 2

Suppose the subject chooses option 1:

You will receive 20 euros if an investment of 1000 euros in the AEX is worth less than 1050 euros on 31 October 2019.

On October 31, 2019, we look at how the AEX has performed. Suppose the AEX has achieved a result of 1030 euro. Would you receive 20 euro? yes/no

[if yes: Yes, that's right. The value of the investment is 1030 euros and that is lower than 1050 euros, so you get 20 euros.

if no: No, that is not correct. Because the value of the investment is 1030 euros and that is lower than 1050 euros, you do get 20 euros.]

We then also explain the other option.

We will now give you an example of how it works if you had chosen option 2.

Imagine that six months have passed and you fill out another questionnaire. Press the orange button of the wheel of fortune.

[If the respondent clicked the button, the picture rotated and ended in the red part]

Would you get 20 euros? yes/no

[if yes: No, that is not correct. The pointer of the wheel has stopped in the red part and that means you do not win. You would have won if the pointer of the wheel had stopped in the orange part.

if no: Yes, that is correct. The pointer of the wheel has stopped in the red part and that means that you do not win. You would have won if the pointer of the wheel was stopped in the orange section].

B.3 Draw payout question

If we selected one of the answered questions for pay-out ex-post, the design would not be incentive compatible. Inspired by Bardsley (2000) and Johnson, Baillon, Bleichrodt, Li, van Dolder, et al. (2021), we let subjects start a random number generator to select the question to be paid out before they make any decisions as seen below.

You will get the real questions now. You choose again a number of times from two options. Six months from now, we just show one of these choices and you can again earn 20 euros or nothing. This again depends on your choice and (if you chose option 1) the developments on the AEX or (if you chose option 2) on coincidence. There are no right or wrong choices. Just choose the option you prefer.

Of all the choices you have made, one will be used for a possible payout. Which one that is is will be determined now, but you won't see it until the end of this questionnaire. Now click on the orange "Choose Payout" button to determine this. When the payout has been determined, click on continue.

After the subjects clicks "Choose Payout". The selected question was displayed as a meaningless sequence of characters. The next screen reads:

Which questions you get next depends on the choices you made. If question SQKDC was chosen by you, we will use your choice on this question for any payout. But we ask you to make another choice at the end of the questionnaire if question SQKDC was not among your choices. You have no influence on which choice will be used to perhaps pay out, this has already been decided.

We now begin with the actual questions.

B.4 Core ambiguity module

In order to measure ambiguity attitudes, we adapt the method developed by Baillon, Huang, Selim, and Wakker (2018) and Baillon, Bleichrodt, Li, et al. (2021) for use in a general population. Eliciting attitudes about ambiguous events is cognitively demanding for participants. To keep this burden low, we confront subjects with binary choices only. Compared to a choice list format (Baillon, Huang, et al., 2018), we expect this procedure to reduce complexity as subjects can focus on one question at a time.

Individuals make a series of choices, which all share the structure shown in Figure 1. For each binary choice situation, we include a help button that reveals a detailed description of both choice options when clicked on. One example for event E_0^{AEX} is:

The payout of option 1 depends on the value that an investment of 1000 euros in the AEX index will have on October 31, 2019. You will get 20 euros if the value is more than 1000 euros, otherwise you will get nothing.

If you choose option 2, you have a 50 % chance of earning 20 euros. In six months' time, chance (the wheel of fortune) will then determine whether this is so, when you complete the next questionnaire. If your choice falls into the orange section (which is 50 % of the total), you win. If your choice falls into the red section (which is 50 % of the total), you get nothing.

The other AEX events (Option 1) are described as flows:

E_1^{AEX} …*if the value is more than 1100 euros* ….

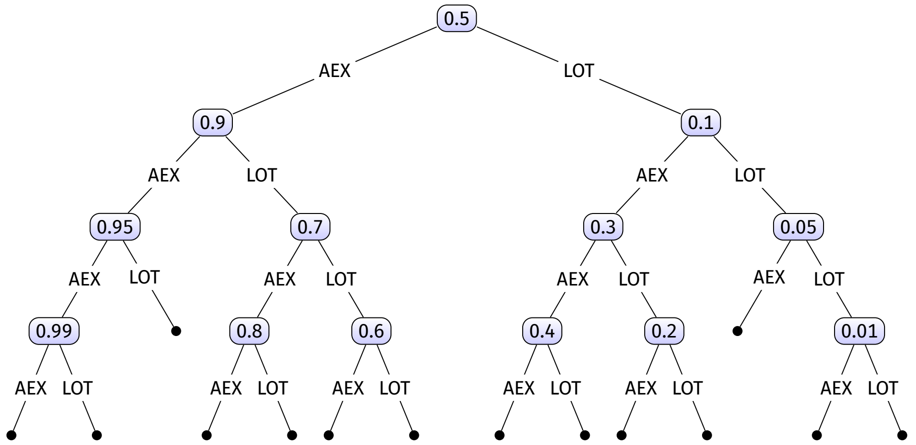


Figure B.1. Iterative sequence of lottery probabilities for any AEX event. Nodes display the probability for winning 20 €in the lottery task.

E_2^{AEX} *…if the value is less than 950 euros ….*

E_3^{AEX} *…if the value is between 950 and 1100 euros ….*

$E_{1,C}^{AEX}$ *…if the value is 1100 euros or less ….*

$E_{2,C}^{AEX}$ *…if the value is 950 euros or more ….*

$E_{3,C}^{AEX}$ *…if the value is less than 950 euros or more than 1100 euros ….*

Depending on her choice between the AEX event and the lottery, a subject is presented another choice with the same AEX event and a different lottery. Figure B.1 shows the sequence of lottery win probabilities based on the previous choices. After the three to four choices, matching probabilities are pinned down to intervals of 0.1 or less. 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 %.

The remainder of our design closely follows Baillon, Huang, et al. (2018). We partition the space of possible values the AEX investment can take into three events: $E_1^{AEX} : Y_{t+6} \in (1100, \infty]$, $E_2^{AEX} : Y_{t+6} \in [0, 950)$, and $E_3^{AEX} : Y_{t+6} \in [950, 1100]$, see Figure 2. This partition leads to balanced historical 6-month returns of the AEX with frequencies of 0.24, 0.28, and 0.48, respectively. We elicit matching probabilities for each of these events along with their complements. We additionally include the event $E_0^{AEX} : Y_{t+6} \in (1000, \infty]$. This is arguably the most intuitive event and it should ease the entry for participants. Between the AEX event, we included separator screens stating

> *Part X of 7*
> *Option 1 has now changed, but will remain the same on subsequent screens. Only option 2 keeps changing.*

In the November 2018 wave, we used cutoffs for the AEX events at 951, 1001 and 1101 accounting for the potential return of a savings account (at this time roughly 0.1 % over six months). In later waves we dropped this addition, returns on a savings account were almost zero anyway, and specified the cutoffs and events exactly as described above.

B.5 Answer payout question

If the subject did not encounter the choice situation selected for payout during the questionnaire—i.e., she took a different branch in the decision tree—we presented it after all other decisions had been made.

> *As a reminder, question SQKDC was selected to play for 20 euros in six months. That's the question with these options [Show graphics for option 1 and option 2 for this question]*
>
> *You have chosen option 1 for this question./ You have chosen option 2 for this question./ You have not answered this question. On the next screen, we will ask you to choose between two options one more time.*

B.6 Additional Variables

In this section, we document the measurement of additional variables that we elicited alongside the basic module described above.

Our three measures of numeracy and our measure of risk aversion were each elicited twice. In Section D.4, we describe how we calculate the indices for numeracy and risk aversion.

Financial Numeracy (elicited November 2018 and November 2020)

The financial numeracy component involves interest rates and inflation. We use a subset of the questions of van Rooij, Lusardi, and Alessie (2011). Correct answers are marked in **bold**.

Question 1 Suppose you have 1000 euros in a savings account and the interest rate is 1 % per year. How much do you think you will have in the savings account after three years if you leave all the money in this account:

1. **more than 1010 euros**
2. exactly 1010 euros
3. less than 1010 euros
4. you can't say with the information given

Question 2 Suppose you put 1000 euros into a savings account with a guaranteed interest rate of 0.3 % per year. You don't make any further payments into this account and you don't withdraw any money. How much would be in the account at the end of the first year, once the interest payment is made? (Correct answer: **1003**)

Question 3 And how much would be in the account at the end of five years? Would it be:

1. **more than 1015 euros**
2. exactly 1015 euros
3. less than 1015 euros
4. you can't say with the information given

Question 4 Suppose the interest rate on your savings account is 1 % per year, and inflation is equal to 2 % per year. Would you then be able to buy more, exactly the same, or less after 1 year than you could do today with the money in this account?

1. more than today
2. exactly the same as today
3. **less than today**
4. you can't say with the information given

Probabilistic Numeracy (elicited November 2018 and November 2020)

The first five questions measuring probability numeracy were proposed by Hudomiet, Hurd, and Rohwedder (2018). They test both basic understanding of probabilities and more advanced concepts such as independence and additivity. The last two questions were added by us due to their relation to set-monotonicity violations. Correct answers are marked in **bold**.

Question 1 Finally, we would like to ask you about the probability that something will happen. 0 means you think it will definitely not happen, and 100 means you think it will definitely happen. Think of a bin with a total of 10 balls. Some of the balls may be white and some may be red.

First, suppose the bin contains 10 white balls and no red ones. Without looking, you pick a ball from the bin. On a scale of 0 to 100 how likely is it that you will take a ball that is red out of the bin? (Correct answer: **0**)

Question 2 Now suppose the bin contains 7 white balls and 3 red balls. Without looking you take a ball out of the bin. On a scale of 0 to 100 how likely is it that you will pick a ball that is white from the bin? 0 means you think it will definitely not happen, and 100 means you think it will definitely happen. (Correct answer: **70**)

Question 3 Suppose the weather report predicts that the probability of it raining tomorrow is 70 %. Assume that the weather forecast correctly predicted this probability, what is the probability that it will not rain tomorrow? (Correct answer: **30**)

Question 4 Suppose that whether it rains tomorrow in your hometown and whether it rains tomorrow in New York have nothing to do with each other. The probability of it raining in your hometown is 50 %. The probability that it rains in New York is also 50 %. What is the probability that it will rain tomorrow in your hometown and also in New York? (Correct answer: **25**)

Question 5 Suppose a friend has a regular coin. When you flip this coin you have an equal chance of being heads and being tails. Your friend tosses this coin 3 times and each time it is heads. What is the probability that if your friend tosses the coin again it will be heads? (Correct answer: **50**)

Question 6 Suppose the probability that it will be at least 10 degrees Celsius tomorrow is 50 %. Then what do you think is the probability that it will be at least 15 degrees Celsius tomorrow?

1. **less than 50 %**
2. exactly 50 %
3. more than 50 %

Question 7 Suppose the probability that it will be at least 10 degrees Celsius tomorrow is 50 %. Then what do you think is the probability that it will be warmer than 0 degrees Celsius tomorrow?

1. less than 50 %
2. exactly 50 %
3. **more than 50 %**

Basic Numeracy (elicited January 2019 (extra wave) and November 2020)

The basic numeracy component is asked for, e.g., in the English Longitudinal Study of Ageing (Steptoe, Breeze, Banks, and Nazroo, 2013). Subjects are asked four to five questions with the first three questions being the same for every subject. The difficulty of the later questions are adjusted based on the correctness of the first questions. Correct answers are marked in **bold**.

Question 1 Finally, we now ask you some questions about how people use numbers in their daily lives.

In a sale, a shop is selling all items at half price. Before the sale, a sofa costs 300 euros. How much will it cost in the sale?

1. 100 euros
2. **150 euros**
3. 200 euros
4. 250 euros
5. 600 euros

6. Other
7. Don‘t know

Question 2 If the chance of getting a disease is 10 percent, how many people out of 1,000 (one thousand) would be expected to get the disease?

1. 10
2. 90
3. **100**
4. 900
5. Other
6. Don‘t know

Question 3 A used car dealer is selling a car for 6,000 euros. This is two-thirds of what it cost new. How much did the car cost new?

1. 2,000 euros
2. 3,000 euros
3. 4,000 euros
4. 8,000 euros
5. **9,000 euros**
6. 12,000 euros
7. 18,000 euros
8. Other
9. Don‘t know

Question 4 [If all of (Q1), (Q2) and (Q3) incorrect] If you buy a drink for 85 cent and pay with a one euro coin, how much change should you get back?

1. **15 cent**
2. 25 cent
3. Other
4. Don‘t know

Question 5 [If any of (Q1), (Q2), (Q3) correct] If 5 people all have the winning numbers in the lottery and the prize is 2 euros million, how much will each of them get?

1. 200,000 euros
2. 250,000 euros
3. **400,000 euros**
4. 500,000 euros
5. Other

6. Don‘t know

Question 6 [If any of (Q2), (Q3), (Q5) correct] Say you have 200 euros in a savings account. The interest rate on the account is 10 % each year. How much would you have in the account at the end of two years?

1. 202 euros
2. 204 euros
3. 210 euros
4. 220 euros
5. 240 euros
6. **242 euros**
7. Other
8. Don‘t know

Risk aversion (elicited January 2019 (extra wave) and November 2020)

We measure households' risk aversion using the preference survey module developed by Falk, Becker, Dohmen, Huffman, and Sunde (2016). The module includes a qualitative component, a general risk question, and a quantitative component that is based on elicited certainty equivalents for risky lotteries.

Qualitative Component. We asked the following question:

> *Are you, in general, willing to take risks? Please give your answer on a scale of 0 to 10, where 0 means you are 'completely unwilling to take risks' and 10 means you are 'very willing to take risks'.*

Quantitative Component. We presented the subjects with a series of five (hypothetical) binary choices:

> *We now give you five different situations: You can choose each time between a draw where you have an equal chance of getting 300 euros or getting nothing, OR a certain payment of a certain amount of money.*
>
> *What would you prefer: a 50 percent chance of winning 300 euros with a simultaneous 50 percent chance of winning nothing, or would you rather have the amount of 160 euros as a fixed payment?*

Each choice is accompanied by a visualization for which an example is shown in Figure B.2. Over the five choices, the value of the fixed payment is varied based on previous choices (in the extremes, from 10 to 310) such that the valuation of the lottery is pinned down up to an interval spanning 10 euros. We take the mid point of the interval as quantitative measure of willingness to take risk.

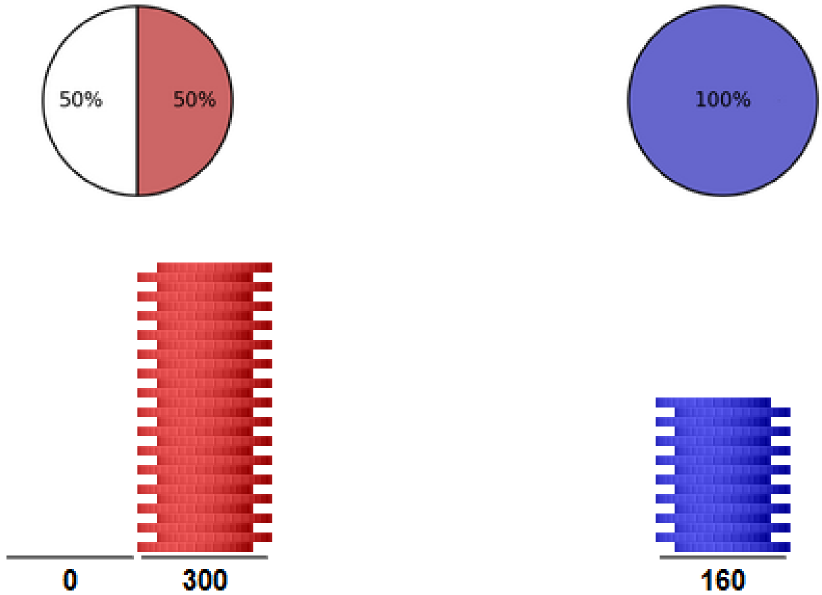


Figure B.2. Exemplary visualization for the elicitation of quantitative risk aversion

Notes:

Judged empirical frequencies (elicited May 2019)

We ask subjects about their perceived empirical frequencies of the AEX events we use in our study.

> *Now we ask you how the AEX has done over the past twenty years.*
>
> *Suppose someone invested 1000 euros in the AEX at some point in the last twenty years and six months later they look at what the AEX has done.*
>
> *What percentage of the time was this investment then ...*
>
> *Enter a whole number between 0 and 100.*
>
> *worth more than 1100 euros: worth at least 950 euros and at most 1100 euros: worth less than 950 euros:*

We first do not enforce that the entered numbers sum up to 100 and save the answers. Subjects whose numbers do not sum up to 100 or which enter a number below 0 or 100 receive a prompt to correct their responses:

> *Always enter an integer from 0 to 100./ The percentages you entered must total 100.*
>
> *Please improve your answer.*

For the study, we always use the corrected responses (if necessary). Finally, we also ask for E_0 for which we only check if the response is between 0 and 100.

> *Suppose someone invested 1,000 euros in the AEX at some point in the last twenty years and six months later they look at what the AEX has done.*
>
> *What percentage of the time was this investment worth more than 1000 euros?*

Ambiguity attitudes about climate (elicited November 2019)

In November 2019, we additionally included a similar design where the source of uncertainty was the average temperature in the Netherlands over the subsequent winter. The payout question for this wave was chosen from all potential AEX or climate binary choice situations.

The elicitation of ambiguity attitudes about the climate starts with the following introduction.

> *We now move on to the second component. In this section, the first choice is always based on the average temperature in the Netherlands this winter (December, January, February) compared to the average temperature during the last five winters. The second choice is always based on a spin of the wheel of fortune, just like before. From all the choices you make in part 1 and in part 2, one is eventually chosen just like that which determines which option is played with and what you get. You must then participate in the same questionnaire that will be presented to you in six months.*

Afterwards, a mandatory tutorial very similar to the usual one appeared. The structure and routing of the choice questions were exactly the same as for the basic module. $E_0^{climate}$ was e.g. described as follows:

> *The payout of option 1 depends on the difference in average temperature next winter compared to the average temperature of the last five winters (December, January, February). You will get 20 euros if it is warmer next winter, i.e. if the increase is more than 0°C (e.g. 0.5°C or 2°C). If there is no difference in average temperature, or it is colder next winter, you earn nothing.*

The explanation for the other events were as shown below:

$E_1^{climate}$ *…You receive 20 euros if the average temperature next winter has increased by more than 1°C. That is, if it is more than 1°C warmer this winter than the average over the past five years (e.g. 1.5°C or 2°C). If the temperature has risen or fallen by no more than 1°C, you earn nothing.*

$E_2^{climate}$ *…You receive 20 euros if the average temperature next winter has dropped more than 0.5°C. So if it is more than 0.5°C colder this winter than the average over the past five years. If the temperature has not decreased more than 0.5°C, or has increased, you earn nothing.*

$E_3^{climate}$ *…You receive 20 euros if the average temperature next winter has not dropped more than 0.5°C and has not risen more than 1°C. If the average temperature has dropped more than 0.5°C or risen more than 1°C, you get nothing. If the temperature has dropped more than 0.5°C or risen more than 1°C, you earn nothing.*

$E_{1,C}^{climate}$ *...You receive 20 euros if the average temperature next winter has not risen more than 1°C, or has fallen. If the temperature has risen more than 1°C (e.g. 1.5°C or 3°C), you earn nothing.*

$E_{2,C}^{climate}$ *...You receive 20 euros if the average temperature has not dropped or risen by more than 0.5°C. So if it is no more than 0.5°C this winter, you receive 20 euros. So if this winter is no more than 0.5°C colder, or if it is warmer, than the average over the past five years. If the temperature has dropped more than 0.5°C, you earn nothing.*

$E_{3,C}^{climate}$ *...You receive 20 euros if the average temperature next winter has decreased more than 0.5°C or increased more than 1°C. If the temperature has not decreased more than 0.5°C and has not increased more than 1°C, you earn nothing.*

We also added the following two questions at the very beginning of the questionnaire in November 2019:
Self reported knowledge of climate change:

> *Climate change has been in the news a lot lately.*
>
> *How would you describe your knowledge of the causes and effects of climate change? (1 means very poor; 5 means very good)*

Concern about climate change:

> *Please indicate whether you agree with the following statement: Climate change is a threat to me and my family.*
>
> *completely disagree; disagree; somewhat disagree; somewhat agree; agree; completely agree*

Appendix C Details of the estimation

We estimate the neo-additive model at the individual level, which allows us to match average levels of ambiguity aversion and likelihood insensitivity while respecting the large heterogeneity in the data.

Our maximum likelihood solver for a single wave optimizes over the following parameters:

- τ_0
- τ_1
- σ
- $\Pr_{\text{subj}}(E_0)$
- $\Pr_{\text{subj}}(E_1)$
- $\Pr_{\text{subj}}(E_2)$

The error parameter σ is bounded at 0.001 below and unrestricted above. All other parameters are bounded between 0 and 1, bounds included.

Additionally, we employ the following restrictions:

- $\tau_0^S + \tau_1^S \leq 1$
- $\Pr_{\text{subj}}(E_0) + \Pr_{\text{subj}}(E_2) \leq 1$
- $\Pr_{\text{subj}}(E_1) \leq \Pr_{\text{subj}}(E_0)$

For the estimation in which we pool estimates of several waves, we estimate only one parameter for τ_0, τ_1, σ assuming those parameters are constant across waves, but estimate the three subjective probabilities separately for each wave (e.g. $\Pr_{\text{subj}}(E_0)^{\text{2018-11}}, \Pr_{\text{subj}}(E_0)^{\text{2019-05}}, \ldots$).

As a solver we use a global optimizer, the differential evolution algorithm (Storn and Price, 1997) as implemented in the Mystic package (McKerns, Strand, Sullivan, Fang, and Aivazis, 2012). We run the differential evolution algorithm with a population size of 1000. After trying out different values of the optimization parameters, we set cross-probability to 0.7 and the scaling factor to 0.6. A global optimization algorithm is necessary as the objective function is not generally globally concave due to complex interactions of the parameters (e.g. for bad starting values the likelihood increases when σ goes to infinity).

We also experimented with pseudo-global optimizers in which several local optimizers are started at various starting points in the parameter space. Those estimation techniques led to very similar parameter estimates for most individuals, but did not converge to the global optimum for a few.

To manage and execute the workflow of the estimation and all analyses, we make use of pytask (Raabe, 2020). Styling of tables relies heavily on the functionality provided by estimagic (Gabler, 2022).

Appendix D Data

D.1 Sample

Table D.1 shows the number of subjects that participated in each wave, completed the elicitation, and gave a proper response in each wave. The number of participants in the final sample, i.e. those with at least two waves of proper responses, is shown in the last column.

Table D.1. Observations

	Participated	Completed elicitation	Proper response	In final data set
2018-11	2253	2172	2124	1991
2019-05	2073	2013	1961	1933
2019-11	2008	1942	1888	1870
2019-11 (Climate Change)	2008	1926	1878	1858
2020-05	1850	1844	1809	1794
2020-11	1798	1791	1759	1748
2021-05	1747	1740	1710	1702
Unique Subjects	2455	2407	2392	2177

Notes: This table reports the number of subjects that participated in each wave (column 1) and completed the elicitation in each wave (column 2). A response is not counted as proper if they exhibit recurring patterns whilst also being entered quicker than 85 % of subjects. Recurring pattern indicates whether a subject choose the same option (AEX or lottery) for all 28 choices in a wave. The final data set (column 4) consists of all waves meeting our inclusion criteria for individuals with at least two such waves.

D.2 Matching probabilities

Table D.2. Average matching probabilities by wave

	2018-11	2019-05	2019-11	2020-05	2020-11
$E_0^{AEX}: Y_{t+6} \in (1000, \infty)$	0.51	0.52	0.49	0.43	0.52
$E_1^{AEX}: Y_{t+6} \in (1100, \infty]$	0.35	0.37	0.36	0.33	0.35
$E_{1,C}^{AEX}: Y_{t+6} \in (-\infty, 1100]$	0.5	0.52	0.52	0.51	0.54
$E_2^{AEX}: Y_{t+6} \in (-\infty, 950)$	0.35	0.34	0.35	0.43	0.36
$E_{2,C}^{AEX}: Y_{t+6} \in [950, \infty)$	0.54	0.56	0.56	0.51	0.58
$E_3^{AEX}: Y_{t+6} \in [950, 1100]$	0.55	0.57	0.57	0.53	0.59
$E_{3,C}^{AEX}: Y_{t+6} \in (-\infty, 950) \cup (1100, \infty)$	0.41	0.41	0.4	0.45	0.41

Notes: Events were asked about in this order: $E_0^{AEX} \cdot E_1^{AEX} \cdot E_2^{AEX} \cdot E_3^{AEX} \cdot E_{1,C}^{AEX} \cdot E_{2,C}^{AEX} \cdot E_{3,C}^{AEX}$. Matching probabilities are set to the midpoint of the interval identified by the design. Mean of the matching probabilities of the seven events. Sample: All waves meeting our inclusion criteria (i.e., there is variation across options and/or completion time is outside the fastest 15 %, see Section 2.3) for individuals with at least two such waves.

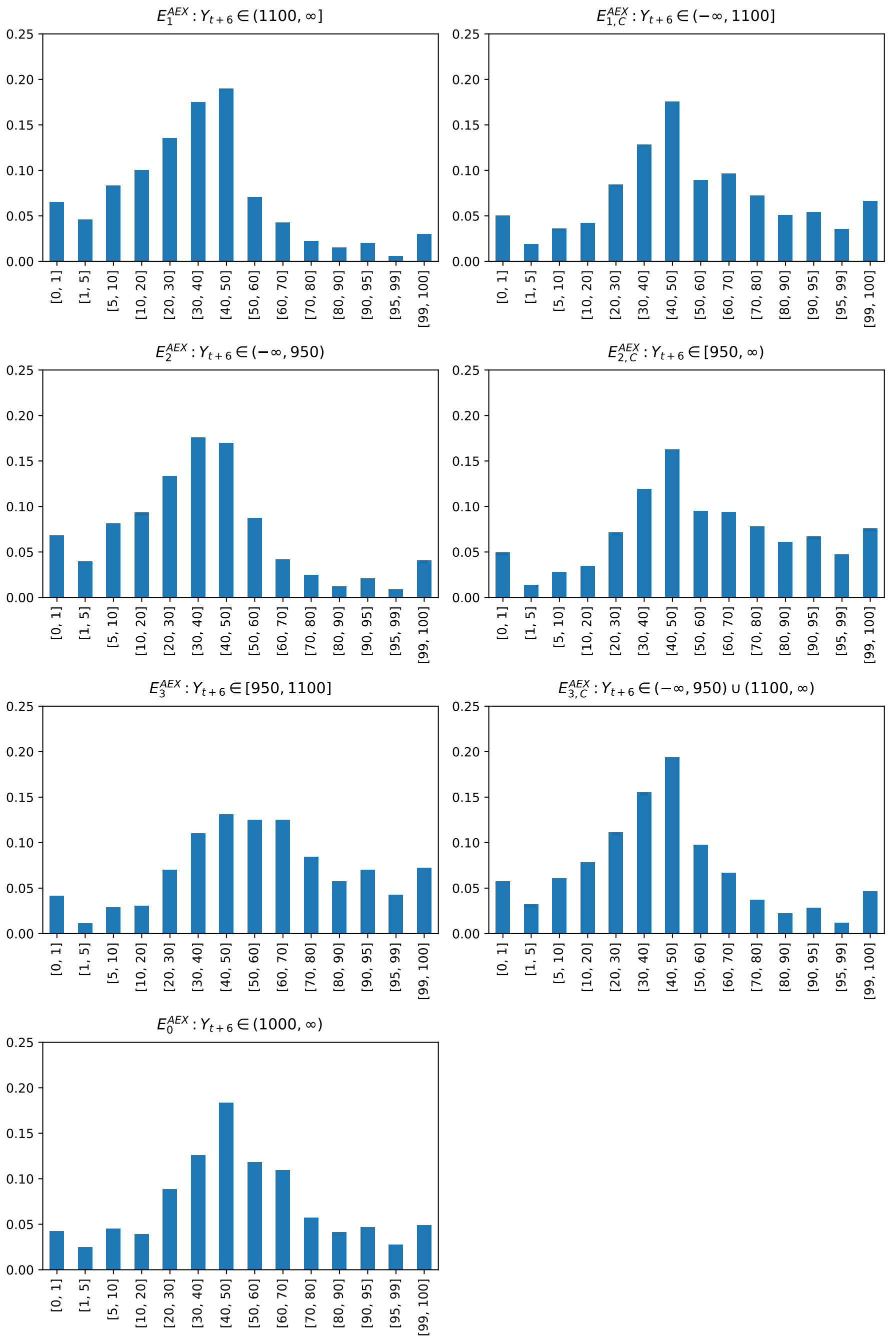


Figure D.1. Distribution of matching probabilities averaged across waves

Notes: Each bar chart shows for one event the share of respondents whose elicited matching probability falls in the respective category. Responses are pooled over all AEX waves. Sample: All waves meeting our inclusion criteria (i.e., there is variation across options and/or completion time is outside the fastest 15 %, see Section 2.3) for individuals with at least two such waves.

Table D.3. Matching probabilities for climate questions

	N subj.	Mean	$q_{0.1}$	$q_{0.5}$	$q_{0.9}$	Empirical Frequency, 1999-2019
$E_0^{climate}: \Delta T \in (0°C, \infty)$	1895	0.52	0.075	0.55	0.93	0.53
$E_1^{climate}: \Delta T \in (1°C, \infty]$	1894	0.45	0.075	0.45	0.93	0.23
$E_{1,C}^{climate}: \Delta T \in (-\infty, 1°C]$	1892	0.52	0.075	0.55	0.93	
$E_2^{climate}: \Delta T \in (-\infty, -0.5°C)$	1892	0.4	0.03	0.35	0.85	0.27
$E_{2,C}^{climate}: \Delta T \in [-0.5°C, \infty)$	1892	0.49	0.075	0.45	0.93	
$E_3^{climate}: \Delta T \in [-0.5°C, 1°C]$	1892	0.5	0.075	0.45	0.93	0.5
$E_{3,C}^{climate}: \Delta T \in (-\infty, -0.5°C) \cup (1°C, \infty)$	1891	0.47	0.075	0.45	0.93	

Notes: Events were elicited in the order $E_0^{climate} \cdot E_1^{climate} \cdot E_2^{climate} \cdot E_3^{climate} \cdot E_{1,C}^{climate} \cdot E_{2,C}^{climate} \cdot E_{3,C}^{climate}$. 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. The last column shows the empirical frequencies (own calculation). Sample: All waves meeting our inclusion criteria (i.e., there is variation across options and/or completion time is outside the fastest 15 %, see Section 2.3) for individuals with at least two such waves.

D.3 Set-monotonicity violations

During the elicitation of matching probabilities, the responses of subjects can violate set-monotonicity for eight pairs of events. Table D.4 presents the share of subjects which violates set-monotonicity for each of these events. While below 10 percent of the sample report a strictly higher matching probability for event E_1^{AEX} than for E_0^{AEX}, almost a quarter does so for E_3^{AEX} relative to $E_{1,C}^{AEX}$. The bottom row shows that 55 % of the subjects violate set-monotonicity for at least one of these eight pairs. As visualized in Figure D.2, less set-monotonicity violations tend to occur at pairs of events with a larger difference in judged frequencies. This relationship holds—both between and within individuals—when we run regressions (Table 2).

Table D.4. Average set-monotonicity violations by superset-subset pair

		Rate of set-monotonicity violations	
		AEX	climate
$E_{1,C}^S$	E_2^S	0.1	0.11
	E_3^S	0.24	0.12
$E_{2,C}^S$	E_1^S	0.086	0.18
	E_3^S	0.18	0.17
$E_{3,C}^S$	E_1^S	0.16	0.19
	E_2^S	0.15	0.15
E_0^S	E_1^S	0.078	0.11
$E_{2,C}^S$	E_0^S	0.15	0.24
Any violation	excluding E_0^S	0.49	0.47
	including E_0^S	0.55	0.54

Notes: The first column reports the rates of set-monotonicity violations for each pair of events. Set-monotonicity is violated if the lower bound of the interval elicited for the matching probability of the subset is strictly larger than the upper bound of the corresponding interval of the superset. The second to last row shows the share of subjects with at least one error in a given wave while the last row reports this statistic, but excludes all superset-subset pairs that include E_0^{AEX} (i.e., $E_0^{AEX} - E_1^{AEX}$ and $E_{2,C}^{AEX} - E_0^{AEX}$). Sample: All waves meeting our inclusion criteria (i.e., there is variation across options and/or completion time is outside the fastest 15 %, see Section 2.3) for individuals with at least two such waves.

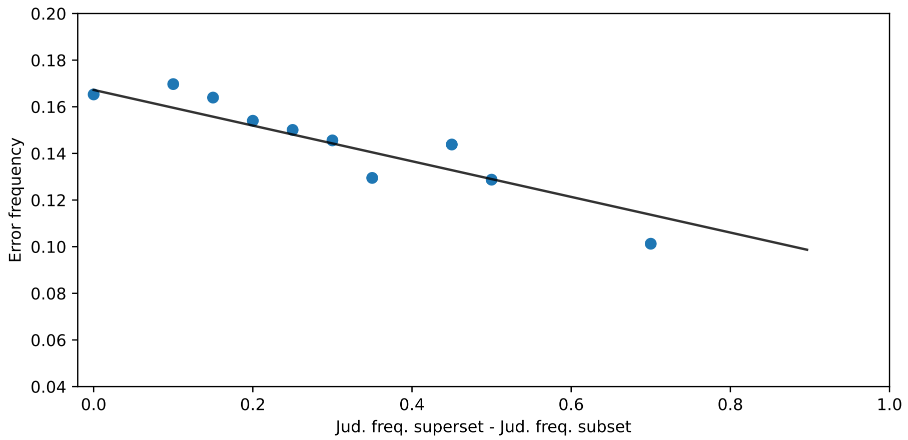


Figure D.2. Set-monotonicity violations and difference in judged historical frequencies (binscatter)

Notes: This figure visualizes the relation between the difference of judged historical frequencies (x-axis) and the error frequency (y-axis) on the subject × superset-subset pair level. The error frequency is averaged across waves. It shows the best fitting linear line, as well as a binscatter in which the 15616 observations are aggregated to 10 bins. Set-monotonicity is violated if the interval of the elicited matching probability of the subset is strictly larger than the interval of the superset. Sample: All waves meeting our inclusion criteria (i.e., there is variation across options and/or completion time is outside the fastest 15 %, see Section 2.3) for individuals with at least two such waves.

D.4 Background variables

This section provides further information about the calculation of background variables.

Age, gender Obtained from the background questionnaire. Refers to the financial decider who is participating in the survey.

Education Obtained from the background questionnaire. Based on achieved educational level. The Dutch educational levels are categorized as follows:

Lower secondary and below: primary school, vmbo

Upper secondary: mbo, havo, vwo

Tertiary: hbo, wo

Net income hh Obtained from the background questionnaire. Monthly net income. The income of both partners is added and divided by the square root of 2 in case the financial decider has a partner in the same household.

Total financial assets Obtained from the assets questionnaire. Sum of safe financial assets and risky financial assets. We consider assets by the financial decider and joint assets that the financial decider owns together with their partner. The value is equivalized by dividing by the square root of 2 in case the financial decider has a partner in the same household.

Risky financial assets Obtained from the assets questionnaire. Risky financial assets include growth funds, share funds, bonds, debentures, stocks, options, and warrants which is in line with the definition of Statistics Netherlands. We consider risky assets by the financial decider and joint assets that the financial decider owns together with their partner. The value is equivalized by dividing by the square root of 2 in case the financial decider has a partner in the same household.

Owns any risky financial assets Dummy variable if risky financial assets are larger than 0.

Share of risky financial assets Risky financial assets divided by total financial assets. Set to missing if total financial assets do not exceed 0. Values below 0 and above 1 are winsorized (this originates from very few subjects who report negative safe or risky financial assets).

Risk aversion index Elicited ourselves (see Online Appendix B). We take the mean over all elicitations for each subject (one or two). We use the experimentally validated weights by Falk et al. (2016) to calculate the index such that the qualitative risk component is weighted slightly higher at 53 % (after standard normalizing both components).

Numeracy index Elicited ourselves (see Online Appendix B). For each component (financial, probabilist, basic, numeracy) we take the mean over all elicitations for each subject (one or two). For each component of numeracy, we count the number of correct answers and standard normalize the measure. We then aggregate all three components into a numeracy index, giving equal weight to each component.

For the income and asset variables, we use the mean over all observations during the time of our data collection (2018 to 2021). For age, gender, and education, we use the first observation in this period.

Table D.5. Relation of risk aversion and numeracy with characteristics

	Risk aversion index	Numeracy index
Intercept	-0.39^{***}	-0.53^{***}
	(0.1)	(0.097)
Age: $\in (35, 50]$	0.24^{***}	-0.2^{***}
	(0.079)	(0.075)
Age: $\in (50, 65]$	0.33^{***}	-0.17^{**}
	(0.076)	(0.072)
Age: ≥ 65	0.33^{***}	-0.44^{***}
	(0.076)	(0.072)
Education: Upper secondary	-0.086	0.32^{***}
	(0.07)	(0.061)
Education: Tertiary	-0.092	0.59^{***}
	(0.073)	(0.06)
Income: $\in (1.1, 1.6]$	0.017	0.14^{**}
	(0.076)	(0.065)
Income: $\in (1.6, 2.2]$	-0.02	0.3^{***}
	(0.074)	(0.061)
Income: ≥ 2.2	-0.21^{***}	0.18^{***}
	(0.077)	(0.069)
Financial assets: $\in (1.8, 11.2]$	0.037	0.57^{***}
	(0.073)	(0.068)
Financial assets: $\in (11.2, 32]$	0.22^{***}	0.67^{***}
	(0.075)	(0.066)
Financial assets: ≥ 32	0.028	0.81^{***}
	(0.076)	(0.067)
Female	0.3^{***}	-0.34^{***}
	(0.049)	(0.041)
Observations	1624	1624
Adj. R^2	0.053	0.34
Note:		$^{***}p<0.01$; $^{**}p<0.05$; $^{*}p<0.1$

Notes: Sample: All waves meeting our inclusion criteria (i.e., there is variation across options and/or completion time is outside the fastest 15 %, see Section 2.3) for individuals with at least two such waves.

Appendix E Additional tables and figures for Section 3

E.1 Marginal distributions

Table E.1. Marginal distributions of estimated parameters, wave by wave

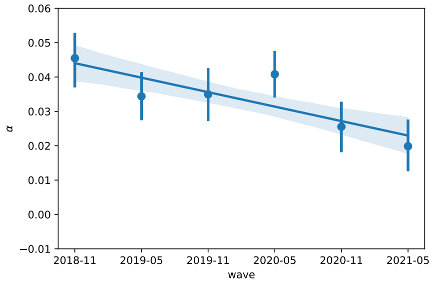
		Mean	Std. dev.	$q_{0.05}$	$q_{0.25}$	$q_{0.5}$	$q_{0.75}$	$q_{0.95}$
α	2018-11	0.045	0.17	−0.24	−0.05	0.037	0.15	0.33
	2019-05	0.034	0.16	−0.22	−0.053	0.026	0.13	0.28
	2019-11	0.035	0.16	−0.22	−0.06	0.03	0.13	0.3
	2020-05	0.041	0.15	−0.2	−0.05	0.04	0.13	0.28
	2020-11	0.026	0.15	−0.2	−0.064	0.021	0.11	0.27
	2021-05	0.02	0.15	−0.22	−0.067	0.0064	0.1	0.29
	Observations from all AEX waves	0.034	0.16	−0.22	−0.057	0.028	0.13	0.3
	2019-11 (Climate Change)	0.02	0.17	−0.27	−0.082	0.015	0.13	0.31
ℓ	2018-11	0.57	0.3	0.068	0.31	0.6	0.83	0.99
	2019-05	0.58	0.29	0.083	0.33	0.61	0.84	0.98
	2019-11	0.59	0.29	0.093	0.35	0.61	0.85	0.98
	2020-05	0.6	0.29	0.085	0.37	0.65	0.85	0.98
	2020-11	0.58	0.29	0.099	0.33	0.6	0.83	0.98
	2021-05	0.58	0.29	0.085	0.35	0.6	0.83	0.98
	Observations from all AEX waves	0.58	0.29	0.084	0.34	0.6	0.84	0.98
	2019-11 (Climate Change)	0.63	0.28	0.12	0.42	0.69	0.88	0.99
σ	2018-11	0.11	0.098	0.0012	0.016	0.087	0.16	0.3
	2019-05	0.097	0.096	0.0003	0.0089	0.076	0.14	0.3
	2019-11	0.1	0.096	0.0005	0.01	0.075	0.15	0.3
	2020-05	0.11	0.1	0.0004	0.015	0.083	0.16	0.31
	2020-11	0.096	0.11	0.0004	0.0086	0.071	0.14	0.3
	2021-05	0.091	0.1	0.0005	0.0083	0.069	0.13	0.27
	Observations from all AEX waves	0.1	0.1	0.0006	0.0095	0.076	0.15	0.3
	2019-11 (Climate Change)	0.1	0.1	0.0012	0.0087	0.082	0.15	0.31

Notes: Parameters are estimated separately for each of 2,407 individuals × up to 6 waves. See Figure 5 for a graphical representation. The rows labelled "Observations from all AEX waves" are the same as the columns in Panel a of Figure 3

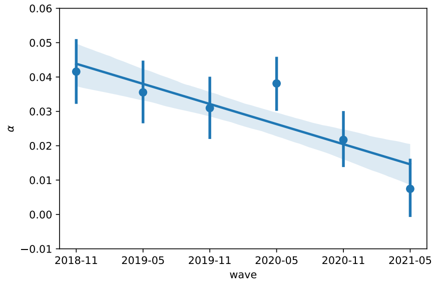
Table E.2. Parameter estimates regressed on wave dummies and controls

	α			ℓ			σ		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	0.045***	0.065***	0.074***	0.57***	0.55***	0.55***	0.11***	0.11***	0.11***
	(0.0038)	(0.011)	(0.014)	(0.0066)	(0.02)	(0.028)	(0.0022)	(0.0065)	(0.0081)
2019-05	−0.011**	−0.0074	−0.0042	0.011	0.018**	0.011	−0.0099***	−0.014***	−0.015***
	(0.0046)	(0.0051)	(0.0061)	(0.0077)	(0.0088)	(0.01)	(0.0026)	(0.003)	(0.0036)
2019-11	−0.011**	−0.013**	−0.014**	0.015*	0.017*	0.0095	−0.0077***	−0.011***	−0.011***
	(0.0048)	(0.0054)	(0.0064)	(0.0077)	(0.0088)	(0.01)	(0.0026)	(0.0029)	(0.0035)
2020-05	−0.0047	0.0013	0.0012	0.025***	0.032***	0.03***	0.0015	−0.0002	0.0024
	(0.0049)	(0.0054)	(0.0064)	(0.0081)	(0.0091)	(0.011)	(0.0028)	(0.0032)	(0.0039)
2020-11	−0.02***	−0.014***	−0.015**	0.0038	0.0079	0.004	−0.012***	−0.014***	−0.016***
	(0.0047)	(0.0051)	(0.0061)	(0.008)	(0.0089)	(0.011)	(0.0031)	(0.0036)	(0.0044)
2021-05	−0.026***	−0.025***	−0.032***	0.012	0.014	0.011	−0.016***	−0.017***	−0.015***
	(0.0049)	(0.0055)	(0.0063)	(0.0082)	(0.0093)	(0.011)	(0.003)	(0.0034)	(0.004)
Age: $\in (35, 50]$		−0.012	−0.024**		0.019	0.018		0.0066	0.0079
		(0.0083)	(0.011)		(0.017)	(0.025)		(0.0041)	(0.0055)
Age: $\in (50, 65]$		−0.015*	−0.03***		0.037**	0.033		0.012***	0.011*
		(0.0078)	(0.0096)		(0.016)	(0.023)		(0.0045)	(0.0057)
Age: ≥ 65		−0.0097	−0.015		0.051***	0.046**		0.028***	0.03***
		(0.0078)	(0.0096)		(0.016)	(0.023)		(0.0047)	(0.0056)
Education: Upper secondary		−0.0058	−0.0013		−0.017	−0.014		−0.0011	0.0019
		(0.0074)	(0.0088)		(0.013)	(0.016)		(0.0048)	(0.0057)
Education: Tertiary		−0.014*	−0.01		−0.057***	−0.05***		−0.0048	−0.0031
		(0.008)	(0.0096)		(0.015)	(0.019)		(0.0049)	(0.0058)
Income: $\in (1.1, 1.6]$		0.012	0.014		0.033**	0.05***		−0.0027	−0.0045
		(0.0075)	(0.0088)		(0.014)	(0.017)		(0.0049)	(0.006)
Income: $\in (1.6, 2.2]$		0.011	0.013		0.032**	0.041**		−0.01**	−0.011*
		(0.0079)	(0.0094)		(0.015)	(0.019)		(0.0046)	(0.0058)
Income: ≥ 2.2		0.0083	0.01		0.044***	0.045**		−0.006	−0.0067
		(0.0084)	(0.01)		(0.016)	(0.02)		(0.005)	(0.006)
Financial assets: $\in (1.8, 11.2]$		−0.021***	−0.031***		−0.024*	−0.024		0.0001	−0.0031
		(0.0076)	(0.0094)		(0.014)	(0.018)		(0.0047)	(0.006)
Financial assets: $\in (11.2, 32]$		−0.013*	−0.017*		−0.067***	−0.063***		0.0086*	0.005
		(0.0075)	(0.0092)		(0.015)	(0.019)		(0.0047)	(0.006)
Financial assets: ≥ 32		−0.026***	−0.029***		−0.058***	−0.048**		0.0082	0.0027
		(0.0081)	(0.0097)		(0.016)	(0.02)		(0.0051)	(0.0063)
Female		0.0038	−0.0031		0.03***	0.028**		−0.014***	−0.014***
		(0.0053)	(0.0064)		(0.01)	(0.013)		(0.0032)	(0.0039)
Risk aversion index		0.0026	0.0055*		0.0088*	0.0076		−0.0027*	−0.0037*
		(0.0027)	(0.0031)		(0.005)	(0.0062)		(0.0017)	(0.002)
Numeracy index		−0.01***	−0.011***		−0.053***	−0.057***		−0.025***	−0.026***
		(0.0033)	(0.0038)		(0.0064)	(0.0085)		(0.0022)	(0.0027)
Balanced sample	No	No	Yes	No	No	Yes	No	No	Yes
Observations	11038	8520	5970	11038	8520	5970	11038	8520	5970
Adj. R^2	0.0025	0.017	0.024	0.0003	0.079	0.072	0.0032	0.08	0.08

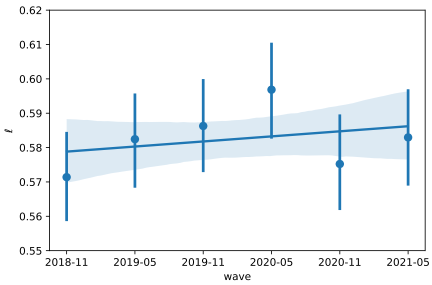
Notes: This table reports OLS regressions of the estimated parameters on wave dummies. The dependent variable is α in the first three columns, ℓ in columns (4) to (6), and σ in the last three columns. For each subject, the estimated parameters for each wave enter as separate observations. Standard errors are clustered at the individual level. Sample for all columns except (3), (6), and (9): All waves meeting our inclusion criteria (i.e., there is variation across options and/or completion time is outside the fastest 15 %, see Section 2.3) for individuals with at least two such waves. In columns (3), (6), and (9) the sample is restricted to a balanced panel which consists only of those individuals who participated in all six waves and met the inclusion criteria in all of them. * $- p < 0.1$, ** $- p < 0.05$, *** $- p < 0.01$.



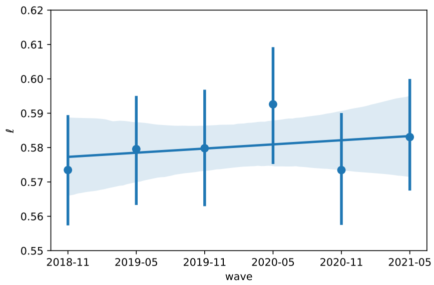
(a) α^{AEX}, baseline sample



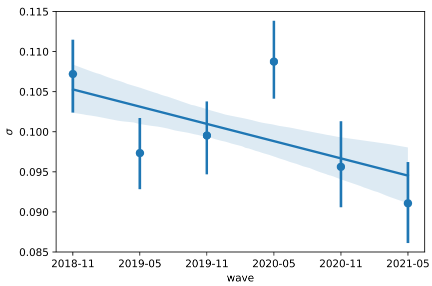
(b) α^{AEX}, balanced sample



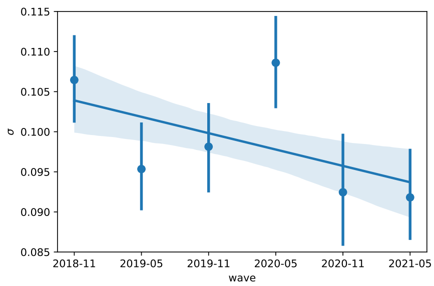
(c) ℓ^{AEX}, baseline sample



(d) ℓ^{AEX}, balanced sample



(e) σ^{AEX}, baseline sample



(f) σ^{AEX}, balanced sample

Figure E.1. Average parameter estimates by wave

Table E.3. Decision weights and choice probabilities for different ambiguity parameters (σ=0.076)

		$\text{Pr}_{\text{subj}} = p = 0.25$		$\text{Pr}_{\text{subj}} = p = 0.5$		$\text{Pr}_{\text{subj}} = p = 0.75$	
		$W(E)-p$	Pr(choice $= AEX$)	$W(E)-p$	Pr(choice $= AEX$)	$W(E)-p$	Pr(choice $= AEX$)
α	ℓ						
-0.22	0.084	0.24	1	0.22	1	0.2	1
	0.34	0.3	1	0.22	1	0.13	0.96
	0.6	0.37	1	0.22	1	0.07	0.81
	0.84	0.43	1	0.22	1	0.01	0.54
	0.98	0.46	1	0.22	1	−0.03	0.36
-0.057	0.084	0.08	0.85	0.06	0.77	0.04	0.68
	0.34	0.14	0.97	0.06	0.77	−0.03	0.36
	0.6	0.21	1	0.06	0.77	−0.09	0.11
	0.84	0.27	1	0.06	0.77	−0.15	0.02
	0.98	0.3	1	0.06	0.77	−0.19	0.01
0.028	0.084	−0.01	0.46	−0.03	0.36	−0.05	0.26
	0.34	0.06	0.77	−0.03	0.36	−0.11	0.07
	0.6	0.12	0.95	−0.03	0.36	−0.18	0.01
	0.84	0.18	0.99	−0.03	0.36	−0.24	0
	0.98	0.22	1	−0.03	0.36	−0.27	0
0.13	0.084	−0.11	0.08	−0.13	0.05	−0.15	0.02
	0.34	−0.04	0.28	−0.13	0.05	−0.21	0
	0.6	0.02	0.62	−0.13	0.05	−0.28	0
	0.84	0.08	0.86	−0.13	0.05	−0.34	0
	0.98	0.12	0.94	−0.13	0.05	−0.37	0
0.3	0.084	−0.28	0	−0.3	0	−0.32	0
	0.34	−0.21	0	−0.3	0	−0.38	0
	0.6	−0.15	0.03	−0.3	0	−0.45	0
	0.84	−0.09	0.13	−0.3	0	−0.51	0
	0.98	−0.05	0.25	−0.3	0	−0.54	0

Table E.4. Decision weights and choice probabilities for different ambiguity parameters (σ=0.15)

		$\mathrm{Pr}_{\mathrm{subj}} = p = 0.25$		$\mathrm{Pr}_{\mathrm{subj}} = p = 0.5$		$\mathrm{Pr}_{\mathrm{subj}} = p = 0.75$	
α	ℓ	$W(E)-p$	$\mathrm{Pr}(\text{choice} = AEX)$	$W(E)-p$	$\mathrm{Pr}(\text{choice} = AEX)$	$W(E)-p$	$\mathrm{Pr}(\text{choice} = AEX)$
-0.22	0.084	0.24	0.95	0.22	0.93	0.2	0.91
	0.34	0.3	0.98	0.22	0.93	0.13	0.82
	0.6	0.37	0.99	0.22	0.93	0.07	0.67
	0.84	0.43	1	0.22	0.93	0.01	0.52
	0.98	0.46	1	0.22	0.93	−0.03	0.42
-0.057	0.084	0.08	0.7	0.06	0.65	0.04	0.6
	0.34	0.14	0.83	0.06	0.65	−0.03	0.43
	0.6	0.21	0.92	0.06	0.65	−0.09	0.26
	0.84	0.27	0.97	0.06	0.65	−0.15	0.15
	0.98	0.3	0.98	0.06	0.65	−0.19	0.1
0.028	0.084	−0.01	0.48	−0.03	0.42	−0.05	0.37
	0.34	0.06	0.65	−0.03	0.42	−0.11	0.22
	0.6	0.12	0.8	−0.03	0.42	−0.18	0.11
	0.84	0.18	0.89	−0.03	0.42	−0.24	0.05
	0.98	0.22	0.93	−0.03	0.42	−0.27	0.03
0.13	0.084	−0.11	0.23	−0.13	0.19	−0.15	0.15
	0.34	−0.04	0.38	−0.13	0.19	−0.21	0.07
	0.6	0.02	0.56	−0.13	0.19	−0.28	0.03
	0.84	0.08	0.71	−0.13	0.19	−0.34	0.01
	0.98	0.12	0.79	−0.13	0.19	−0.37	0.01
0.3	0.084	−0.28	0.03	−0.3	0.02	−0.32	0.02
	0.34	−0.21	0.07	−0.3	0.02	−0.38	0
	0.6	−0.15	0.16	−0.3	0.02	−0.45	0
	0.84	−0.09	0.28	−0.3	0.02	−0.51	0
	0.98	−0.05	0.36	−0.3	0.02	−0.54	0

Table E.5. Decision weights and choice probabilities for different ambiguity parameters (σ=0.3)

		$\text{Pr}_{\text{subj}} = p = 0.25$		$\text{Pr}_{\text{subj}} = p = 0.5$		$\text{Pr}_{\text{subj}} = p = 0.75$	
		$W(E) - p$	Pr(choice $= AEX$)	$W(E) - p$	Pr(choice $= AEX$)	$W(E) - p$	Pr(choice $= AEX$)
α	ℓ						
-0.22	0.084	0.24	0.79	0.22	0.77	0.2	0.75
	0.34	0.3	0.85	0.22	0.77	0.13	0.67
	0.6	0.37	0.89	0.22	0.77	0.07	0.59
	0.84	0.43	0.93	0.22	0.77	0.01	0.51
	0.98	0.46	0.94	0.22	0.77	−0.03	0.46
-0.057	0.084	0.08	0.6	0.06	0.58	0.04	0.55
	0.34	0.14	0.68	0.06	0.58	−0.03	0.46
	0.6	0.21	0.76	0.06	0.58	−0.09	0.38
	0.84	0.27	0.82	0.06	0.58	−0.15	0.3
	0.98	0.3	0.85	0.06	0.58	−0.19	0.26
0.028	0.084	−0.01	0.49	−0.03	0.46	−0.05	0.43
	0.34	0.06	0.57	−0.03	0.46	−0.11	0.35
	0.6	0.12	0.66	−0.03	0.46	−0.18	0.27
	0.84	0.18	0.73	−0.03	0.46	−0.24	0.21
	0.98	0.22	0.77	−0.03	0.46	−0.27	0.18
0.13	0.084	−0.11	0.36	−0.13	0.33	−0.15	0.31
	0.34	−0.04	0.44	−0.13	0.33	−0.21	0.24
	0.6	0.02	0.53	−0.13	0.33	−0.28	0.17
	0.84	0.08	0.61	−0.13	0.33	−0.34	0.13
	0.98	0.12	0.65	−0.13	0.33	−0.37	0.1
0.3	0.084	−0.28	0.18	−0.3	0.16	−0.32	0.14
	0.34	−0.21	0.24	−0.3	0.16	−0.38	0.1
	0.6	−0.15	0.31	−0.3	0.16	−0.45	0.07
	0.84	−0.09	0.39	−0.3	0.16	−0.51	0.04
	0.98	−0.05	0.43	−0.3	0.16	−0.54	0.03

Table E.6. Parameter estimates regressed on climate wave dummy and controls

	α			ℓ			σ		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	0.034***	0.054***	0.062***	0.58***	0.56***	0.55***	0.1***	0.097***	0.097***
	(0.0022)	(0.011)	(0.014)	(0.0045)	(0.019)	(0.026)	(0.0015)	(0.0061)	(0.0074)
Climate wave	−0.014***	−0.019***	−0.02***	0.05***	0.054***	0.059***	0.0047**	0.0056**	0.0031
	(0.0035)	(0.004)	(0.0045)	(0.0063)	(0.0072)	(0.0085)	(0.0022)	(0.0025)	(0.0029)
Age: $\in (35, 50]$		−0.01	−0.021*		0.027*	0.028		0.0069*	0.0092*
		(0.0083)	(0.011)		(0.016)	(0.024)		(0.0041)	(0.0054)
Age: $\in (50, 65]$		−0.014*	−0.028***		0.043***	0.041*		0.011**	0.011**
		(0.0078)	(0.0098)		(0.015)	(0.022)		(0.0045)	(0.0055)
Age: ≥ 65		−0.0091	−0.012		0.058***	0.053**		0.027***	0.03***
		(0.0078)	(0.0098)		(0.015)	(0.021)		(0.0046)	(0.0055)
Education: Upper secondary		−0.0059	−0.0024		−0.016	−0.014		−0.0007	0.0015
		(0.0076)	(0.0089)		(0.012)	(0.015)		(0.0046)	(0.0055)
Education: Tertiary		−0.016**	−0.011		−0.056***	−0.046***		−0.0038	−0.0033
		(0.0082)	(0.0097)		(0.014)	(0.018)		(0.0048)	(0.0058)
Income: $\in (1.1, 1.6]$		0.012	0.015*		0.033**	0.053***		−0.003	−0.0045
		(0.0077)	(0.009)		(0.013)	(0.016)		(0.0048)	(0.0058)
Income: $\in (1.6, 2.2]$		0.013	0.014		0.031**	0.04**		−0.011**	−0.0098*
		(0.0081)	(0.0094)		(0.014)	(0.018)		(0.0046)	(0.0057)
Income: ≥ 2.2		0.011	0.013		0.041***	0.042**		−0.0058	−0.0053
		(0.0085)	(0.01)		(0.015)	(0.019)		(0.005)	(0.0059)
Financial assets: $\in (1.8, 11.2]$		−0.02***	−0.032***		−0.025*	−0.025		0.0006	−0.0025
		(0.0078)	(0.0095)		(0.013)	(0.017)		(0.0046)	(0.0059)
Financial assets: $\in (11.2, 32]$		−0.011	−0.017*		−0.062***	−0.056***		0.0078*	0.0031
		(0.0077)	(0.0094)		(0.015)	(0.019)		(0.0046)	(0.0059)
Financial assets: ≥ 32		−0.024***	−0.028***		−0.058***	−0.046**		0.007	0.0011
		(0.0083)	(0.0099)		(0.015)	(0.019)		(0.0051)	(0.0062)
Female		0.0014	−0.0056		0.029***	0.031**		−0.013***	−0.014***
		(0.0054)	(0.0065)		(0.0096)	(0.012)		(0.0032)	(0.0038)
Risk aversion index		0.0024	0.0059*		0.0093*	0.0085		−0.0028*	−0.0036*
		(0.0028)	(0.0032)		(0.0049)	(0.006)		(0.0017)	(0.002)
Numeracy index		−0.011***	−0.011***		−0.048***	−0.053***		−0.025***	−0.026***
		(0.0033)	(0.0039)		(0.006)	(0.0081)		(0.0021)	(0.0026)
Balanced sample	No	No	Yes	No	No	Yes	No	No	Yes
Observations	12896	9941	6958	12896	9941	6958	12896	9941	6958
Adj. R^2	0.0008	0.015	0.02	0.0036	0.074	0.07	0.0002	0.072	0.074

Notes: This table reports OLS regressions of the estimated parameters on a climate wave dummy indicating if the parameters were elicited with respect to climate change events (as opposed to AEX events). The dependent variable is α in the first three columns, ℓ in columns (4) to (6), and σ in the last three columns. For each subject, the estimated parameters for each wave enter as separate observations. Standard errors are clustered at the individual level. Sample for all columns except (3), (6), and (9): All waves meeting our inclusion criteria (i.e., there is variation across options and/or completion time is outside the fastest 15 %, see Section 2.3) for individuals with at least two such waves. In columns (3), (6), and (9) the sample is restricted to a balanced panel which consists only of those individuals who participated in all six waves and met the inclusion criteria in all of them. $* - p < 0.1, ** - p < 0.05, *** - p < 0.01$.

E.2 Correlations of parameters and alternative ORIV regressions

Table E.7. Cross-wave correlations of estimated parameters

		α	ℓ	σ
2018-11	2019-05	0.26	0.35	0.32
	2019-11	0.21	0.36	0.32
	2020-05	0.17	0.31	0.30
	2020-11	0.22	0.33	0.26
	2021-05	0.19	0.31	0.25
2019-05	2019-11	0.33	0.42	0.36
	2020-05	0.31	0.36	0.30
	2020-11	0.34	0.40	0.27
	2021-05	0.32	0.37	0.24
2019-11	2020-05	0.29	0.37	0.37
	2020-11	0.33	0.45	0.29
	2021-05	0.26	0.42	0.32
2020-05	2020-11	0.32	0.40	0.29
	2021-05	0.25	0.32	0.23
2020-11	2021-05	0.44	0.43	0.26
Average		0.28	0.37	0.29

Notes: Table reports Pearson correlations of parameter estimates between the respective survey waves indicated by the two columns of the index. Parameter estimates are obtained from the model described in Section 3.1 separately for each survey wave and individual. The last row shows the average correlation coefficient over all pairs of waves. Sample: All waves meeting our inclusion criteria (i.e., there is variation across options and/or completion time is outside the fastest 15 %, see Section 2.3) for individuals with at least two such waves.

Table E.8. Predicting last three waves of ambiguity parameters with first three waves (full list of coefficients)

	$\alpha^{AEX}_{\text{last 3 waves}}$	$\ell^{AEX}_{\text{last 3 waves}}$	$\sigma^{AEX}_{\text{last 3 waves}}$
	ORIV	ORIV	ORIV
Intercept	-0.018	0.0001	-0.0039
	(0.015)	(0.037)	(0.011)
AEX parameter first 3 waves	0.98^{***}	0.95^{***}	0.97^{***}
	(0.09)	(0.05)	(0.079)
Age: $\in (35, 50]$	-0.002	0.033	-0.0011
	(0.012)	(0.021)	(0.0062)
Age: $\in (50, 65]$	-0.0057	0.037^{*}	-0.0059
	(0.011)	(0.02)	(0.0062)
Age: ≥ 65	0.0027	0.029	0.0006
	(0.012)	(0.021)	(0.0066)
Education: Upper secondary	0.0019	-0.024	0.012^{*}
	(0.0095)	(0.015)	(0.0065)
Education: Tertiary	-0.0059	-0.022	0.016^{**}
	(0.01)	(0.016)	(0.0062)
Female	0.011	0.0074	0.0012
	(0.0067)	(0.011)	(0.0046)
Income: $\in (1.1, 1.6]$	-0.0047	0.021	-0.0012
	(0.0096)	(0.016)	(0.0069)
Income: $\in (1.6, 2.2]$	0.011	0.029^{*}	-0.0034
	(0.0097)	(0.016)	(0.0064)
Income: ≥ 2.2	0.0006	0.017	-0.0058
	(0.01)	(0.017)	(0.0072)
Numeracy index	-0.011^{**}	-0.011	-0.003
	(0.0046)	(0.0076)	(0.0039)
Risk aversion index	-0.0064^{*}	-0.001	0.0037^{*}
	(0.0036)	(0.0057)	(0.0023)
Financial assets: $\in (1.8, 11.2]$	0.0022	0.012	0.0029
	(0.0099)	(0.016)	(0.0071)
Financial assets: $\in (11.2, 32]$	0.019^{*}	0.02	-0.0024
	(0.01)	(0.016)	(0.006)
Financial assets: ≥ 32	0.013	-0.012	-0.0026
	(0.011)	(0.017)	(0.0064)
N Subjects	1452	1452	1452
1st st. F	101	292	129

Notes: This table shows the full list of coefficients for the regressions reported in Table 4. Table shows OLS and ORIV regressions with the parameter estimates of the May 2020, November 2020, and May 2021 waves as dependent variables and the parameter estimates of the three earlier waves as potential independent variables and instruments. Parameter estimates are obtained from the model described in Section 3.1 separately for each survey wave and individual. In line with the ORIV approach, we use a stacked data set in which all respective combinations of dependent, independent, and (for the ORIV regressions) instrumental variables enter as a separate observation. Standard errors are clustered on the individual level and reported in parentheses. Sample: All waves meeting our inclusion criteria (i.e., there is variation across options and/or completion time is outside the fastest 15 %, see Section 2.3) for individuals with at least two such waves in 2018/2019 and at least one such wave in 2020/2021 (This is required for ORIV regressions and we impose the same restriction for the OLS regression).

Table E.9. Predicting last four waves of ambiguity parameters with first two waves

		OLS	ORIV	
		(1)	(2)	(3)
$\alpha^{AEX}_{\text{last 4 waves}}$	Intercept	0.018^{***}	-0.0093^{*}	
		(0.0025)	(0.005)	
	$\alpha^{AEX}_{\text{first 2 waves}}$	0.24^{***}	0.94^{***}	0.88^{***}
		(0.02)	(0.10)	(0.11)
	Adj. R^2	0.067		
	1st st. F		77	57
$\ell^{AEX}_{\text{last 4 waves}}$	Intercept	0.38^{***}	-0.015	
		(0.0092)	(0.036)	
	$\ell^{AEX}_{\text{first 2 waves}}$	0.36^{***}	1.04^{***}	1.00^{***}
		(0.01)	(0.06)	(0.08)
	Adj. R^2	0.13		
	1st st. F		220	126
$\sigma^{AEX}_{\text{last 4 waves}}$	Intercept	0.067^{***}	-0.0025	
		(0.0019)	(0.0078)	
	$\sigma^{AEX}_{\text{first 2 waves}}$	0.31^{***}	1.00^{***}	0.96^{***}
		(0.02)	(0.08)	(0.11)
	Adj. R^2	0.08		
	1st st. F		125	59
Controls		No	No	Yes
N Subjects		1740	1740	1366

Notes: Table shows OLS and ORIV regressions with the parameter estimates of the May 2020, November 2020, and May 2021 waves as dependent variables and the parameter estimates of the three earlier waves as potential independent variables and instruments. The table is split vertically, such that the first set of rows reports the regressions based on α^{AEX} as dependent and independent variables. The middle set of rows shows the results for ℓ^{AEX} and the last part of the table those for σ^{AEX}. Parameter estimates are obtained from the model described in Section 3.1 separately for each survey wave and individual. Controls are age dummies, gender, education, income and assets dummies, risk aversion, and numeracy. In line with the ORIV approach, we use a stacked data set in which all respective combinations of dependent, independent, and (for the ORIV regressions) instrumental variables enter as a separate observation. Standard errors are clustered on the individual level and reported in parentheses. Sample: All waves meeting our inclusion criteria (i.e., there is variation across options and/or completion time is outside the fastest 15 %, see Section 2.3) for individuals with at least two such waves.

Table E.10. Predicting last two waves of ambiguity parameters with first four waves

		OLS	ORIV	
		(1)	(2)	(3)
$\alpha^{AEX}_{\text{last 2 waves}}$	Intercept	0.01^{***}	-0.022^{***}	
		(0.0029)	(0.0039)	
	$\alpha^{AEX}_{\text{first 4 waves}}$	0.26^{***}	1.07^{***}	1.06^{***}
		(0.02)	(0.07)	(0.08)
	Adj. R^2	0.074		
	1st st. F		202	134
$\ell^{AEX}_{\text{last 2 waves}}$	Intercept	0.36^{***}	-0.026	
		(0.0095)	(0.022)	
	$\ell^{AEX}_{\text{first 4 waves}}$	0.37^{***}	1.04^{***}	1.03^{***}
		(0.01)	(0.04)	(0.05)
	Adj. R^2	0.14		
	1st st. F		665	386
$\sigma^{AEX}_{\text{last 2 waves}}$	Intercept	0.062^{***}	-0.0038	
		(0.002)	(0.0052)	
	$\sigma^{AEX}_{\text{first 4 waves}}$	0.30^{***}	0.95^{***}	0.95^{***}
		(0.02)	(0.06)	(0.08)
	Adj. R^2	0.072		
	1st st. F		350	173
Controls		No	No	Yes
N Subjects		1833	1833	1433

Notes: Table shows OLS and ORIV regressions with the parameter estimates of the May 2020, November 2020, and May 2021 waves as dependent variables and the parameter estimates of the three earlier waves as potential independent variables and instruments. The table is split vertically, such that the first set of rows reports the regressions based on α^{AEX} as dependent and independent variables. The middle set of rows shows the results for ℓ^{AEX} and the last part of the table those for σ^{AEX}. Parameter estimates are obtained from the model described in Section 3.1 separately for each survey wave and individual. Controls are age dummies, gender, education, income and assets dummies, risk aversion, and numeracy. In line with the ORIV approach, we use a stacked data set in which all respective combinations of dependent, independent, and (for the ORIV regressions) instrumental variables enter as a separate observation. Standard errors are clustered on the individual level and reported in parentheses. Sample: All waves meeting our inclusion criteria (i.e., there is variation across options and/or completion time is outside the fastest 15 %, see Section 2.3) for individuals with at least two such waves.

Table E.11. Predicting last wave of ambiguity parameters with first five waves

		OLS	ORIV	
		(1)	(2)	(3)
$\alpha^{AEX}_{2021-05}$	Intercept	0.0057	-0.025^{***}	
		(0.0035)	(0.0042)	
	$\alpha^{AEX}_{\text{first 5 waves}}$	0.28^{***}	1.10^{***}	1.06^{***}
		(0.02)	(0.07)	(0.08)
	Adj. R^2	0.081		
	1st st. F		277	194
$\ell^{AEX}_{2021-05}$	Intercept	0.37^{***}	0.0059	
		(0.012)	(0.025)	
	$\ell^{AEX}_{\text{first 5 waves}}$	0.37^{***}	0.99^{***}	0.99^{***}
		(0.02)	(0.04)	(0.05)
	Adj. R^2	0.14		
	1st st. F		847	493
$\sigma^{AEX}_{2021-05}$	Intercept	0.065^{***}	0.0003	
		(0.0035)	(0.0061)	
	$\sigma^{AEX}_{\text{first 5 waves}}$	0.27^{***}	0.91^{***}	0.95^{***}
		(0.03)	(0.06)	(0.09)
	Adj. R^2	0.067		
	1st st. F		110	51
Controls		No	No	Yes
N Subjects		1681	1681	1313

Notes: Table shows OLS and ORIV regressions with the parameter estimates of the May 2020, November 2020, and May 2021 waves as dependent variables and the parameter estimates of the three earlier waves as potential independent variables and instruments. The table is split vertically, such that the first set of rows reports the regressions based on α^{AEX} as dependent and independent variables. The middle set of rows shows the results for ℓ^{AEX} and the last part of the table those for σ^{AEX}. Parameter estimates are obtained from the model described in Section 3.1 separately for each survey wave and individual. Controls are age dummies, gender, education, income and assets dummies, risk aversion, and numeracy. In line with the ORIV approach, we use a stacked data set in which all respective combinations of dependent, independent, and (for the ORIV regressions) instrumental variables enter as a separate observation. Standard errors are clustered on the individual level and reported in parentheses. Sample: All waves meeting our inclusion criteria (i.e., there is variation across options and/or completion time is outside the fastest 15 %, see Section 2.3) for individuals with at least two such waves.

Table E.12. Predicting climate ambiguity parameters with AEX parameters (full list of coefficients)

	$\alpha^{climate}_{2019-11}$	$\ell^{climate}_{2019-11}$	$\sigma^{climate}_{2019-11}$
	2SLS	2SLS	2SLS
Intercept	-0.015	0.23^{***}	-0.0002
	(0.021)	(0.053)	(0.017)
AEX parameter 2019-11	1.1^{***}	0.63^{***}	0.88^{***}
	(0.067)	(0.052)	(0.074)
Age: $\in (35, 50]$	0.012	0.075^{***}	0.0028
	(0.011)	(0.027)	(0.0084)
Age: $\in (50, 65]$	0.0065	0.061^{**}	-0.0029
	(0.011)	(0.025)	(0.0081)
Age: ≥ 65	0.0089	0.06^{**}	-0.013
	(0.011)	(0.027)	(0.0087)
Education: Upper secondary	0.0017	0.0063	0.004
	(0.012)	(0.021)	(0.0077)
Education: Tertiary	-0.012	-0.0023	0.006
	(0.012)	(0.023)	(0.0083)
Female	-0.0016	-0.0039	0.011^{*}
	(0.0085)	(0.016)	(0.0059)
Income: $\in (1.1, 1.6]$	-0.0026	0.031	-0.0018
	(0.012)	(0.022)	(0.0081)
Income: $\in (1.6, 2.2]$	0.023^{*}	0.02	-0.0036
	(0.012)	(0.023)	(0.0078)
Income: ≥ 2.2	0.024^{*}	-0.002	-0.0004
	(0.012)	(0.024)	(0.0085)
Numeracy index	-0.0022	0.016	0.0003
	(0.0057)	(0.011)	(0.0041)
Risk aversion index	-0.0095^{**}	0.0009	0.0025
	(0.0043)	(0.0079)	(0.0028)
Threatened by climate change	0.0066	0.0004	0.0044
	(0.019)	(0.035)	(0.013)
Financial assets: $\in (1.8, 11.2]$	-0.0002	-0.027	0.0032
	(0.012)	(0.023)	(0.008)
Financial assets: $\in (11.2, 32]$	0.011	0.013	-0.0079
	(0.013)	(0.023)	(0.0083)
Financial assets: ≥ 32	0.0093	-0.01	-0.0065
	(0.013)	(0.025)	(0.0088)
Understands climate change	-0.044^{**}	-0.052	0.032^{**}
	(0.02)	(0.037)	(0.013)
N Subjects	1411	1411	1411
1st st. F	148	406	51

Notes: This table shows the full list of coefficients for the regressions reported in Table 5. This table shows OLS and 2SLS regressions with the parameter estimates for the decisions about changes in climate (elicited in November 2019) as dependent variable and the parameter estimates for the decisions about the AEX elicited in November 2019 as independent variable. For the 2SLS regressions, the parameters of all other AEX waves are used as instruments. Parameter estimates are obtained from the model described in Section 3.1 separately for each survey wave and individual. For 2SLS, we use a stacked data set in which all instrumental variables enter as a separate observation and we cluster standard errors on the individual level. The measures of self-assessed understanding and perceived threat of climate change vary between 0 and 1. Robust standard errors in parentheses. Sample: All waves meeting our inclusion criteria (i.e., there is variation across options and/or completion time is outside the fastest 15 %, see Section 2.3) for individuals with at least two such waves.

Appendix F Additional tables and figures for Section 4

F.1 Background on ambiguity types with $k = 4$ and additional tables

Table F.1. Example situations: Decision weights and choice probabilities for ambiguity types

				$\text{Pr}_{\text{subj}} = p = 0.25$		$\text{Pr}_{\text{subj}} = p = 0.5$		$\text{Pr}_{\text{subj}} = p = 0.75$	
				$W(E) - p$	Pr(choice $= AEX$)	$W(E) - p$	Pr(choice $= AEX$)	$W(E) - p$	Pr(choice $= AEX$)
Ambiguity type	α	ℓ	σ						
Near SEU	-0.0002	0.28	0.14	0.07	0.7	0.0002	0.5	−0.07	0.31
Ambiguity averse	0.15	0.71	0.14	0.031	0.58	−0.15	0.15	−0.32	0.012
Ambiguity seeking	-0.054	0.64	0.15	0.21	0.93	0.054	0.64	−0.11	0.24
High noise	0.038	0.47	0.29	0.079	0.61	−0.038	0.45	−0.15	0.3

Notes: For this table we consider a decision maker who chooses between a lottery yielding €x with probability p and a prospect x_E0 with $\text{Pr}_{\text{subj}}(E) = p$ for three values of p: 0.25, 0.5, and 0.75. The table reports the difference between decision weights and subjective probabilities and the choice probability to choose the ambiguous option for each of the estimated ambiguity types.

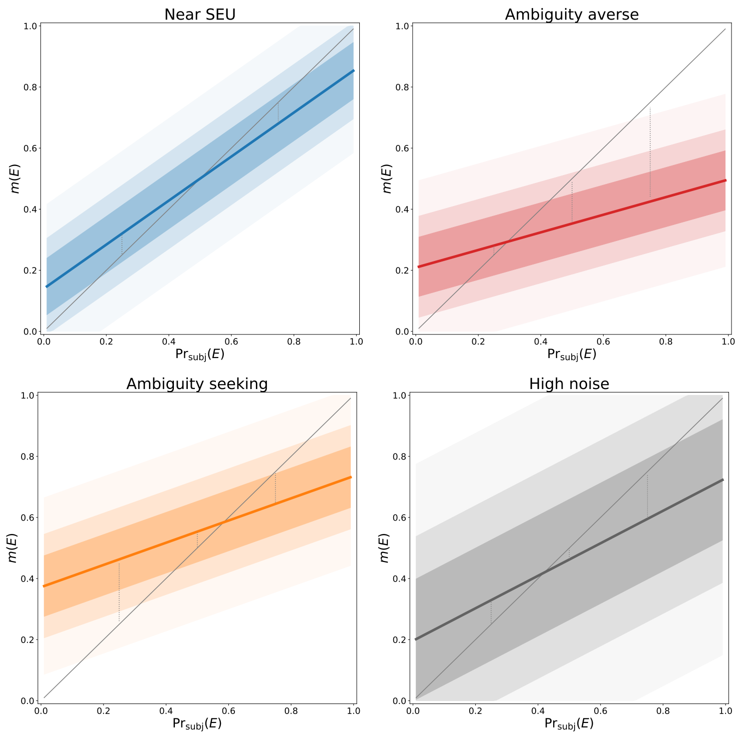


Figure F.1. Decision weights as a function of subjective probabilities, by group

Notes: The solid lines plot the decision weights $W(E)$ for the estimated group-level average ambiguity parameters $\bar{\alpha}^{AEX}$ and $\bar{\ell}^{AEX}$. The vertical difference to the 45-degree line measures the extent of ambiguity seeking for different subjective probabilities w.r.t. gains from events whose source of uncertainty is the future development of the AEX. The shaded areas around the lines depict the 50 %, 75 % and 95 % confidence intervals of $m(p)$. Sample: All waves meeting our inclusion criteria (i.e., there is variation across options and/or completion time is outside the fastest 15 %, see Section 2.3) for individuals with at least two such waves.

Table F.2. Predictors of groups, marginal effects

	Ambiguity types			
	Near SEU	Ambiguity averse	Ambiguity seeking	High noise
Age: $\in (35, 50]$	-0.047	-0.017	-0.011	0.075^{*}
	(0.037)	(0.038)	(0.039)	(0.041)
Age: $\in (50, 65]$	-0.055	-0.045	-0.0071	0.11^{***}
	(0.035)	(0.036)	(0.037)	(0.039)
Age: ≥ 65	-0.078^{**}	-0.087^{**}	-0.032	0.2^{***}
	(0.035)	(0.036)	(0.037)	(0.038)
Education: Upper secondary	0.063^{**}	-0.014	-0.023	-0.026
	(0.032)	(0.028)	(0.029)	(0.024)
Education: Tertiary	0.081^{**}	-0.057^{*}	-0.027	0.0025
	(0.032)	(0.031)	(0.031)	(0.026)
Income: $\in (1.1, 1.6]$	-0.041	0.035	0.011	-0.0052
	(0.032)	(0.03)	(0.032)	(0.025)
Income: $\in (1.6, 2.2]$	-0.047	0.075^{**}	0.019	-0.046^{*}
	(0.032)	(0.032)	(0.033)	(0.028)
Income: ≥ 2.2	-0.079^{**}	0.061^{*}	0.017	0.0015
	(0.034)	(0.036)	(0.035)	(0.03)
Financial assets: $\in (1.8, 11.2]$	0.08^{**}	-0.028	0.042	-0.093^{***}
	(0.035)	(0.03)	(0.031)	(0.027)
Financial assets: $\in (11.2, 32]$	0.15^{***}	-0.07^{**}	-0.046	-0.035
	(0.034)	(0.032)	(0.035)	(0.027)
Financial assets: ≥ 32	0.1^{***}	-0.11^{***}	0.023	-0.016
	(0.034)	(0.036)	(0.035)	(0.029)
Female	0.0046	0.077^{***}	0.016	-0.098^{***}
	(0.022)	(0.022)	(0.022)	(0.019)
Risk aversion index	-0.018	0.021^{**}	-0.0061	0.0028
	(0.011)	(0.011)	(0.012)	(0.0088)
Numeracy index	0.23^{***}	-0.071^{***}	-0.03^{**}	-0.13^{***}
	(0.017)	(0.012)	(0.013)	(0.01)
Observations	1624	1624	1624	1624
Pseudo R^2	0.14	0.14	0.14	0.14

Notes: This table reports marginal effects of a multinomial logit regression that predicts the ambiguity type based on a set of individual characteristics. Reported are the average marginal effects over all observations. Dummy variables are treated as continuous. The groups are obtained from clustering individuals with the k-means algorithm on the parameters α^{AEX}, ℓ^{AEX} and σ^{AEX} into four groups. Robust standard errors in parentheses. Income and financial assets are in thousands, pooled over partners and equivalized for couples. Risk aversion and numeracy are normalized to have mean zero and unit variance. Sample: All waves meeting our inclusion criteria (i.e., there is variation across options and/or completion time is outside the fastest 15 %, see Section 2.3) for individuals with at least two such waves.
$* - p < 0.1$, $** - p < 0.05$, $*** - p < 0.01$.

Table F.3. Average within subject standard deviation of wave-by-wave parameters by ambiguity type

	α^{AEX}	ℓ^{AEX}	σ^{AEX}
Near SEU	0.084	0.21	0.06
	(0.0016)	(0.0038)	(0.0014)
Ambiguity averse	0.11	0.18	0.062
	(0.0022)	(0.0039)	(0.0016)
Ambiguity seeking	0.11	0.19	0.062
	(0.0026)	(0.0037)	(0.0028)
High noise	0.18	0.27	0.1
	(0.0045)	(0.0043)	(0.002)

Notes: Table shows average within subject standard deviations of wave-by-wave parameters for all ambiguity types. Parameter estimates are obtained from the model described in Section 3.1 separately for each survey wave and individual. Standard errors are reported in parantheses. Sample: All waves meeting our inclusion criteria (i.e., there is variation across options and/or completion time is outside the fastest 15 %, see Section 2.3) for individuals with at least two such waves. * $- p < 0.1$, ** $- p < 0.05$, *** $- p < 0.01$.

Table F.4. Predictors of marginal parameter estimates

	α^{AEX}	ℓ^{AEX}	σ^{AEX}
Intercept	0.053^{***}	0.5^{***}	0.17^{***}
	(0.011)	(0.021)	(0.007)
Age: $\in (35, 50]$	-0.008	0.016	0.015^{***}
	(0.0087)	(0.018)	(0.0049)
Age: $\in (50, 65]$	-0.011	0.027	0.022^{***}
	(0.0084)	(0.017)	(0.005)
Age: ≥ 65	-0.0091	0.034^{*}	0.05^{***}
	(0.0083)	(0.017)	(0.0054)
Education: Upper secondary	-0.0066	-0.0024	-0.01^{*}
	(0.0078)	(0.015)	(0.0052)
Education: Tertiary	-0.015^{*}	-0.05^{***}	-0.011^{*}
	(0.0083)	(0.016)	(0.0056)
Income: $\in (1.1, 1.6]$	0.012	0.031^{**}	-0.004
	(0.008)	(0.015)	(0.0054)
Income: $\in (1.6, 2.2]$	0.0078	0.03^{*}	-0.012^{**}
	(0.0084)	(0.016)	(0.0054)
Income: ≥ 2.2	0.007	0.042^{**}	-0.0072
	(0.0087)	(0.018)	(0.0056)
Financial assets: $\in (1.8, 11.2]$	-0.016^{**}	-0.015	-0.0098^{*}
	(0.0083)	(0.016)	(0.0051)
Financial assets: $\in (11.2, 32]$	-0.011	-0.06^{***}	-0.0013
	(0.0078)	(0.017)	(0.0054)
Financial assets: ≥ 32	-0.026^{***}	-0.058^{***}	0.0002
	(0.0085)	(0.018)	(0.0058)
Female	0.0059	0.032^{***}	-0.015^{***}
	(0.0055)	(0.011)	(0.0036)
Risk aversion index	0.001	0.0092	-0.0014
	(0.0031)	(0.0057)	(0.002)
Numeracy index	-0.0095^{***}	-0.048^{***}	-0.034^{***}
	(0.0035)	(0.0069)	(0.0023)
Observations	1624	1624	1624
Adj. R^2	0.026	0.11	0.29

Notes: This table reports OLS regressions with the estimated ambiguity and error parameters as dependent variable and several independent variables. Robust standard errors in parentheses. Income and financial assets are in thousands, pooled over partners and equivalized for couples. Risk aversion and numeracy are normalized to have mean zero and unit variance. Sample: All waves meeting our inclusion criteria (i.e., there is variation across options and/or completion time is outside the fastest 15 %, see Section 2.3) for individuals with at least two such waves. $* - p < 0.1$, $** - p < 0.05$, $*** - p < 0.01$.

Table F.5. Ambiguity attitudes and portfolio choice: Marginal effects (full list of coefficients)

	Owns risky assets (Probit)		Share risky assets (Tobit)	
	(1)	(2)	(3)	(4)
Ambiguity averse type	-0.23^{***}	-0.084^{***}	-0.44^{***}	-0.17^{***}
	(0.024)	(0.023)	(0.059)	(0.055)
Ambiguity seeking type	-0.1^{***}	-0.018	-0.15^{***}	-0.028
	(0.028)	(0.024)	(0.05)	(0.046)
High noise type	-0.18^{***}	-0.053^{*}	-0.24^{***}	-0.083
	(0.027)	(0.027)	(0.059)	(0.059)
Age: $\in (35, 50]$		-0.03		-0.024
		(0.034)		(0.067)
Age: $\in (50, 65]$		-0.0015		0.038
		(0.033)		(0.063)
Age: ≥ 65		-0.017		0.038
		(0.034)		(0.064)
Female		-0.027		-0.028
		(0.018)		(0.04)
Education: Upper secondary		0.017		0.062
		(0.026)		(0.059)
Education: Tertiary		0.037		0.13^{**}
		(0.026)		(0.059)
Income: $\in (1.1, 1.6]$		0.017		0.071
		(0.027)		(0.063)
Income: $\in (1.6, 2.2]$		0.014		0.062
		(0.028)		(0.062)
Income: ≥ 2.2		0.078^{***}		0.14^{**}
		(0.029)		(0.062)
Financial assets: $\in (1.8, 11.2]$		0.045^{**}		0.12
		(0.019)		(0.084)
Financial assets: $\in (11.2, 32]$		0.14^{***}		0.34^{***}
		(0.023)		(0.083)
Financial assets: ≥ 32		0.39^{***}		0.69^{***}
		(0.029)		(0.085)
Risk aversion index		-0.046^{***}		-0.12^{***}
		(0.0095)		(0.021)
Numeracy index		0.035^{**}		0.068^{**}
		(0.017)		(0.03)
Observations	1727	1624	1584	1502
Pseudo R^2	0.054	0.3	0.042	0.28
p-values for differences between				
Ambiguity averse, Ambiguity seeking	0	0.0086	0	0.012
Ambiguity averse, High noise	0.034	0.25	0.0041	0.18
Ambiguity seeking, High noise	0.0079	0.22	0.19	0.36

Notes: The table reports the full list of coefficients for the regressions shown in Table 7. Marginal effects are calculated as a change from 0 to 1 for dummy variables, as a change from a category to the left-out category for categorical variables, and as an increase of a standard deviation for continuous variables.

Table F.6. Ambiguity attitudes and portfolio choice (OLS)

	Owns risky financial assets		Share risky financial assets	
	(1)	(2)	(3)	(4)
Intercept (left-out type: Near SEU)	0.31^{***}	0.095^{***}	0.11^{***}	-0.0095
	(0.02)	(0.036)	(0.009)	(0.018)
Ambiguity averse type	-0.23^{***}	-0.1^{***}	-0.072^{***}	-0.032^{***}
	(0.024)	(0.023)	(0.011)	(0.011)
Ambiguity seeking type	-0.1^{***}	-0.035	-0.031^{**}	-0.0097
	(0.028)	(0.026)	(0.013)	(0.013)
High noise type	-0.18^{***}	-0.07^{**}	-0.041^{***}	-0.018
	(0.027)	(0.028)	(0.015)	(0.014)
Age: $\in (35, 50]$		-0.011		0.017
		(0.032)		(0.014)
Age: $\in (50, 65]$		0.02		0.033^{**}
		(0.03)		(0.014)
Age: ≥ 65		-0.0037		0.038^{***}
		(0.031)		(0.014)
Education: Upper secondary		0.0016		0.0083
		(0.021)		(0.0099)
Education: Tertiary		0.036		0.036^{***}
		(0.024)		(0.012)
Income: $\in (1.1, 1.6]$		-0.0002		0.0092
		(0.021)		(0.011)
Income: $\in (1.6, 2.2]$		-0.0038		0.0068
		(0.025)		(0.013)
Income: ≥ 2.2		0.094^{***}		0.025^{*}
		(0.029)		(0.015)
Financial assets: $\in (1.8, 11.2]$		0.011		-0.0056
		(0.017)		(0.0094)
Financial assets: $\in (11.2, 32]$		0.1^{***}		0.018
		(0.023)		(0.012)
Financial assets: ≥ 32		0.39^{***}		0.13^{***}
		(0.029)		(0.016)
Female		-0.04^{**}		-0.0026
		(0.017)		(0.009)
Risk aversion index		-0.042^{***}		-0.027^{***}
		(0.0085)		(0.0047)
Numeracy index		0.022^{**}		0.0085
		(0.01)		(0.0054)
Mean dependent variable	0.2	0.2	0.074	0.074
Observations	1727	1624	1584	1502
R^2	0.052	0.29	0.022	0.18
Adj. R^2	0.051	0.28	0.02	0.17

Notes: This table reports OLS regressions for the specifications shown in Table 7.

Table F.7. Ambiguity attitudes and portfolio choice (administrative asset data, OLS)

	Owns risky financial assets		Share risky financial assets	
	(0)	(1)	(2)	(3)
Intercept	0.334***	0.060	0.119***	0.011
	(0.019)	(0.037)	(0.009)	(0.017)
Ambiguity averse	−0.206***	−0.101***	−0.073***	−0.033***
	(0.023)	(0.023)	(0.011)	(0.011)
Ambiguity seeking	−0.114***	−0.037	−0.041***	−0.007
	(0.027)	(0.025)	(0.013)	(0.013)
High noise	−0.113***	−0.021	−0.036***	−0.003
	(0.028)	(0.029)	(0.014)	(0.014)
Female		−0.037**		−0.015*
		(0.017)		(0.009)
Age: $\in (35, 50]$		0.021		0.005
		(0.033)		(0.014)
Age: $\in (50, 65]$		0.022		0.018
		(0.031)		(0.014)
Age: ≥ 65		0.005		0.022
		(0.031)		(0.015)
Education: Upper secondary		0.004		0.002
		(0.020)		(0.010)
Education: Tertiary		0.082***		0.034***
		(0.023)		(0.012)
Income: Quartile 2		0.001		−0.004
		(0.022)		(0.010)
Income: Quartile 3		−0.005		−0.012
		(0.023)		(0.011)
Income: Quartile 4		0.043*		0.025*
		(0.026)		(0.014)
Financial assets: Quartile 2		0.055***		0.009
		(0.016)		(0.007)
Financial assets: Quartile 3		0.190***		0.056***
		(0.021)		(0.010)
Financial assets: Quartile 4		0.432***		0.150***
		(0.026)		(0.013)
Risk aversion index		−0.041***		−0.021***
		(0.008)		(0.004)
Numeracy index		0.012		0.005
		(0.010)		(0.004)
Observations	2115	2002	2104	1992
R^2	0.034	0.242	0.018	0.159

Notes: This table reports OLS regressions using administrative asset data based on official tax records by Statistics Netherlands (CBS) for the specifications shown in Table 7. Income, gender, and age are also based on administrative records while we use survey measures of educational level, numeracy, and risk aversion.

Table F.8. Individual ambiguity parameters and portfolio choice: Marginal effects

	Owns risky assets (Probit)		Share risky assets (Tobit)	
	(1)	(2)	(3)	(4)
α	-0.047^{***}	-0.029^{***}	-0.092^{***}	-0.058^{***}
	(0.0099)	(0.0096)	(0.023)	(0.021)
ℓ	-0.069^{***}	-0.022^{**}	-0.13^{***}	-0.043^{**}
	(0.009)	(0.0087)	(0.021)	(0.02)
σ	-0.043^{***}	-0.013	-0.053^{**}	-0.016
	(0.0095)	(0.01)	(0.022)	(0.023)
Age: $\in (35, 50]$		-0.031		-0.025
		(0.034)		(0.067)
Age: $\in (50, 65]$		-0.0027		0.035
		(0.033)		(0.063)
Age: ≥ 65		-0.013		0.044
		(0.034)		(0.065)
Female		-0.026		-0.027
		(0.018)		(0.04)
Education: Upper secondary		0.017		0.061
		(0.026)		(0.059)
Education: Tertiary		0.034		0.13^{**}
		(0.026)		(0.059)
Income: $\in (1.1, 1.6]$		0.02		0.079
		(0.028)		(0.063)
Income: $\in (1.6, 2.2]$		0.013		0.061
		(0.028)		(0.062)
Income: ≥ 2.2		0.078^{***}		0.14^{**}
		(0.029)		(0.062)
Financial assets: $\in (1.8, 11.2]$		0.045^{**}		0.12
		(0.019)		(0.084)
Financial assets: $\in (11.2, 32]$		0.14^{***}		0.34^{***}
		(0.023)		(0.083)
Financial assets: ≥ 32		0.39^{***}		0.68^{***}
		(0.029)		(0.085)
Risk aversion index		-0.047^{***}		-0.12^{***}
		(0.0095)		(0.021)
Numeracy index		0.031^{*}		0.064^{**}
		(0.017)		(0.031)
Observations	1727	1624	1584	1502
Pseudo R^2	0.068	0.31	0.053	0.28

Notes: The first two columns display Probit regressions where the dependent variables is a dummy indicating whether the subject holds any risky financial assets and in the last two columns, we run Tobit regressions with the share of risky financial assets of all financial assets as dependent variable. Marginal effects are calculated as a change from 0 to 1 for dummy variables, as a change from a category to the left-out category for categorical variables, and as an increase of a standard deviation for continuous variables. Sample: All waves meeting our inclusion criteria (i.e., there is variation across options and/or completion time is outside the fastest 15 %, see Section 2.3) for individuals with at least two such waves.

F.2 Ambiguity types with $k = 3$

This section displays our main results of Section 4 when we classify individuals into three ambiguity groups.

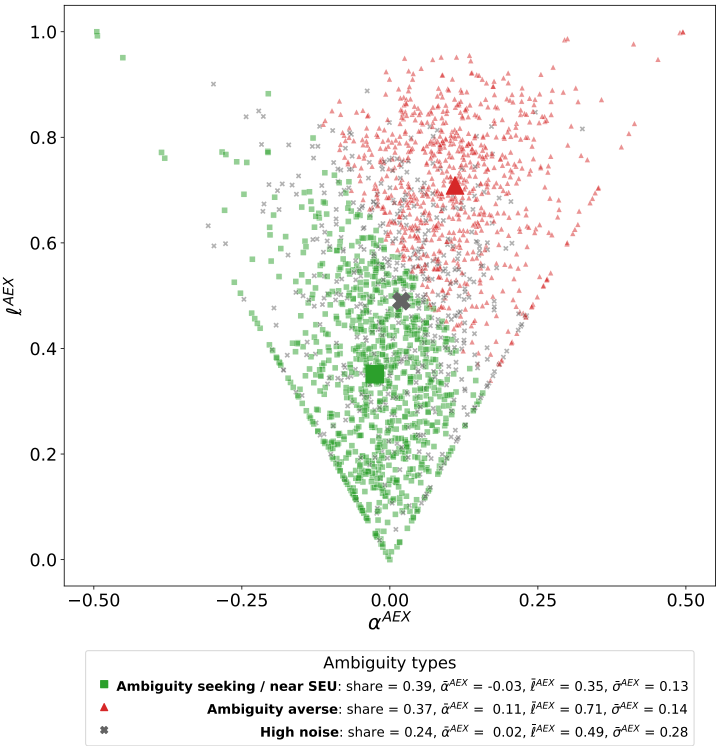


Figure F.2. Summarizing heterogeneity in ambiguity profiles with $k = 3$ discrete groups

Notes: The small symbols depict individual preference parameter estimates $(\alpha_i^{AEX}, \ell_i^{AEX})$ obtained from estimating (8) under the assumption that these two parameters and σ_i^{AEX} do not vary across waves. The large symbols are group centers resulting from clustering individuals with the k-means algorithm on the three parameters into three groups. Sample: All waves meeting our inclusion criteria (i.e., there is variation across options and/or completion time is outside the fastest 15 %, see Section 2.3) for individuals with at least two such waves.

Table F.9. Example situations: Decision weights and choice probabilities for ambiguity types (3 groups)

				$\Pr_{\text{subj}} = p = 0.25$		$\Pr_{\text{subj}} = p = 0.5$		$\Pr_{\text{subj}} = p = 0.75$	
Ambiguity type	α	ℓ	σ	$W(E) - p$	$\Pr(\text{choice} = AEX)$	$W(E) - p$	$\Pr(\text{choice} = AEX)$	$W(E) - p$	$\Pr(\text{choice} = AEX)$
Ambiguity seeking / near SEU	-0.026	0.35	0.13	0.11	0.8	0.026	0.58	−0.062	0.32
Ambiguity averse	0.11	0.71	0.14	0.067	0.68	−0.11	0.22	−0.29	0.023
High noise	0.02	0.49	0.28	0.1	0.64	−0.02	0.47	−0.14	0.31

Notes: For this table we consider a decision maker who chooses between a lottery yielding €x with probability p and a prospect $x_E 0$ with $\Pr_{\text{subj}}(E) = p$ for three values of p: 0.25, 0.5, and 0.75. The table reports the difference between decision weights and subjective probabilities and the choice probability to choose the ambiguous option for each of the estimated ambiguity types.

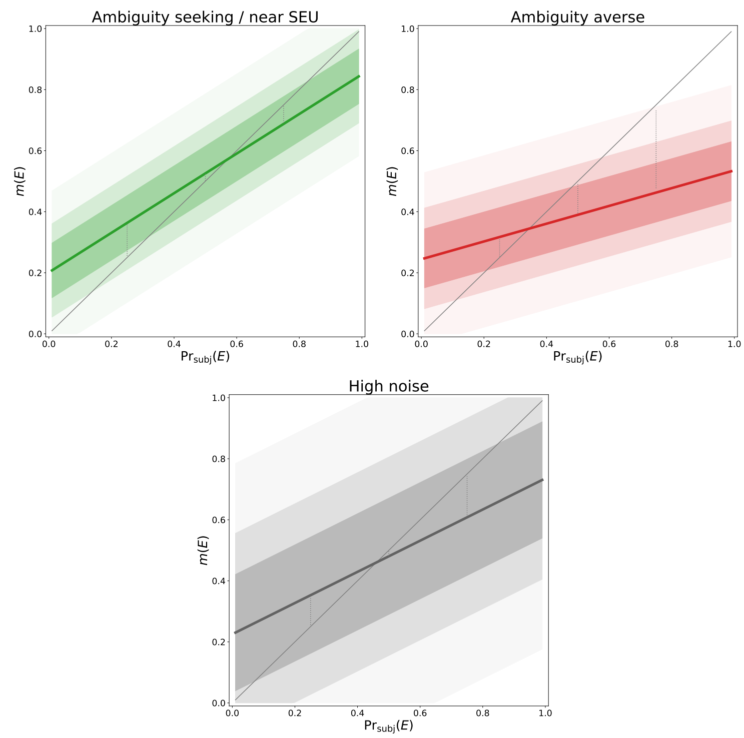


Figure F.3. Event weights as a function of subjective probabilities, by group (3 groups)

Notes: The solid lines plot the decision weights $W(E)$ for the estimated group-level average ambiguity parameters $\bar{\alpha}^{AEX}$ and $\bar{\ell}^{AEX}$. The vertical difference to the 45-degree line measures the extent of ambiguity seeking for different subjective probabilities w.r.t. gains from events whose source of uncertainty is the future development of the AEX. The shaded areas around the lines depict the 50 %, 75 % and 95 % confidence intervals of $m(p)$. Sample: All waves meeting our inclusion criteria (i.e., there is variation across options and/or completion time is outside the fastest 15 %, see Section 2.3) for individuals with at least two such waves.

Table F.10. Average characteristics of group members (3 groups)

	Ambiguity types		
	Ambiguity seeking / near SEU	Ambiguity averse	High noise
Share	0.39	0.37	0.24
α^{AEX}	−0.026	0.11	0.02
	(0.0027)	(0.0033)	(0.0044)
ℓ^{AEX}	0.35	0.71	0.49
	(0.0057)	(0.0044)	(0.0078)
σ^{AEX}	0.13	0.14	0.28
	(0.0015)	(0.0019)	(0.0024)
Education: Lower secondary and below	0.14	0.29	0.41
	(0.012)	(0.016)	(0.022)
Education: Upper secondary	0.31	0.38	0.31
	(0.016)	(0.017)	(0.02)
Education: Tertiary	0.55	0.33	0.27
	(0.017)	(0.017)	(0.02)
Age	54	55	64
	(0.55)	(0.55)	(0.61)
Female	0.42	0.59	0.48
	(0.017)	(0.017)	(0.022)
Monthly hh net income (equiv., thousands)	2.5	2.1	2
	(0.037)	(0.034)	(0.038)
Total hh financial assets (equiv., thousands)	52	27	33
	(5.7)	(3.4)	(3.9)
Risk aversion index	−0.056	0.058	0.0027
	(0.032)	(0.036)	(0.049)
Numeracy index	0.56	−0.16	−0.68
	(0.023)	(0.032)	(0.05)

Notes: The first row shows the share of individuals classified into a given group. For each group, the mean of several variables are shown. For income and total assets, the median is reported instead. Risk aversion and numeracy are normalized to have mean zero and unit variance. Sample: All waves meeting our inclusion criteria (i.e., there is variation across options and/or completion time is outside the fastest 15 %, see Section 2.3) for individuals with at least two such waves.

Table F.11. Predictors of groups, marginal effects (3 groups)

	Ambiguity types		
	Ambiguity seeking / near SEU	Ambiguity averse	High noise
Age: $\in (35, 50]$	-0.028	-0.046	0.074^{*}
	(0.039)	(0.043)	(0.042)
Age: $\in (50, 65]$	-0.074^{**}	-0.044	0.12^{***}
	(0.036)	(0.041)	(0.039)
Age: ≥ 65	-0.14^{***}	-0.067^{*}	0.21^{***}
	(0.037)	(0.04)	(0.038)
Education: Upper secondary	0.021	0.0074	-0.029
	(0.032)	(0.031)	(0.026)
Education: Tertiary	0.072^{**}	-0.07^{**}	-0.0014
	(0.032)	(0.034)	(0.028)
Income: $\in (1.1, 1.6]$	-0.067^{**}	0.067^{**}	-0.0002
	(0.033)	(0.033)	(0.026)
Income: $\in (1.6, 2.2]$	-0.027	0.084^{**}	-0.057^{*}
	(0.033)	(0.036)	(0.029)
Income: ≥ 2.2	-0.076^{**}	0.074^{*}	0.0018
	(0.035)	(0.039)	(0.031)
Financial assets: $\in (1.8, 11.2]$	0.11^{***}	-0.035	-0.076^{***}
	(0.034)	(0.034)	(0.028)
Financial assets: $\in (11.2, 32]$	0.13^{***}	-0.086^{**}	-0.041
	(0.034)	(0.036)	(0.028)
Financial assets: ≥ 32	0.13^{***}	-0.11^{***}	-0.022
	(0.035)	(0.039)	(0.031)
Female	-0.0098	0.11^{***}	-0.096^{***}
	(0.023)	(0.023)	(0.02)
Risk aversion index	-0.0093	0.011	-0.0021
	(0.012)	(0.012)	(0.0094)
Numeracy index	0.23^{***}	-0.083^{***}	-0.14^{***}
	(0.016)	(0.014)	(0.011)
Observations	1624	1624	1624
Pseudo R^2	0.18	0.18	0.18

Notes: Multinomial logit regression. Robust standard errors. For the thresholds of the income and asset quartiles see Table 3. Income and financial assets are in thousands, pooled over partners and equivalized for couples. Risk aversion and numeracy are normalized to have mean zero and unit variance. Sample: All waves meeting our inclusion criteria (i.e., there is variation across options and/or completion time is outside the fastest 15 %, see Section 2.3) for individuals with at least two such waves.

Table F.12. Ambiguity attitudes and portfolio choice: Marginal effects (3 groups)

	Owns risky assets (Probit)		Share risky assets (Tobit)	
	(1)	(2)	(3)	(4)
Ambiguity averse type	-0.18^{***}	-0.061^{***}	-0.32^{***}	-0.11^{**}
	(0.021)	(0.021)	(0.048)	(0.045)
High noise type	-0.17^{***}	-0.056^{**}	-0.23^{***}	-0.082
	(0.024)	(0.025)	(0.054)	(0.055)
Controls	No	Yes	No	Yes
Observations	1727	1624	1584	1502
Pseudo R^2	0.049	0.3	0.035	0.28
p-values for differences between				
Ambiguity averse, High noise	0.55	0.86	0.14	0.63

Notes: This table replicates the regressions shown in Table 7 when we classify individuals into three ambiguity groups.

F.3 Ambiguity types with $k = 5$

This section displays our main results of Section 4 when we classify individuals into five ambiguity groups.

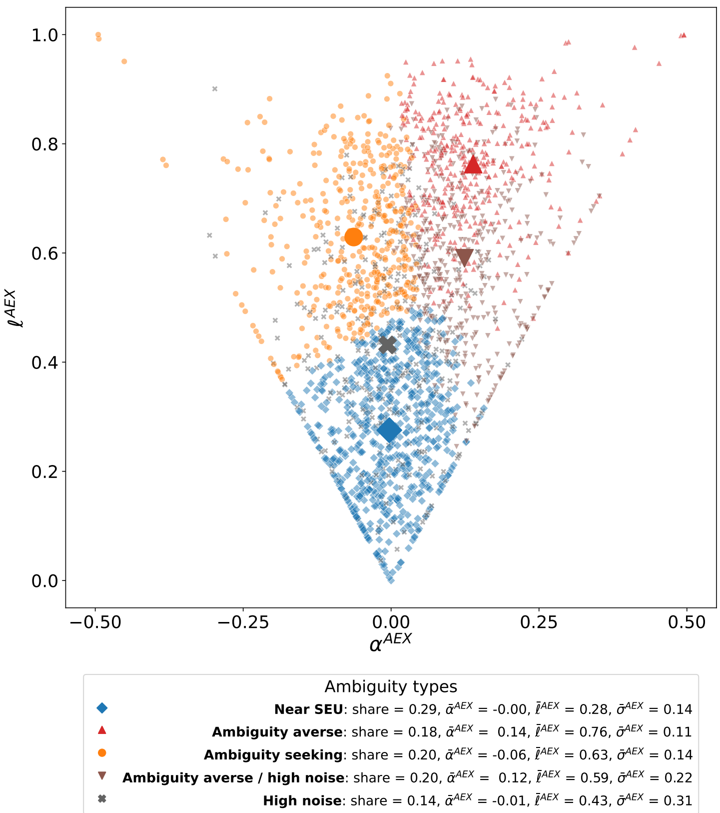


Figure F.4. Summarizing heterogeneity in ambiguity profiles with $k = 5$ discrete groups

Notes: The small symbols depict individual preference parameter estimates $(\alpha_i^{AEX}, \ell_i^{AEX})$ obtained from estimating (8) under the assumption that these two parameters and σ_i^{AEX} do not vary across waves. The large symbols are group centers resulting from clustering individuals with the k-means algorithm on the three parameters into five groups. Sample: All waves meeting our inclusion criteria (i.e., there is variation across options and/or completion time is outside the fastest 15 %, see Section 2.3) for individuals with at least two such waves.

Table F.13. Example situations: Decision weights and choice probabilities for ambiguity types (5 groups)

				$\text{Pr}_{\text{subj}} = p = 0.25$		$\text{Pr}_{\text{subj}} = p = 0.5$		$\text{Pr}_{\text{subj}} = p = 0.75$	
Ambiguity type	α	ℓ	σ	$W(E)-p$	Pr(choice $= AEX$)	$W(E)-p$	Pr(choice $= AEX$)	$W(E)-p$	Pr(choice $= AEX$)
Near SEU	-0.003	0.28	0.14	0.072	0.7	0.003	0.51	−0.066	0.31
Ambiguity averse	0.14	0.76	0.11	0.052	0.68	−0.14	0.1	−0.33	0.0013
Ambiguity seeking	-0.063	0.63	0.14	0.22	0.94	0.063	0.67	−0.094	0.26
Ambiguity averse / high noise	0.12	0.59	0.22	0.023	0.54	−0.12	0.28	−0.27	0.1
High noise	-0.006	0.43	0.31	0.11	0.64	0.006	0.51	−0.1	0.37

Notes: For this table we consider a decision maker who chooses between a lottery yielding €x with probability p and a prospect x_E0 with $\text{Pr}_{\text{subj}}(E) = p$ for three values of p: 0.25, 0.5, and 0.75. The table reports the difference between decision weights and subjective probabilities and the choice probability to choose the ambiguous option for each of the estimated ambiguity types.

Table F.14. Average characteristics of group members (5 groups)

	Ambiguity types				
	Near SEU	Ambiguity averse	Ambiguity seeking	Ambiguity averse / high noise	High noise
Share	0.29	0.18	0.2	0.2	0.14
α^{AEX}	−0.003	0.14	−0.063	0.12	−0.006
	(0.0024)	(0.0042)	(0.004)	(0.0033)	(0.0049)
ℓ^{AEX}	0.28	0.76	0.63	0.59	0.43
	(0.0046)	(0.0055)	(0.006)	(0.0065)	(0.0099)
σ^{AEX}	0.14	0.11	0.14	0.22	0.31
	(0.0018)	(0.002)	(0.0024)	(0.0022)	(0.0028)
Education: Lower secondary and below	0.12	0.26	0.25	0.36	0.42
	(0.013)	(0.022)	(0.021)	(0.023)	(0.029)
Education: Upper secondary	0.31	0.39	0.34	0.35	0.29
	(0.018)	(0.025)	(0.023)	(0.023)	(0.026)
Education: Tertiary	0.57	0.35	0.41	0.28	0.28
	(0.02)	(0.024)	(0.024)	(0.022)	(0.026)
Age	53	53	56	59	65
	(0.65)	(0.77)	(0.74)	(0.76)	(0.78)
Female	0.39	0.62	0.52	0.53	0.46
	(0.02)	(0.025)	(0.024)	(0.024)	(0.029)
Monthly hh net income (equiv., thousands)	2.5	2.1	2.2	2.1	2
	(0.042)	(0.047)	(0.056)	(0.044)	(0.05)
Total hh financial assets (equiv., thousands)	55	20	40	34	33
	(7)	(2.4)	(6.7)	(4.9)	(4.9)
Risk aversion index	−0.1	0.097	−0.0024	0.12	−0.074
	(0.036)	(0.049)	(0.052)	(0.049)	(0.068)
Numeracy index	0.64	−0.13	0.08	−0.32	−0.83
	(0.024)	(0.043)	(0.045)	(0.048)	(0.07)

Notes: The first row shows the share of individuals classified into a given group. For each group, the mean of several variables are shown. For income and total assets, the median is reported instead. Risk aversion and numeracy are normalized to have mean zero and unit variance. Sample: All waves meeting our inclusion criteria (i.e., there is variation across options and/or completion time is outside the fastest 15 %, see Section 2.3) for individuals with at least two such waves.

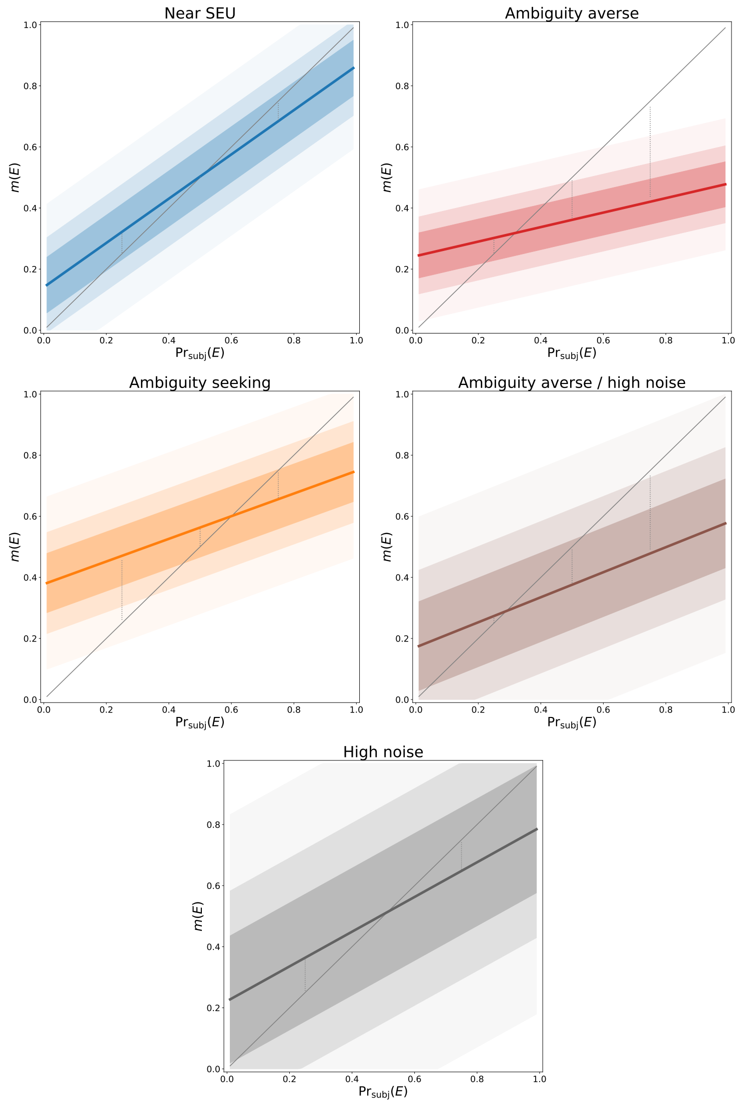


Figure F.5. Event weights as a function of subjective probabilities, by group (5 groups)

Notes: The solid lines plot the decision weights $W(E)$ for the estimated group-level average ambiguity parameters $\bar{\alpha}^{AEX}$ and $\bar{\ell}^{AEX}$. The vertical difference to the 45-degree line measures the extent of ambiguity seeking for different subjective probabilities w.r.t. gains from events whose source of uncertainty is the future development of the AEX. The shaded areas around the lines depict the 50 %, 75 % and 95 % confidence intervals of $m(p)$. Sample: All waves meeting our inclusion criteria (i.e., there is variation across options and/or completion time is outside the fastest 15 %, see Section 2.3) for individuals with at least two such waves.

Table F.15. Predictors of groups, marginal effects (5 groups)

	Ambiguity types				
	Near SEU	Ambiguity averse	Ambiguity seeking	Ambiguity averse / high noise	High noise
Age: $\in (35, 50]$	-0.033	-0.015	0.0004	0.019	0.029
	(0.036)	(0.032)	(0.036)	(0.038)	(0.036)
Age: $\in (50, 65]$	-0.047	-0.0081	0.0013	-0.02	0.074^{**}
	(0.035)	(0.03)	(0.034)	(0.036)	(0.033)
Age: ≥ 65	-0.068^{**}	-0.061^{*}	-0.041	0.032	0.14^{***}
	(0.035)	(0.031)	(0.035)	(0.035)	(0.033)
Education: Upper secondary	0.071^{**}	0.012	-0.034	-0.036	-0.013
	(0.032)	(0.025)	(0.028)	(0.025)	(0.021)
Education: Tertiary	0.09^{***}	-0.0062	-0.012	-0.099^{***}	0.027
	(0.032)	(0.028)	(0.029)	(0.028)	(0.023)
Income: $\in (1.1, 1.6]$	-0.041	0.028	0.0019	0.045^{*}	-0.034
	(0.032)	(0.027)	(0.03)	(0.027)	(0.021)
Income: $\in (1.6, 2.2]$	-0.06^{*}	0.06^{**}	0.01	0.029	-0.04
	(0.032)	(0.028)	(0.031)	(0.03)	(0.024)
Income: ≥ 2.2	-0.084^{**}	0.043	0.0026	0.068^{**}	-0.03
	(0.034)	(0.032)	(0.032)	(0.033)	(0.027)
Financial assets: $\in (1.8, 11.2]$	0.073^{**}	-0.058^{**}	0.043	0.016	-0.074^{***}
	(0.034)	(0.026)	(0.03)	(0.027)	(0.024)
Financial assets: $\in (11.2, 32]$	0.14^{***}	-0.072^{***}	-0.048	-0.01	-0.011
	(0.033)	(0.028)	(0.034)	(0.029)	(0.023)
Financial assets: ≥ 32	0.099^{***}	-0.1^{***}	0.019	-0.031	0.013
	(0.034)	(0.032)	(0.033)	(0.032)	(0.025)
Female	-0.005	0.068^{***}	0.014	-0.01	-0.067^{***}
	(0.022)	(0.019)	(0.021)	(0.02)	(0.016)
Risk aversion index	-0.014	0.015	-0.0088	0.019^{**}	-0.011
	(0.011)	(0.0093)	(0.011)	(0.0097)	(0.0078)
Numeracy index	0.23^{***}	-0.038^{***}	-0.025^{*}	-0.067^{***}	-0.1^{***}
	(0.017)	(0.0098)	(0.013)	(0.011)	(0.0088)
Observations	1624	1624	1624	1624	1624
Pseudo R^2	0.13	0.13	0.13	0.13	0.13

Notes: Multinomial logit regression. Robust standard errors. For the thresholds of the income and asset quartiles see Table 3. Income and financial assets are in thousands, pooled over partners and equivalized for couples. Risk aversion and numeracy are normalized to have mean zero and unit variance. Sample: All waves meeting our inclusion criteria (i.e., there is variation across options and/or completion time is outside the fastest 15 %, see Section 2.3) for individuals with at least two such waves.

Table F.16. Ambiguity attitudes and portfolio choice: Marginal effects (5 groups)

	Owns risky assets (Probit)		Share risky assets (Tobit)	
	(1)	(2)	(3)	(4)
Ambiguity averse type	-0.25^{***}	-0.11^{***}	-0.53^{***}	-0.26^{***}
	(0.025)	(0.025)	(0.073)	(0.066)
Ambiguity seeking type	-0.093^{***}	-0.0059	-0.13^{**}	-0.0032
	(0.03)	(0.025)	(0.052)	(0.047)
Ambiguity averse / high noise type	-0.18^{***}	-0.045^{*}	-0.29^{***}	-0.093^{*}
	(0.028)	(0.027)	(0.059)	(0.056)
High noise type	-0.18^{***}	-0.054^{*}	-0.24^{***}	-0.093
	(0.03)	(0.031)	(0.068)	(0.066)
Controls	No	Yes	No	Yes
Observations	1727	1624	1584	1502
Pseudo R^2	0.057	0.31	0.048	0.29
p-values for differences between				
Ambiguity averse, Ambiguity seeking	0	0.0002	0	0.0002
Ambiguity averse, Ambiguity averse / high noise	0.0043	0.017	0.0028	0.021
Ambiguity seeking, Ambiguity averse / high noise	0.0047	0.18	0.015	0.13
Ambiguity averse, High noise	0.011	0.061	0.0009	0.037
Ambiguity seeking, High noise	0.0079	0.14	0.15	0.19
Ambiguity averse / high noise, High noise	0.9	0.76	0.51	1

Notes: This table replicates the regressions shown in Table 7 when we classify individuals into five ambiguity groups.

F.4 Ambiguity types with $k = 8$

This section displays our main results of Section 4 when we classify individuals into eight ambiguity groups.

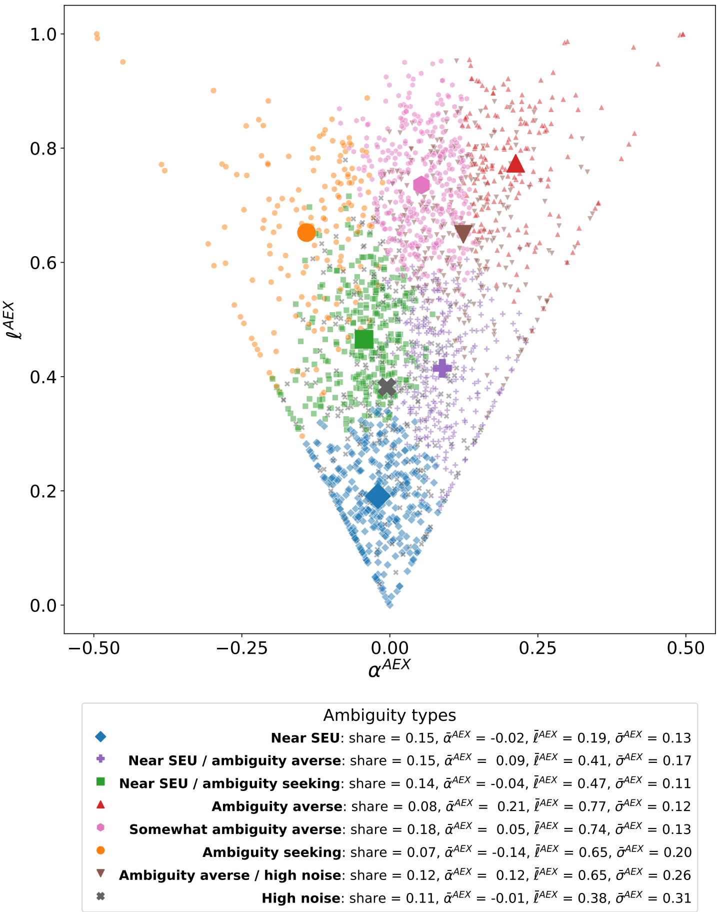


Figure F.6. Summarizing heterogeneity in ambiguity profiles with $k = 8$ discrete groups

Notes: The small symbols depict individual preference parameter estimates $(\alpha_i^{AEX}, \ell_i^{AEX})$ obtained from estimating (8) under the assumption that these two parameters and σ_i^{AEX} do not vary across waves. The large symbols are group centers resulting from clustering individuals with the k-means algorithm on the three parameters into eight groups. Sample: All waves meeting our inclusion criteria (i.e., there is variation across options and/or completion time is outside the fastest 15 %, see Section 2.3) for individuals with at least two such waves.

Table F.17. Example situations: Decision weights and choice probabilities for ambiguity types (8 groups)

				$\text{Pr}_{\text{subj}} = p = 0.25$		$\text{Pr}_{\text{subj}} = p = 0.5$		$\text{Pr}_{\text{subj}} = p = 0.75$	
				$W(E)-p$	Pr(choice $= AEX$)	$W(E)-p$	Pr(choice $= AEX$)	$W(E)-p$	Pr(choice $= AEX$)
Ambiguity type	α	ℓ	σ						
Near SEU	-0.02	0.19	0.13	0.068	0.7	0.02	0.56	−0.028	0.42
Near SEU / ambiguity averse	0.089	0.41	0.17	0.015	0.54	−0.089	0.3	−0.19	0.12
Near SEU / ambiguity seeking	-0.044	0.47	0.11	0.16	0.92	0.044	0.65	−0.073	0.26
Ambiguity averse	0.21	0.77	0.12	−0.019	0.43	−0.21	0.033	−0.41	0.0002
Somewhat ambiguity averse	0.053	0.74	0.13	0.13	0.84	−0.053	0.34	−0.24	0.033
Ambiguity seeking	-0.14	0.65	0.2	0.3	0.94	0.14	0.76	−0.022	0.45
Ambiguity averse / high noise	0.12	0.65	0.26	0.038	0.56	−0.12	0.32	−0.29	0.14
High noise	-0.005	0.38	0.31	0.1	0.63	0.005	0.51	−0.09	0.38

Notes: For this table we consider a decision maker who chooses between a lottery yielding €x with probability p and a prospect $x_E 0$ with $\text{Pr}_{\text{subj}}(E) = p$ for three values of p: 0.25, 0.5, and 0.75. The table reports the difference between decision weights and subjective probabilities and the choice probability to choose the ambiguous option for each of the estimated ambiguity types.

Table F.18. Average characteristics of group members (8 groups)

	Ambiguity types							
	Near SEU	Near SEU / ambiguity averse	Near SEU / ambiguity seeking	Ambiguity averse	Somewhat ambiguity averse	Ambiguity seeking	Ambiguity averse / high noise	High noise
Share	0.15	0.15	0.14	0.08	0.18	0.07	0.12	0.11
α^{AEX}	−0.02	0.089	−0.044	0.21	0.053	−0.14	0.12	−0.005
	(0.0027)	(0.0027)	(0.003)	(0.0054)	(0.0025)	(0.0071)	(0.0047)	(0.0044)
ℓ^{AEX}	0.19	0.41	0.47	0.77	0.74	0.65	0.65	0.38
	(0.0042)	(0.0055)	(0.0051)	(0.0078)	(0.0047)	(0.011)	(0.0073)	(0.0096)
σ^{AEX}	0.13	0.17	0.11	0.12	0.13	0.2	0.26	0.31
	(0.0026)	(0.002)	(0.002)	(0.0035)	(0.0022)	(0.0045)	(0.003)	(0.0032)
Education: Lower secondary and below	0.11	0.2	0.13	0.32	0.25	0.36	0.43	0.42
	(0.017)	(0.022)	(0.019)	(0.035)	(0.022)	(0.038)	(0.031)	(0.032)
Education: Upper secondary	0.27	0.36	0.32	0.35	0.4	0.35	0.33	0.3
	(0.025)	(0.027)	(0.027)	(0.035)	(0.025)	(0.038)	(0.029)	(0.029)
Education: Tertiary	0.62	0.45	0.55	0.33	0.35	0.29	0.23	0.27
	(0.027)	(0.028)	(0.029)	(0.035)	(0.024)	(0.036)	(0.026)	(0.029)
Age	55	54	51	55	56	60	62	66
	(0.86)	(0.96)	(0.91)	(1.1)	(0.79)	(1.1)	(0.94)	(0.84)
Female	0.35	0.47	0.44	0.59	0.61	0.59	0.51	0.47
	(0.026)	(0.028)	(0.029)	(0.036)	(0.025)	(0.039)	(0.031)	(0.032)
Monthly hh net income (equiv., thousands)	2.6	2.3	2.5	2	2.2	2.1	2	2
	(0.058)	(0.051)	(0.064)	(0.065)	(0.051)	(0.092)	(0.056)	(0.056)
Total hh financial assets (equiv., thousands)	64	35	50	20	32	33	26	34
	(10)	(5.1)	(11)	(3.7)	(6.1)	(5.8)	(5.1)	(5.6)
Risk aversion index	−0.094	−0.032	−0.054	0.068	0.034	0.092	0.12	−0.054
	(0.048)	(0.052)	(0.054)	(0.074)	(0.053)	(0.096)	(0.067)	(0.073)
Numeracy index	0.72	0.3	0.57	−0.33	−0.045	−0.42	−0.62	−0.81
	(0.032)	(0.045)	(0.036)	(0.071)	(0.041)	(0.086)	(0.064)	(0.077)

Notes: The first row shows the share of individuals classified into a given group. For each group, the mean of several variables are shown. For income and total assets, the median is reported instead. Risk aversion and numeracy are normalized to have mean zero and unit variance. Sample: All waves meeting our inclusion criteria (i.e., there is variation across options and/or completion time is outside the fastest 15 %, see Section 2.3) for individuals with at least two such waves.

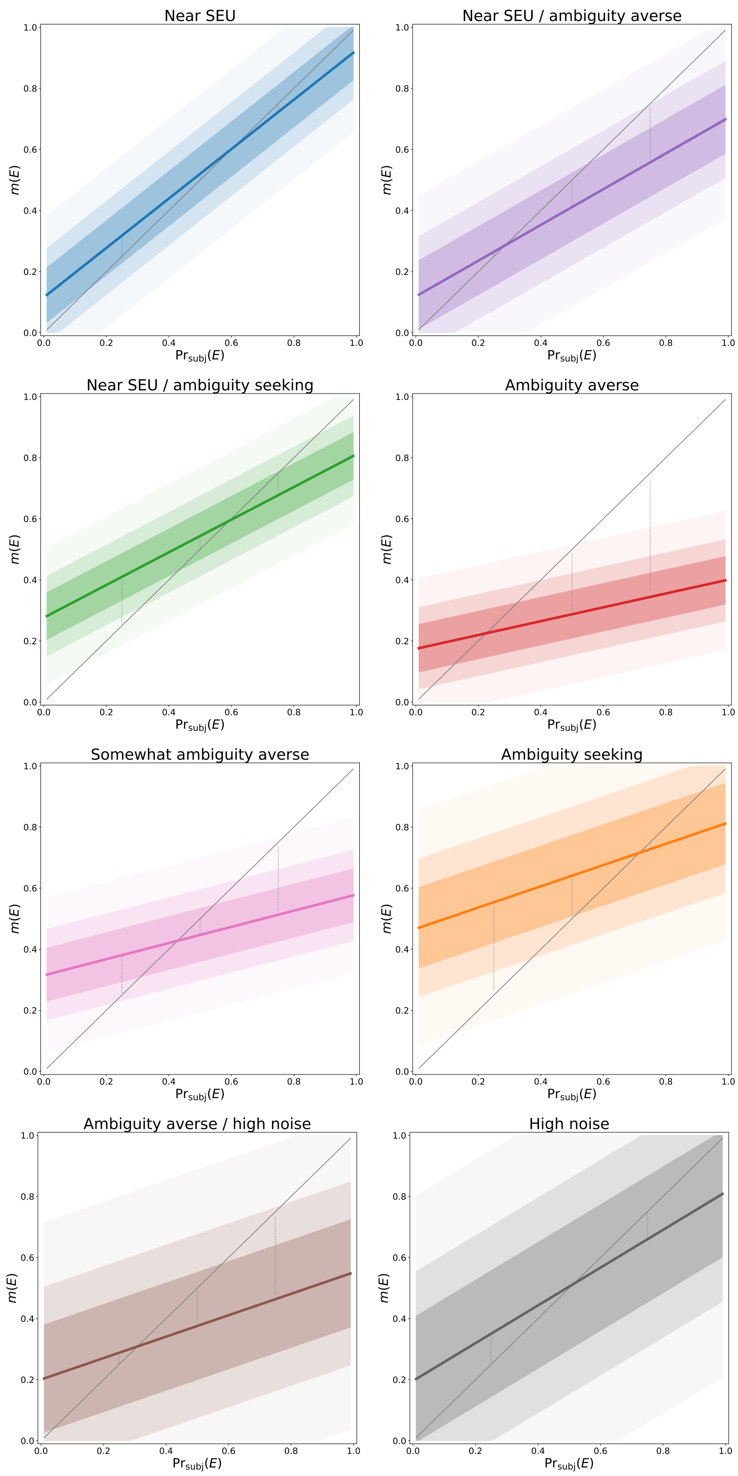


Figure F.7. Event weights as a function of subjective probabilities, by group (8 groups)

Notes: The solid lines plot the decision weights $W(E)$ for the estimated group-level average ambiguity parameters $\bar{\alpha}^{AEX}$ and $\bar{\ell}^{AEX}$. The vertical difference to the 45-degree line measures the extent of ambiguity seeking for different subjective probabilities w.r.t. gains from events whose source of uncertainty is the future development of the AEX. The shaded areas around the lines depict the 50 %, 75 % and 95 % confidence intervals of $m(p)$. Sample: All waves meeting our inclusion criteria (i.e., there is variation across options and/or completion time is outside the fastest 15 %, see Section 2.3) for individuals with at least two such waves.

Table F.19. Predictors of groups, marginal effects (8 groups)

	Ambiguity types							
	Near SEU	Near SEU / ambiguity averse	Near SEU / ambiguity seeking	Ambiguity averse	Somewhat ambiguity averse	Ambiguity seeking	Ambiguity averse / high noise	High noise
Age: $\in (35, 50]$	0.018	−0.032	−0.025	−0.045*	−0.02	0.026	0.073*	0.0052
	(0.029)	(0.03)	(0.026)	(0.023)	(0.035)	(0.028)	(0.038)	(0.038)
Age: $\in (50, 65]$	0.016	−0.066**	−0.053**	−0.02	0.0026	0.024	0.045	0.052
	(0.028)	(0.029)	(0.026)	(0.02)	(0.032)	(0.027)	(0.036)	(0.034)
Age: ≥ 65	0.0031	−0.062**	−0.13***	−0.042**	−0.0028	0.025	0.1***	0.11***
	(0.028)	(0.029)	(0.028)	(0.021)	(0.032)	(0.026)	(0.036)	(0.033)
Education: Upper secondary	0.02	0.0095	−0.0016	−0.014	0.029	−0.014	−0.023	−0.0051
	(0.03)	(0.026)	(0.029)	(0.017)	(0.025)	(0.016)	(0.019)	(0.019)
Education: Tertiary	0.059**	0.0034	0.0024	−0.016	−0.002	−0.0069	−0.058**	0.018
	(0.029)	(0.027)	(0.029)	(0.018)	(0.027)	(0.018)	(0.023)	(0.022)
Income: $\in (1.1, 1.6]$	−0.024	−0.033	0.011	−0.028	0.081***	−0.027	0.028	−0.0081
	(0.028)	(0.027)	(0.029)	(0.018)	(0.027)	(0.019)	(0.019)	(0.019)
Income: $\in (1.6, 2.2]$	−0.0005	−0.022	−0.001	0.0064	0.057*	−0.0061	−0.0027	−0.032
	(0.027)	(0.026)	(0.029)	(0.018)	(0.029)	(0.019)	(0.024)	(0.023)
Income: ≥ 2.2	−0.051*	−0.057**	0.045	−0.013	0.064**	−0.0085	0.036	−0.016
	(0.029)	(0.028)	(0.028)	(0.022)	(0.032)	(0.02)	(0.025)	(0.026)
Financial assets: $\in (1.8, 11.2]$	0.0053	0.052*	0.055*	−0.042**	−0.01	0.023	−0.036*	−0.047**
	(0.032)	(0.027)	(0.028)	(0.018)	(0.027)	(0.017)	(0.02)	(0.022)
Financial assets: $\in (11.2, 32]$	0.078***	0.045	0.016	−0.033*	−0.029	−0.026	−0.054**	0.0024
	(0.029)	(0.028)	(0.031)	(0.019)	(0.029)	(0.023)	(0.022)	(0.022)
Financial assets: ≥ 32	0.059**	−0.019	0.051*	−0.045**	−0.053*	0.034*	−0.049**	0.022
	(0.03)	(0.031)	(0.03)	(0.022)	(0.032)	(0.019)	(0.024)	(0.024)
Female	−0.0094	0.005	−0.0097	0.019	0.079***	0.0069	−0.043***	−0.049***
	(0.019)	(0.018)	(0.019)	(0.013)	(0.019)	(0.013)	(0.016)	(0.015)
Risk aversion index	−0.0031	−0.0064	0.0066	−0.0008	0.0038	−0.0022	0.014*	−0.012*
	(0.0098)	(0.0095)	(0.0098)	(0.0065)	(0.01)	(0.0065)	(0.0074)	(0.0069)
Numeracy index	0.16***	0.023*	0.06***	−0.02***	−0.039***	−0.038***	−0.056***	−0.086***
	(0.019)	(0.013)	(0.016)	(0.0065)	(0.01)	(0.0071)	(0.0084)	(0.0084)
Observations	1624	1624	1624	1624	1624	1624	1624	1624
Pseudo R^2	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13

Notes: Multinomial logit regression. Robust standard errors. For the thresholds of the income and asset quartiles see Table 3. Income and financial assets are in thousands, pooled over partners and equivalized for couples. Risk aversion and numeracy are normalized to have mean zero and unit variance. Sample: All waves meeting our inclusion criteria (i.e., there is variation across options and/or completion time is outside the fastest 15 %, see Section 2.3) for individuals with at least two such waves.

Table F.20. Ambiguity attitudes and portfolio choice: Marginal effects (8 groups)

	Owns risky assets (Probit)		Share risky assets (Tobit)	
	(1)	(2)	(3)	(4)
Near SEU / ambiguity averse type	-0.19^{***}	-0.063^{**}	-0.29^{***}	-0.12^{**}
	(0.037)	(0.029)	(0.065)	(0.058)
Near SEU / ambiguity seeking type	-0.07^{*}	-0.021	-0.14^{**}	-0.07
	(0.041)	(0.029)	(0.061)	(0.054)
Ambiguity averse type	-0.32^{***}	-0.14^{***}	-0.67^{***}	-0.32^{***}
	(0.035)	(0.039)	(0.11)	(0.1)
Somewhat ambiguity averse type	-0.24^{***}	-0.086^{***}	-0.39^{***}	-0.15^{**}
	(0.035)	(0.03)	(0.067)	(0.062)
Ambiguity seeking type	-0.19^{***}	-0.044	-0.26^{***}	-0.055
	(0.046)	(0.044)	(0.088)	(0.083)
Ambiguity averse / high noise type	-0.28^{***}	-0.095^{***}	-0.47^{***}	-0.18^{**}
	(0.036)	(0.037)	(0.086)	(0.081)
High noise type	-0.21^{***}	-0.048	-0.26^{***}	-0.057
	(0.039)	(0.037)	(0.075)	(0.073)
Controls	No	Yes	No	Yes
Observations	1727	1624	1584	1502
Pseudo R^2	0.066	0.31	0.052	0.29
p-values for differences between				
Near SEU / ambiguity averse, Near SEU / ambiguity seeking	0.0016	0.17	0.023	0.44
Near SEU / ambiguity averse, Ambiguity averse	0.0005	0.042	0.0009	0.046
Near SEU / ambiguity seeking, Ambiguity averse	0	0.0039	0	0.013
Near SEU / ambiguity averse, Somewhat ambiguity averse	0.073	0.43	0.14	0.57
Near SEU / ambiguity seeking, Somewhat ambiguity averse	0	0.033	0.0002	0.19
Ambiguity averse, Somewhat ambiguity averse	0.02	0.13	0.017	0.1
Near SEU / ambiguity averse, Ambiguity seeking	0.91	0.64	0.74	0.47
Near SEU / ambiguity seeking, Ambiguity seeking	0.012	0.61	0.17	0.86
Ambiguity averse, Ambiguity seeking	0.0026	0.033	0.0014	0.021
Somewhat ambiguity averse, Ambiguity seeking	0.2	0.29	0.14	0.25
Near SEU / ambiguity averse, Ambiguity averse / high noise	0.0049	0.37	0.042	0.46
Near SEU / ambiguity seeking, Ambiguity averse / high noise	0	0.053	0.0001	0.19
Ambiguity averse, Ambiguity averse / high noise	0.23	0.24	0.11	0.21
Somewhat ambiguity averse, Ambiguity averse / high noise	0.19	0.79	0.4	0.77
Ambiguity seeking, Ambiguity averse / high noise	0.025	0.24	0.048	0.21
Near SEU / ambiguity averse, High noise	0.51	0.69	0.69	0.44
Near SEU / ambiguity seeking, High noise	0.0005	0.48	0.12	0.87
Ambiguity averse, High noise	0.0039	0.028	0.0007	0.015
Somewhat ambiguity averse, High noise	0.34	0.27	0.093	0.2
Ambiguity seeking, High noise	0.68	0.91	0.99	0.98
Ambiguity averse / high noise, High noise	0.04	0.23	0.028	0.17

Notes: This table replicates the regressions shown in Table 7 when we classify individuals into eight ambiguity groups.

Appendix G Robustness within the model

G.1 Using all observations

This section reports on changes to our results when we drop all restrictions that limit our sample size. In particular, we keep waves regardless of whether there is variation across options, whether completion time is among the fastest 15 % (see Section 2.3), and whether we have at least two waves per individual. Of course, the latter restriction may become binding implicitly—e.g., when considering stability over time—which was a reason for including it in the first place. The section is structured so that we repeat all tables and figures from the paper as well as those from this Online Appendix, which seem useful for the reader to obtain a complete picture.

The number of individuals rises from 2177 to 2407. None of the descriptive statistics from Section 2 is affected in a meaningful way. Wave-by-wave parameter estimates remain very similar—if anything, likelihood insensitivity is slightly higher in Table G.6 compared to Table E.1—and stability over time / across domains remains very similar, too (cf. Table G.7 vs. 4 and Table G.8 vs. 5).

Perhaps more interestingly, the estimated types in Figure G.2 are very similar to those in Figure 6. This includes both the shares—none of which changes by more that 2 percentage points—and the characteristics in terms of structural parameters. The choice probabilities for our examples are often the same in Table G.9 as in Table F.1; none of them differs by more than 5 percentage points. The ambiguity groups look similar regarding their observable characteristics (Table G.10). The coefficients for portfolio choice behavior attenuate slightly toward zero and p-values for some comparisons become larger (Table G.12). However, all comparisons we have highlighted in the main text—less risky investing among the ambiguity averse compared to near SEU or ambiguity seeking types—remain significant.

Tables and figures corresponding to Section 2

Table G.1. Matching probabilities, empirical frequencies and judged historical frequencies

	Mean	Std. Dev.	$q_{0.1}$	$q_{0.5}$	$q_{0.9}$	Empir. Freq. '99-'19	Judged Freq., '99-'19
$E_0^{AEX}: Y_{t+6} \in (1000, \infty)$	0.49	0.28	0.075	0.45	0.93	0.63	0.52
$E_1^{AEX}: Y_{t+6} \in (1100, \infty]$	0.35	0.25	0.03	0.35	0.65	0.24	0.31
$E_{1,C}^{AEX}: Y_{t+6} \in (-\infty, 1100]$	0.51	0.29	0.075	0.45	0.97	0.76	
$E_2^{AEX}: Y_{t+6} \in (-\infty, 950)$	0.37	0.26	0.03	0.35	0.75	0.28	0.22
$E_{2,C}^{AEX}: Y_{t+6} \in [950, \infty)$	0.55	0.3	0.15	0.55	0.97	0.72	
$E_3^{AEX}: Y_{t+6} \in [950, 1100]$	0.56	0.29	0.15	0.55	0.97	0.48	0.47
$E_{3,C}^{AEX}: Y_{t+6} \in (-\infty, 950) \cup (1100, \infty)$	0.42	0.27	0.075	0.45	0.85	0.52	

Notes: This table replicates Table 1 using all observations.

Table G.2. Average matching probabilities by wave

	2018-11	2019-05	2019-11	2020-05	2020-11
$E_0^{AEX}: Y_{t+6} \in (1000, \infty)$	0.5	0.52	0.48	0.43	0.52
$E_1^{AEX}: Y_{t+6} \in (1100, \infty]$	0.35	0.37	0.36	0.33	0.36
$E_{1,C}^{AEX}: Y_{t+6} \in (-\infty, 1100]$	0.5	0.51	0.51	0.51	0.54
$E_2^{AEX}: Y_{t+6} \in (-\infty, 950)$	0.35	0.35	0.35	0.43	0.36
$E_{2,C}^{AEX}: Y_{t+6} \in [950, \infty)$	0.54	0.56	0.56	0.51	0.58
$E_3^{AEX}: Y_{t+6} \in [950, 1100]$	0.54	0.57	0.57	0.53	0.59
$E_{3,C}^{AEX}: Y_{t+6} \in (-\infty, 950) \cup (1100, \infty)$	0.41	0.41	0.4	0.44	0.41

Notes: This table replicates Table D.2 using all observations.

Table G.3. Matching probabilities for climate questions

	N subj.	Mean	$q_{0.1}$	$q_{0.5}$	$q_{0.9}$	Empirical Frequency, 1999-2019
$E_0^{climate} : \Delta T \in (0°C, \infty)$	1932	0.52	0.075	0.55	0.93	0.53
$E_1^{climate} : \Delta T \in (1°C, \infty]$	1930	0.45	0.075	0.45	0.93	0.23
$E_{1,C}^{climate} : \Delta T \in (-\infty, 1°C]$	1928	0.52	0.075	0.55	0.97	
$E_2^{climate} : \Delta T \in (-\infty, -0.5°C)$	1928	0.4	0.03	0.35	0.85	0.27
$E_{2,C}^{climate} : \Delta T \in [-0.5°C, \infty)$	1928	0.49	0.075	0.45	0.93	
$E_3^{climate} : \Delta T \in [-0.5°C, 1°C]$	1928	0.5	0.075	0.45	0.93	0.5
$E_{3,C}^{climate} : \Delta T \in (-\infty, -0.5°C) \cup (1°C, \infty)$	1926	0.47	0.075	0.45	0.93	

Notes: This table replicates Table D.3 using all observations.

Table G.4. Judged historical frequencies and set-monotonicity violations

	Dependent variable: Set-monotonicity violation			
	(1)	(2)	(3)	(4)
Intercept	0.14***	0.16***		
	(0.0024)	(0.003)		
Judged frequencies (superset - subset)		−0.074***	−0.044***	−0.037***
		(0.0054)	(0.0052)	(0.0058)
Superset-subset pair fixed effects	No	No	Yes	Yes
Individual fixed effects	No	No	No	Yes
Observations	16000	16000	16000	16000

Notes: This table replicates Table 2 using all observations.

Table G.5. Descriptive statistics on key variables

	N Subj.	Mean	Std. Dev.	$q_{0.25}$	$q_{0.5}$	$q_{0.75}$
Female	2407	0.5				
Education: Lower secondary and below	2407	0.26				
Education: Upper secondary	2407	0.34				
Education: Tertiary	2407	0.4				
Age	2407	56	16	44	59	69
Monthly hh net income (equiv., thousands)	2327	2.2	0.99	1.6	2.1	2.7
Total hh financial assets (equiv., thousands)	1853	38	110	2.5	11	34
Owns risky financial assets	1853	0.19				
Share risky financial assets (if any)	358	0.35	0.26	0.12	0.29	0.53
Risk aversion index	2285	0	1	−0.67	−0.035	0.67
Numeracy index	2186	0	1	−0.57	0.24	0.8
Understands climate change	1988	0.54	0.21	0.5	0.5	0.75
Threatened by climate change	1988	0.55	0.22	0.4	0.6	0.6

Notes: This table replicates Table 3 using all observations.

Tables and figures corresponding to Section 3

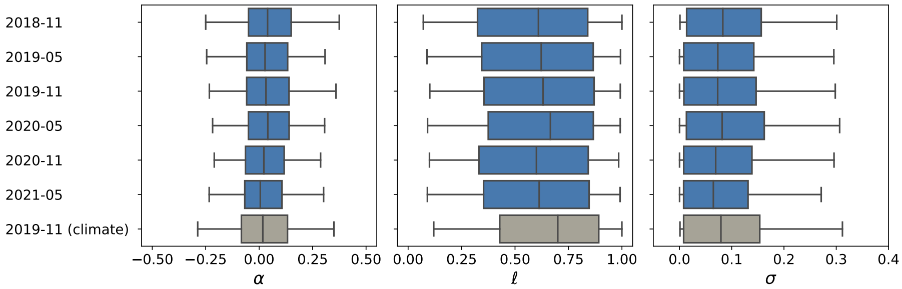


Figure G.1. Distributions of estimated parameters, wave by wave

Notes: This figure replicates Figure 5 using all observations.

Table G.6. Marginal distributions of estimated parameters, wave by wave

		Mean	Std. dev.	$q_{0.05}$	$q_{0.25}$	$q_{0.5}$	$q_{0.75}$	$q_{0.95}$
α	2018-11	0.049	0.19	−0.25	−0.05	0.039	0.15	0.37
	2019-05	0.035	0.18	−0.25	−0.058	0.028	0.13	0.31
	2019-11	0.041	0.18	−0.23	−0.059	0.032	0.14	0.36
	2020-05	0.043	0.17	−0.22	−0.05	0.041	0.14	0.31
	2020-11	0.027	0.16	−0.21	−0.064	0.022	0.12	0.29
	2021-05	0.02	0.17	−0.23	−0.067	0.0054	0.11	0.3
	Observations from all AEX waves	0.036	0.17	−0.23	−0.059	0.03	0.13	0.33
	2019-11 (Climate Change)	0.025	0.19	−0.29	−0.083	0.017	0.13	0.35
ℓ	2018-11	0.58	0.3	0.071	0.32	0.61	0.84	1
	2019-05	0.6	0.29	0.088	0.34	0.62	0.87	0.99
	2019-11	0.6	0.29	0.1	0.35	0.63	0.87	0.99
	2020-05	0.61	0.29	0.09	0.37	0.67	0.87	0.99
	2020-11	0.58	0.29	0.1	0.33	0.6	0.84	0.98
	2021-05	0.59	0.29	0.09	0.35	0.61	0.85	0.99
	Observations from all AEX waves	0.59	0.29	0.087	0.35	0.62	0.86	0.99
	2019-11 (Climate Change)	0.64	0.28	0.12	0.43	0.7	0.89	1
σ	2018-11	0.11	0.1	0.001	0.014	0.083	0.16	0.3
	2019-05	0.095	0.096	0.0002	0.0082	0.073	0.14	0.3
	2019-11	0.097	0.096	0.0002	0.0085	0.073	0.15	0.3
	2020-05	0.11	0.1	0.0002	0.013	0.082	0.16	0.31
	2020-11	0.093	0.1	0.0003	0.0081	0.069	0.14	0.3
	2021-05	0.088	0.09	0.0003	0.008	0.065	0.13	0.27
	Observations from all AEX waves	0.098	0.098	0.0003	0.0086	0.075	0.15	0.3
	2019-11 (Climate Change)	0.1	0.1	0.001	0.008	0.079	0.15	0.31

Notes: This table replicates Table E.1 using all observations.

Table G.7. Predicting last three waves of ambiguity parameters with first three waves

		OLS	ORIV	
		(1)	(2)	(3)
$\alpha^{AEX}_{\text{last 3 waves}}$	Intercept	0.018^{***}	-0.0098^{**}	
		(0.0027)	(0.0042)	
	$\alpha^{AEX}_{\text{first 3 waves}}$	0.26^{***}	0.93^{***}	0.95^{***}
		(0.02)	(0.07)	(0.10)
	Adj. R^2	0.078		
	1st st. F		137	81
$\ell^{AEX}_{\text{last 3 waves}}$	Intercept	0.37^{***}	0.032	
		(0.0087)	(0.021)	
	$\ell^{AEX}_{\text{first 3 waves}}$	0.37^{***}	0.95^{***}	0.93^{***}
		(0.01)	(0.03)	(0.05)
	Adj. R^2	0.14		
	1st st. F		563	319
$\sigma^{AEX}_{\text{last 3 waves}}$	Intercept	0.065^{***}	-0.0005	
		(0.0017)	(0.0055)	
	$\sigma^{AEX}_{\text{first 3 waves}}$	0.31^{***}	0.98^{***}	0.94^{***}
		(0.01)	(0.06)	(0.07)
	Adj. R^2	0.095		
	1st st. F		249	134
Controls		No	No	Yes
N Subjects		1900	1900	1478

Notes: This table replicates the regressions shown in Table 4 using all observations.

Table G.8. Predicting climate ambiguity parameters with AEX parameters

		OLS	2SLS	
		(1)	(2)	(3)
$\alpha^{climate}_{2019-11}$	Intercept	-0.0034	-0.016^{***}	
		(0.0034)	(0.0038)	
	$\alpha^{AEX}_{2019-11}$	0.71^{***}	0.99^{***}	1.01^{***}
		(0.03)	(0.04)	(0.06)
	Adj. R^2	0.44		
	1st st. F		223	148
$\ell^{climate}_{2019-11}$	Intercept	0.42^{***}	0.28^{***}	
		(0.014)	(0.024)	
	$\ell^{AEX}_{2019-11}$	0.37^{***}	0.61^{***}	0.63^{***}
		(0.02)	(0.04)	(0.05)
	Adj. R^2	0.14		
	1st st. F		784	434
$\sigma^{climate}_{2019-11}$	Intercept	0.055^{***}	0.022^{***}	
		(0.0029)	(0.0054)	
	$\sigma^{AEX}_{2019-11}$	0.49^{***}	0.84^{***}	0.88^{***}
		(0.03)	(0.06)	(0.08)
	Adj. R^2	0.21		
	1st st. F		233	204
Controls		No	No	Yes
N Subjects		1915	1915	1456

Notes: This table replicates the regressions shown in Table 5 using all observations.

Tables and figures corresponding to Section 4

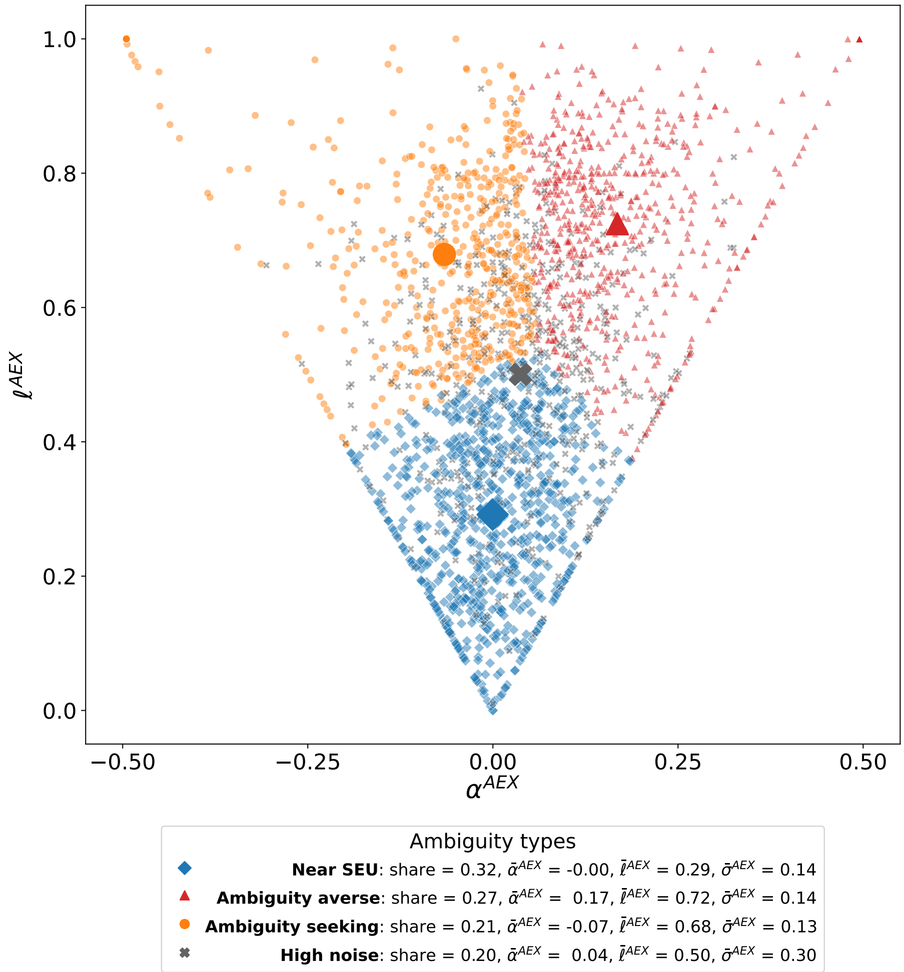


Figure G.2. Summarizing heterogeneity in ambiguity profiles with K=4 discrete groups

Notes: This figure replicates Figure 6 using all observations.

	Mean	Std. dev.	$q_{0.05}$	$q_{0.25}$	$q_{0.5}$	$q_{0.75}$	$q_{0.95}$
α^{AEX}	0.038	0.13	−0.14	−0.032	0.033	0.11	0.24
ℓ^{AEX}	0.53	0.23	0.15	0.35	0.54	0.71	0.87
σ^{AEX}	0.17	0.088	0.052	0.11	0.16	0.22	0.34

Table G.9. Example situations: Decision weights and choice probabilities for ambiguity types

				$\text{Pr}_{\text{subj}} = p = 0.25$		$\text{Pr}_{\text{subj}} = p = 0.5$		$\text{Pr}_{\text{subj}} = p = 0.75$	
				$W(E) - p$	Pr(choice $= AEX$)	$W(E) - p$	Pr(choice $= AEX$)	$W(E) - p$	Pr(choice $= AEX$)
Ambiguity type	α	ℓ	σ						
Near SEU	-0.0004	0.29	0.14	0.073	0.7	0.0004	0.5	−0.073	0.3
Ambiguity averse	0.17	0.72	0.14	0.013	0.54	−0.17	0.11	−0.35	0.006
Ambiguity seeking	-0.066	0.68	0.13	0.24	0.96	0.066	0.69	−0.1	0.22
High noise	0.037	0.5	0.3	0.088	0.61	−0.037	0.45	−0.16	0.3

Notes: This table replicates Table F.1 using all observations.

Table G.10. Average characteristics of group members

	Ambiguity types			
	Near SEU	Ambiguity averse	Ambiguity seeking	High noise
Share	0.32	0.27	0.21	0.2
α^{AEX}	−0.0004	0.17	−0.066	0.037
	(0.0025)	(0.0037)	(0.0051)	(0.0045)
ℓ^{AEX}	0.29	0.72	0.68	0.5
	(0.0044)	(0.0052)	(0.006)	(0.0075)
σ^{AEX}	0.14	0.14	0.13	0.3
	(0.0018)	(0.0026)	(0.0027)	(0.0027)
Education: Lower secondary and below	0.13	0.3	0.27	0.42
	(0.012)	(0.018)	(0.02)	(0.022)
Education: Upper secondary	0.32	0.36	0.36	0.31
	(0.017)	(0.019)	(0.021)	(0.021)
Education: Tertiary	0.55	0.34	0.37	0.27
	(0.018)	(0.019)	(0.022)	(0.02)
Age	53	54	57	64
	(0.6)	(0.64)	(0.68)	(0.63)
Female	0.4	0.61	0.55	0.47
	(0.018)	(0.019)	(0.022)	(0.023)
Monthly hh net income (equiv., thousands)	2.4	2.1	2.2	2
	(0.038)	(0.038)	(0.047)	(0.04)
Total hh financial assets (equiv., thousands)	52	23	37	36
	(6)	(2.4)	(6)	(4.3)
Risk aversion index	−0.088	0.082	0.016	0.02
	(0.032)	(0.041)	(0.048)	(0.051)
Numeracy index	0.59	−0.22	0.051	−0.71
	(0.024)	(0.039)	(0.042)	(0.052)

Notes: This table replicates Table 6 using all observations.

Table G.11. Predictors of groups, marginal effects

	Ambiguity types			
	Near SEU	Ambiguity averse	Ambiguity seeking	High noise
Age: $\in (35, 50]$	-0.058	-0.013	-0.019	0.089^{**}
	(0.036)	(0.036)	(0.037)	(0.04)
Age: $\in (50, 65]$	-0.077^{**}	-0.055	0.0081	0.12^{***}
	(0.035)	(0.035)	(0.035)	(0.038)
Age: ≥ 65	-0.11^{***}	-0.077^{**}	-0.023	0.21^{***}
	(0.035)	(0.035)	(0.035)	(0.037)
Education: Upper secondary	0.068^{**}	-0.029	-0.026	-0.012
	(0.032)	(0.027)	(0.027)	(0.024)
Education: Tertiary	0.078^{**}	-0.052^{*}	-0.034	0.0082
	(0.032)	(0.03)	(0.029)	(0.026)
Income: $\in (1.1, 1.6]$	-0.054^{*}	0.038	0.017	-0.0001
	(0.032)	(0.03)	(0.03)	(0.024)
Income: $\in (1.6, 2.2]$	-0.058^{*}	0.083^{***}	0.021	-0.046^{*}
	(0.032)	(0.031)	(0.03)	(0.027)
Income: ≥ 2.2	-0.086^{**}	0.067^{*}	0.019	-0.0001
	(0.034)	(0.035)	(0.032)	(0.028)
Financial assets: $\in (1.8, 11.2]$	0.07^{**}	-0.018	0.031	-0.084^{***}
	(0.034)	(0.028)	(0.03)	(0.026)
Financial assets: $\in (11.2, 32]$	0.15^{***}	-0.081^{***}	-0.042	-0.027
	(0.033)	(0.031)	(0.033)	(0.026)
Financial assets: ≥ 32	0.087^{**}	-0.085^{**}	-0.0014	0
	(0.034)	(0.035)	(0.033)	(0.029)
Female	-0.017	0.088^{***}	0.027	-0.098^{***}
	(0.022)	(0.021)	(0.021)	(0.019)
Risk aversion index	-0.013	0.016	-0.0045	0.0014
	(0.011)	(0.011)	(0.011)	(0.0088)
Numeracy index	0.22^{***}	-0.063^{***}	-0.021^{*}	-0.14^{***}
	(0.017)	(0.012)	(0.013)	(0.01)
Observations	1692	1692	1692	1692
Pseudo R^2	0.14	0.14	0.14	0.14

Notes: This table replicates Table F.2 using all observations.

Table G.12. Ambiguity attitudes and portfolio choice: Marginal effects

	Owns risky assets (Probit)		Share risky assets (Tobit)	
	(1)	(2)	(3)	(4)
Ambiguity averse type	-0.21^{***}	-0.071^{***}	-0.42^{***}	-0.15^{***}
	(0.022)	(0.023)	(0.059)	(0.055)
Ambiguity seeking type	-0.099^{***}	-0.0086	-0.14^{***}	-0.0067
	(0.027)	(0.023)	(0.051)	(0.047)
High noise type	-0.16^{***}	-0.042	-0.2^{***}	-0.064
	(0.026)	(0.026)	(0.057)	(0.057)
Age: $\in (35, 50]$		-0.033		-0.025
		(0.034)		(0.066)
Age: $\in (50, 65]$		-0.0067		0.023
		(0.032)		(0.063)
Age: ≥ 65		-0.022		0.024
		(0.033)		(0.064)
Female		-0.025		-0.035
		(0.017)		(0.04)
Education: Upper secondary		0.015		0.053
		(0.025)		(0.058)
Education: Tertiary		0.034		0.12^{**}
		(0.026)		(0.058)
Income: $\in (1.1, 1.6]$		0.0035		0.044
		(0.027)		(0.062)
Income: $\in (1.6, 2.2]$		0.0005		0.034
		(0.028)		(0.061)
Income: ≥ 2.2		0.063^{**}		0.11^{*}
		(0.029)		(0.061)
Financial assets: $\in (1.8, 11.2]$		0.037^{**}		0.1
		(0.018)		(0.085)
Financial assets: $\in (11.2, 32]$		0.15^{***}		0.36^{***}
		(0.022)		(0.083)
Financial assets: ≥ 32		0.39^{***}		0.71^{***}
		(0.028)		(0.085)
Risk aversion index		-0.048^{***}		-0.12^{***}
		(0.0094)		(0.021)
Numeracy index		0.039^{**}		0.073^{**}
		(0.016)		(0.03)
Observations	1853	1692	1690	1561
Pseudo R^2	0.047	0.3	0.036	0.28
p-values for differences between				
Ambiguity averse, Ambiguity seeking	0	0.015	0	0.015
Ambiguity averse, High noise	0.023	0.28	0.0014	0.19
Ambiguity seeking, High noise	0.031	0.23	0.39	0.34

Notes: This table replicates the regressions shown in Table 7 using all observations.

G.2 Balanced panel only

This section reports on changes to our results when require full six waves of data that meet our inclusion criteria, i.e., variation across options and, if there is no variation, completion time outside the fastest 15 % (see Section 2.3). The section is structured so that we repeat all tables and figures from the paper as well as those from this Online Appendix, which seem useful for the reader to obtain a complete picture.

The number individuals drops by more than 40%, from 2177 to 1239. Nevertheless, the descriptive statistics on matching probabilities from Section 2 remain essentially the same. In terms of sample composition (cf. Tables G.17 and 3), the female share drops by 5 percentage points and average age goes up by two years. Wave-by-wave parameter estimates are similar with slightly lower average values of ambiguity aversion in Table G.18 compared to Table E.1. Parameter estimates for stability over time / across domains are economically the same and statistically indistinguishable from each other (cf. Table G.19 vs. 4 and Table G.20 vs. 5).

Despite the large change in the number of individuals, the estimated types in Figure G.4 are almost identical to those in Figure 6. For the ambiguity averse type, $\bar{\alpha}^{AEX}$ is estimated to be 0.12 instead of 0.15; there are small shifts in $\bar{\ell}^{AEX}$ for the high noise and ambiguity seeking types. Estimated population shares are virtually the same and so are most choice probabilities for our examples. The only exception is for the ambiguity averse type, where the just-noted decrease in $\bar{\alpha}^{AEX}$ implies up to 7 percentage point greater probabilities to choose the ambiguous option. Of course, the changes in demographics are reflected in average group characteristics, too. However, differences between groups remain the same. Broad patterns of portfolio choice behavior (Table G.24) remain broadly similar. The much-reduced sample size appears to be balanced by a sharper distinction of types, as all differences between the ambiguity averse on the one hand compared to near SEU or ambiguity seeking types on the other hand continue to be significant with various p-values decreasing even more. The ambiguity seeking and near SEU types look much more like each other than in their portfolio choice behavior than in our main specification. Differences are never significant and point estimates flip sign when controlling for covariates. In all specifications, the ambiguity seeking take more risk than the high noise types. These comparisons were all insignificant in our main specification.

Tables and figures corresponding to Section 2

Table G.13. Matching probabilities, empirical frequencies and judged historical frequencies

	Mean	Std. Dev.	$q_{0.1}$	$q_{0.5}$	$q_{0.9}$	Empir. Freq. '99-'19	Judged Freq., '99-'19
$E_0^{AEX}: Y_{t+6} \in (1000, \infty)$	0.5	0.27	0.15	0.45	0.93	0.63	0.52
$E_1^{AEX}: Y_{t+6} \in (1100, \infty]$	0.35	0.24	0.075	0.35	0.65	0.24	0.31
$E_{1,C}^{AEX}: Y_{t+6} \in (-\infty, 1100]$	0.52	0.28	0.15	0.45	0.93	0.76	
$E_2^{AEX}: Y_{t+6} \in (-\infty, 950)$	0.37	0.25	0.075	0.35	0.65	0.28	0.22
$E_{2,C}^{AEX}: Y_{t+6} \in [950, \infty)$	0.56	0.28	0.15	0.55	0.97	0.72	
$E_3^{AEX}: Y_{t+6} \in [950, 1100]$	0.58	0.27	0.25	0.55	0.97	0.48	0.47
$E_{3,C}^{AEX}: Y_{t+6} \in (-\infty, 950) \cup (1100, \infty)$	0.42	0.26	0.075	0.45	0.75	0.52	

Notes: This table replicates Table 1 in a balanced panel.

Table G.14. Average matching probabilities by wave

	2018-11	2019-05	2019-11	2020-05	2020-11
$E_0^{AEX}: Y_{t+6} \in (1000, \infty)$	0.51	0.53	0.51	0.43	0.52
$E_1^{AEX}: Y_{t+6} \in (1100, \infty]$	0.36	0.36	0.36	0.33	0.35
$E_{1,C}^{AEX}: Y_{t+6} \in (-\infty, 1100]$	0.51	0.52	0.53	0.52	0.55
$E_2^{AEX}: Y_{t+6} \in (-\infty, 950)$	0.35	0.33	0.36	0.43	0.36
$E_{2,C}^{AEX}: Y_{t+6} \in [950, \infty)$	0.54	0.57	0.57	0.52	0.59
$E_3^{AEX}: Y_{t+6} \in [950, 1100]$	0.56	0.59	0.59	0.54	0.61
$E_{3,C}^{AEX}: Y_{t+6} \in (-\infty, 950) \cup (1100, \infty)$	0.42	0.4	0.4	0.45	0.41

Notes: This table replicates Table D.2 in a balanced panel.

Table G.15. Matching probabilities for climate questions

	N subj.	Mean	$q_{0.1}$	$q_{0.5}$	$q_{0.9}$	Empirical Frequency, 1999-2019
$E_0^{climate}: \Delta T \in (0°C, \infty)$	1234	0.53	0.15	0.55	0.93	0.53
$E_1^{climate}: \Delta T \in (1°C, \infty]$	1234	0.46	0.075	0.45	0.93	0.23
$E_{1,C}^{climate}: \Delta T \in (-\infty, 1°C]$	1234	0.53	0.15	0.55	0.93	
$E_2^{climate}: \Delta T \in (-\infty, -0.5°C)$	1234	0.4	0.03	0.35	0.75	0.27
$E_{2,C}^{climate}: \Delta T \in [-0.5°C, \infty)$	1234	0.5	0.075	0.45	0.93	
$E_3^{climate}: \Delta T \in [-0.5°C, 1°C]$	1234	0.51	0.15	0.45	0.93	0.5
$E_{3,C}^{climate}: \Delta T \in (-\infty, -0.5°C) \cup (1°C, \infty)$	1234	0.48	0.075	0.45	0.93	

Notes: This table replicates Table D.3 in a balanced panel.

Table G.16. Judged historical frequencies and set-monotonicity violations

	Dependent variable: Set-monotonicity violation			
	(1)	(2)	(3)	(4)
Intercept	0.14***	0.17***		
	(0.0029)	(0.0036)		
Judged frequencies (superset - subset)		−0.078***	−0.045***	−0.037***
		(0.0064)	(0.0059)	(0.0066)
Superset-subset pair fixed effects	No	No	Yes	Yes
Individual fixed effects	No	No	No	Yes
Observations	9912	9912	9912	9912

Notes: This table replicates Table 2 in a balanced panel.

Table G.17. Descriptive statistics on key variables

	N Subj.	Mean	Std. Dev.	$q_{0.25}$	$q_{0.5}$	$q_{0.75}$
Female	1239	0.45				
Education: Lower secondary and below	1239	0.28				
Education: Upper secondary	1239	0.33				
Education: Tertiary	1239	0.39				
Age	1239	59	15	50	63	71
Monthly hh net income (equiv., thousands)	1205	2.2	1	1.6	2.1	2.7
Total hh financial assets (equiv., thousands)	1010	46	120	3.5	15	41
Owns risky financial assets	1010	0.22				
Share risky financial assets (if any)	220	0.32	0.26	0.11	0.26	0.5
Risk aversion index	1239	0	1	−0.68	−0.0042	0.7
Numeracy index	1239	0	1	−0.48	0.26	0.74
Understands climate change	1239	0.55	0.21	0.5	0.5	0.75
Threatened by climate change	1239	0.54	0.22	0.4	0.6	0.6

Notes: This table replicates Table 3 in a balanced panel.

Tables and figures corresponding to Section 3

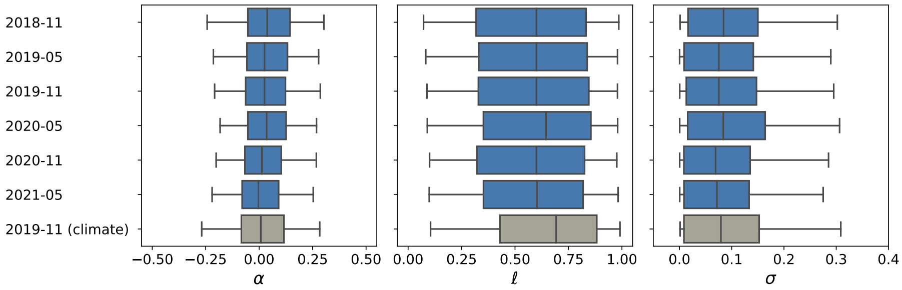


Figure G.3. Distributions of estimated parameters, wave by wave

Notes: This figure replicates Figure 5 in a balanced panel.

Table G.18. Marginal distributions of estimated parameters, wave by wave

		Mean	Std. dev.	$q_{0.05}$	$q_{0.25}$	$q_{0.5}$	$q_{0.75}$	$q_{0.95}$
α	2018-11	0.042	0.17	−0.24	−0.053	0.038	0.14	0.3
	2019-05	0.036	0.15	−0.21	−0.057	0.025	0.13	0.28
	2019-11	0.031	0.15	−0.21	−0.063	0.025	0.12	0.29
	2020-05	0.038	0.14	−0.18	−0.053	0.035	0.13	0.27
	2020-11	0.022	0.14	−0.2	−0.066	0.013	0.1	0.27
	2021-05	0.0075	0.15	−0.22	−0.08	−0.0037	0.091	0.25
	Observations from all AEX waves	0.029	0.15	−0.21	−0.063	0.022	0.12	0.28
	2019-11 (Climate Change)	0.014	0.17	−0.27	−0.083	0.0078	0.12	0.29
ℓ	2018-11	0.57	0.29	0.072	0.32	0.6	0.83	0.99
	2019-05	0.58	0.29	0.082	0.33	0.6	0.84	0.98
	2019-11	0.58	0.29	0.088	0.33	0.6	0.85	0.98
	2020-05	0.59	0.29	0.089	0.35	0.64	0.85	0.98
	2020-11	0.57	0.29	0.1	0.32	0.6	0.83	0.98
	2021-05	0.58	0.28	0.099	0.35	0.6	0.82	0.98
	Observations from all AEX waves	0.58	0.29	0.09	0.33	0.6	0.84	0.98
	2019-11 (Climate Change)	0.63	0.28	0.1	0.43	0.69	0.88	0.99
σ	2018-11	0.11	0.098	0.0012	0.016	0.085	0.15	0.3
	2019-05	0.095	0.093	0.0003	0.0088	0.075	0.14	0.29
	2019-11	0.098	0.094	0.0006	0.013	0.075	0.15	0.3
	2020-05	0.11	0.1	0.0005	0.016	0.084	0.16	0.31
	2020-11	0.092	0.12	0.0005	0.0085	0.069	0.14	0.29
	2021-05	0.092	0.1	0.0006	0.0087	0.072	0.13	0.28
	Observations from all AEX waves	0.099	0.1	0.0006	0.0098	0.076	0.14	0.29
	2019-11 (Climate Change)	0.1	0.1	0.0012	0.0086	0.079	0.15	0.31

Notes: This table replicates Table E.1 in a balanced panel.

Table G.19. Predicting last three waves of ambiguity parameters with first three waves

		OLS	ORIV	
		(1)	(2)	(3)
$\alpha^{AEX}_{\text{last 3 waves}}$	Intercept	0.013^{***}	-0.013^{***}	
		(0.0029)	(0.0043)	
	$\alpha^{AEX}_{\text{first 3 waves}}$	0.25^{***}	0.98^{***}	1.04^{***}
		(0.02)	(0.08)	(0.11)
	Adj. R^2	0.073		
	1st st. F		110	74
$\ell^{AEX}_{\text{last 3 waves}}$	Intercept	0.37^{***}	0.034	
		(0.0099)	(0.025)	
	$\ell^{AEX}_{\text{first 3 waves}}$	0.36^{***}	0.95^{***}	0.95^{***}
		(0.01)	(0.04)	(0.05)
	Adj. R^2	0.14		
	1st st. F		403	243
$\sigma^{AEX}_{\text{last 3 waves}}$	Intercept	0.066^{***}	-0.0019	
		(0.0022)	(0.0062)	
	$\sigma^{AEX}_{\text{first 3 waves}}$	0.31^{***}	1.00^{***}	0.98^{***}
		(0.02)	(0.06)	(0.09)
	Adj. R^2	0.077		
	1st st. F		182	96
Controls		No	No	Yes
N Subjects		1239	1239	995

Notes: This table replicates the regressions shown in Table 4 in a balanced panel.

Table G.20. Predicting climate ambiguity parameters with AEX parameters

		OLS	2SLS	
		(1)	(2)	(3)
$\alpha^{climate}_{2019-11}$	Intercept	-0.0055	-0.018^{***}	
		(0.0041)	(0.0047)	
	$\alpha^{AEX}_{2019-11}$	0.65^{***}	1.07^{***}	1.11^{***}
		(0.04)	(0.07)	(0.08)
	Adj. R^2	0.34		
	1st st. F		156	113
$\ell^{climate}_{2019-11}$	Intercept	0.43^{***}	0.29^{***}	
		(0.018)	(0.028)	
	$\ell^{AEX}_{2019-11}$	0.35^{***}	0.60^{***}	0.65^{***}
		(0.03)	(0.05)	(0.06)
	Adj. R^2	0.14		
	1st st. F		546	319
$\sigma^{climate}_{2019-11}$	Intercept	0.05^{***}	0.02^{***}	
		(0.0032)	(0.0059)	
	$\sigma^{AEX}_{2019-11}$	0.54^{***}	0.84^{***}	0.86^{***}
		(0.03)	(0.06)	(0.09)
	Adj. R^2	0.24		
	1st st. F		56	33
Controls		No	No	Yes
N Subjects		1230	1230	988

Notes: This table replicates the regressions shown in Table 5 in a balanced panel.

Tables and figures corresponding to Section 4

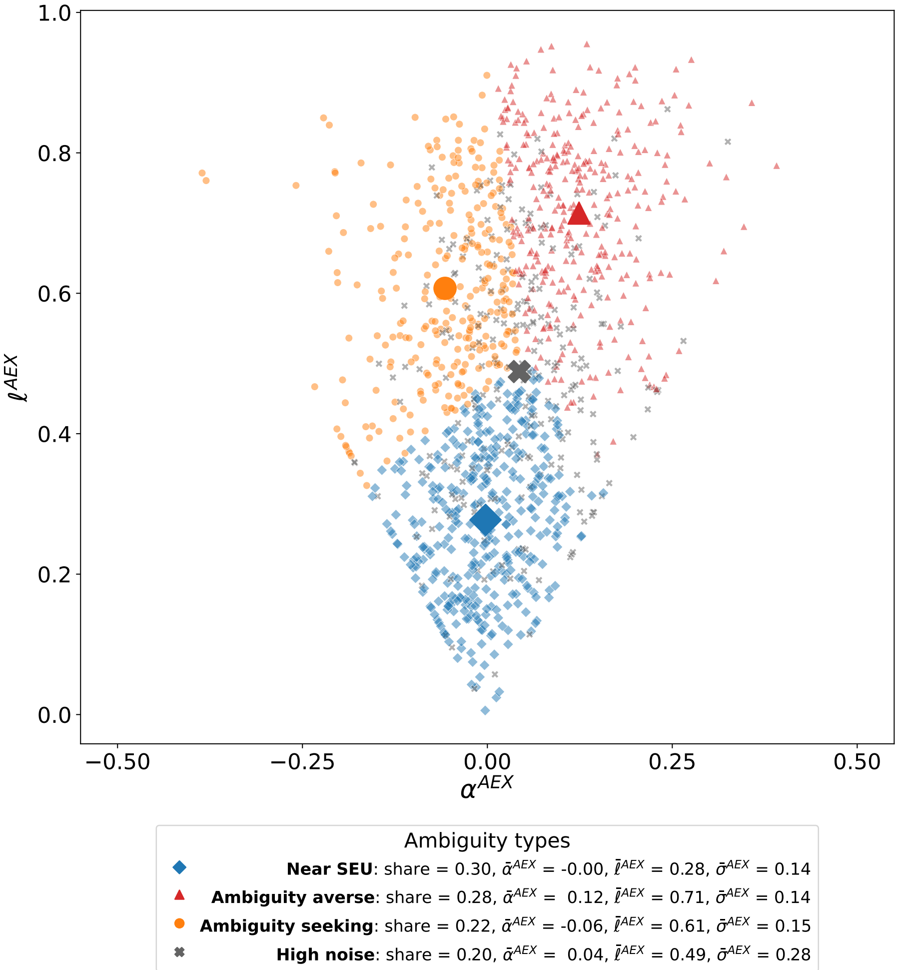


Figure G.4. Summarizing heterogeneity in ambiguity profiles with K=4 discrete groups

Notes: This figure replicates Figure 6 in a balanced panel.

	Mean	Std. dev.	$q_{0.05}$	$q_{0.25}$	$q_{0.5}$	$q_{0.75}$	$q_{0.95}$
α^{AEX}	0.029	0.096	−0.12	−0.033	0.026	0.089	0.2
ℓ^{AEX}	0.51	0.22	0.16	0.34	0.52	0.69	0.85
σ^{AEX}	0.17	0.073	0.072	0.12	0.16	0.21	0.31

Table G.21. Example situations: Decision weights and choice probabilities for ambiguity types

				$\text{Pr}_{\text{subj}} = p = 0.25$		$\text{Pr}_{\text{subj}} = p = 0.5$		$\text{Pr}_{\text{subj}} = p = 0.75$	
				$W(E) - p$	Pr(choice $= AEX$)	$W(E) - p$	Pr(choice $= AEX$)	$W(E) - p$	Pr(choice $= AEX$)
Ambiguity type	α	ℓ	σ						
Near SEU	-0.0024	0.28	0.14	0.072	0.7	0.0024	0.51	−0.067	0.32
Ambiguity averse	0.12	0.71	0.14	0.055	0.65	−0.12	0.2	−0.3	0.018
Ambiguity seeking	-0.057	0.61	0.15	0.21	0.92	0.057	0.65	−0.095	0.26
High noise	0.043	0.49	0.28	0.079	0.61	−0.043	0.44	−0.17	0.28

Notes: This table replicates Table F.1 in a balanced panel.

Table G.22. Average characteristics of group members

	Ambiguity types			
	Near SEU	Ambiguity averse	Ambiguity seeking	High noise
Share	0.3	0.28	0.22	0.2
α^{AEX}	−0.0024	0.12	−0.057	0.043
	(0.003)	(0.0037)	(0.0043)	(0.0053)
ℓ^{AEX}	0.28	0.71	0.61	0.49
	(0.0055)	(0.0067)	(0.0077)	(0.011)
σ^{AEX}	0.14	0.14	0.15	0.28
	(0.0022)	(0.0028)	(0.0029)	(0.003)
Education: Lower secondary and below	0.14	0.31	0.28	0.44
	(0.018)	(0.025)	(0.027)	(0.032)
Education: Upper secondary	0.32	0.37	0.33	0.3
	(0.024)	(0.026)	(0.028)	(0.03)
Education: Tertiary	0.54	0.32	0.38	0.25
	(0.026)	(0.025)	(0.029)	(0.028)
Age	57	57	59	66
	(0.8)	(0.82)	(0.84)	(0.8)
Female	0.34	0.56	0.48	0.44
	(0.025)	(0.027)	(0.03)	(0.032)
Monthly hh net income (equiv., thousands)	2.5	2.2	2.2	2
	(0.054)	(0.049)	(0.075)	(0.053)
Total hh financial assets (equiv., thousands)	61	32	51	34
	(8.7)	(4.3)	(9.7)	(5.4)
Risk aversion index	−0.081	0.11	−0.021	−0.0034
	(0.045)	(0.056)	(0.063)	(0.069)
Numeracy index	0.61	−0.18	0.067	−0.76
	(0.03)	(0.045)	(0.054)	(0.078)

Notes: This table replicates Table 6 in a balanced panel.

Table G.23. Predictors of groups, marginal effects

	Ambiguity types			
	Near SEU	Ambiguity averse	Ambiguity seeking	High noise
Age: $\in(35, 50]$	0.021	−0.055	−0.051	0.085
	(0.055)	(0.057)	(0.057)	(0.059)
Age: $\in(50, 65]$	−0.056	-0.1^{**}	0.045	0.11^{**}
	(0.052)	(0.053)	(0.051)	(0.055)
Age: ≥ 65	−0.049	-0.11^{**}	−0.07	0.23^{***}
	(0.052)	(0.052)	(0.052)	(0.054)
Education: Upper secondary	0.061	−0.01	−0.032	−0.019
	(0.04)	(0.036)	(0.036)	(0.03)
Education: Tertiary	0.068	-0.07^{*}	0.0075	−0.0064
	(0.042)	(0.042)	(0.037)	(0.033)
Income: $\in(1.1, 1.6]$	-0.11^{***}	0.098^{**}	0.001	0.0092
	(0.041)	(0.04)	(0.039)	(0.031)
Income: $\in(1.6, 2.2]$	-0.086^{**}	0.14^{***}	−0.012	−0.04
	(0.041)	(0.044)	(0.041)	(0.035)
Income: ≥ 2.2	-0.12^{***}	0.14^{***}	−0.043	0.033
	(0.043)	(0.048)	(0.043)	(0.037)
Financial assets: $\in(1.8, 11.2]$	0.11^{**}	-0.076^{*}	0.09^{**}	-0.12^{***}
	(0.044)	(0.039)	(0.039)	(0.034)
Financial assets: $\in(11.2, 32]$	0.14^{***}	-0.077^{*}	−0.023	−0.043
	(0.043)	(0.041)	(0.044)	(0.033)
Financial assets: ≥ 32	0.11^{**}	-0.092^{**}	0.056	-0.076^{**}
	(0.044)	(0.045)	(0.043)	(0.037)
Female	−0.022	0.072^{**}	0.036	-0.086^{***}
	(0.028)	(0.028)	(0.028)	(0.024)
Risk aversion index	−0.006	0.027^{**}	−0.019	−0.0022
	(0.014)	(0.014)	(0.014)	(0.011)
Numeracy index	0.25^{***}	-0.086^{***}	-0.036^{**}	-0.13^{***}
	(0.023)	(0.016)	(0.017)	(0.013)
Observations	995	995	995	995
Pseudo R^2	0.15	0.15	0.15	0.15

Notes: This table replicates Table F.2 in a balanced panel.

Table G.24. Ambiguity attitudes and portfolio choice: Marginal effects

	Owns risky assets (Probit)		Share risky assets (Tobit)	
	(1)	(2)	(3)	(4)
Ambiguity averse type	-0.21^{***}	-0.085^{***}	-0.36^{***}	-0.15^{**}
	(0.032)	(0.028)	(0.067)	(0.061)
Ambiguity seeking type	-0.031	0.037	-0.016	0.077
	(0.04)	(0.031)	(0.057)	(0.051)
High noise type	-0.19^{***}	-0.057	-0.25^{***}	-0.079
	(0.035)	(0.039)	(0.071)	(0.068)
Age: $\in (35, 50]$		-0.022		0.033
		(0.053)		(0.087)
Age: $\in (50, 65]$		0.0031		0.057
		(0.051)		(0.081)
Age: ≥ 65		-0.015		0.066
		(0.05)		(0.081)
Female		-0.024		-0.011
		(0.024)		(0.046)
Education: Upper secondary		0.028		0.096
		(0.033)		(0.068)
Education: Tertiary		0.072^{**}		0.2^{***}
		(0.036)		(0.069)
Income: $\in (1.1, 1.6]$		0.0059		0.03
		(0.038)		(0.069)
Income: $\in (1.6, 2.2]$		-0.052		-0.083
		(0.037)		(0.069)
Income: ≥ 2.2		0.047		0.042
		(0.038)		(0.067)
Financial assets: $\in (1.8, 11.2]$		0.045^{*}		0.1
		(0.026)		(0.092)
Financial assets: $\in (11.2, 32]$		0.17^{***}		0.34^{***}
		(0.029)		(0.089)
Financial assets: ≥ 32		0.42^{***}		0.65^{***}
		(0.038)		(0.091)
Risk aversion index		-0.053^{***}		-0.12^{***}
		(0.013)		(0.023)
Numeracy index		0.035		0.067^{**}
		(0.027)		(0.034)
Observations	1010	995	940	933
Pseudo R^2	0.053	0.33	0.046	0.33
p-values for differences between				
Ambiguity averse, Ambiguity seeking	0	0.0002	0	0.0004
Ambiguity averse, High noise	0.39	0.41	0.17	0.36
Ambiguity seeking, High noise	0.0001	0.016	0.0018	0.027

Notes: This table replicates the regressions shown in Table 7 in a balanced panel.

G.3 Relaxing restrictions on model parameters

This section reports on changes to our results when we re-estimate our model relaxing the restrictions we have made on the ambiguity parameters. As in the previous two sections, this section is structured so that we repeat all tables and figures from the paper as well as those from this Online Appendix, which seem useful for the reader to obtain a complete picture. In this case, the sample compositions and matching probabilities are not affected, so we only report tables and figures corresponding to Sections 3 and 4.

Our main specification ensures that parameter estimates lead to valid parameters in a class of multiple prior models (see Section A.2) by requiring $0 \leq \tau_1^S$, $0 \leq \tau_0^S \leq 1 - \tau_1^S$. While $\tau_1^S > 0$ leads to a negative slope of the source function and cannot be accommodated by any sensible choice model, $0 \leq \tau_0^S \leq 1 - \tau_1^S$ can be dropped if we take a more descriptive approach and interpret the parameters only as decision weights, without connection to multiple prior models. Without those restrictions, the slope of the source function can become larger than 1 and it is no longer ensured that $\tau_0^S + \tau_1^S \cdot \mathrm{Pr}_{\mathrm{subj}}(E)$ is bounded between 0 and 1. Therefore, we winsorize the decision weights at 0 and 1 as follows:

$$\begin{aligned} W(E) &= \min\{\max\{\tau_0^S + \tau_1^S \cdot \mathrm{Pr}_{\mathrm{subj}}(E), 0\}, 1\} \text{ for } \mathrm{Pr}_{\mathrm{subj}}(E) \in (0,1) \\ W(E) &= 0 \text{ for } \mathrm{Pr}_{\mathrm{subj}}(E) = 0, \quad W(E) = 1 \text{ for } \mathrm{Pr}_{\mathrm{subj}}(E) = 1 \\ 0 &\leq \tau_1^S \end{aligned} \tag{G.1}$$

Since we bound the decision weight at values below 0 and above 1, the source function is no longer linear for all subjects and the relation of τ_0^S and τ_1^S to the ambiguity parameters α and ℓ becomes more complicated. We calculate the area between the 45 degree line and $W(E)$ to obtain α, and 1 minus the average slope of $W(E)$ over the range $\mathrm{Pr}(E) \in [0.05, 0.95]$ to obtain ℓ. For all subjects whose estimated parameters fulfill the restriction $0 \leq \tau_0^S \leq 1 - \tau_1^S$ (92% of the sample), this calculation is equivalent to the simpler formulas (4) defined in Section 2.1.

Comparing Table G.25 and Table E.1 shows that the mean of ℓ drops by 0.02. At the same time, the distributions of α and σ hardly change. This might not be too surprising given that only 8 % of observations are affected by the restriction. Similarly, parameter estimates for stability over time / across domains are economically the same and statistically indistinguishable from each other (cf. Table G.26 vs. 4 and Table G.27 vs. 5).

The most salient feature in Figure G.6 compared to Figure 6 is that some individuals' estimates now fall outside the range of data considered valid in our main estimation. Most of these are classified as either ambiguity averse or as near SEU types. When it comes to the classification, neither the average parameter estimates per group nor their shares change beyond what shows up as rounding differences. Thus, it does not come as a surprise that group compositions (Table G.29) and patterns of portfolio choice behavior (Table G.31) remain unchanged.

Tables and figures corresponding to Section 3

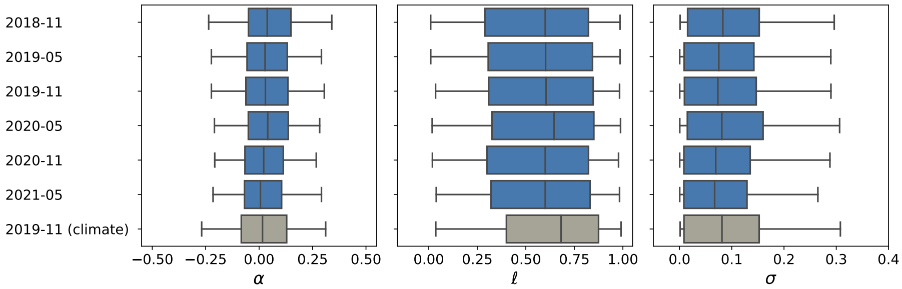


Figure G.5. Distributions of estimated parameters, wave by wave

Notes: This figure replicates Figure 5 without restricting ℓ from below.

Table G.25. Marginal distributions of estimated parameters, wave by wave

		Mean	Std. dev.	$q_{0.05}$	$q_{0.25}$	$q_{0.5}$	$q_{0.75}$	$q_{0.95}$
α	2018-11	0.046	0.17	−0.24	−0.05	0.038	0.15	0.34
	2019-05	0.035	0.16	−0.22	−0.056	0.028	0.13	0.29
	2019-11	0.035	0.16	−0.23	−0.062	0.029	0.13	0.31
	2020-05	0.04	0.15	−0.21	−0.05	0.04	0.14	0.28
	2020-11	0.025	0.15	−0.21	−0.066	0.021	0.11	0.27
	2021-05	0.02	0.15	−0.22	−0.069	0.0062	0.11	0.29
	Observations from all AEX waves	0.034	0.16	−0.22	−0.059	0.028	0.13	0.3
	2019-11 (Climate Change)	0.02	0.17	−0.27	−0.083	0.016	0.13	0.31
ℓ	2018-11	0.55	0.32	0.0099	0.29	0.6	0.82	0.99
	2019-05	0.56	0.31	0.01	0.31	0.6	0.84	0.99
	2019-11	0.57	0.31	0.035	0.31	0.6	0.85	0.98
	2020-05	0.58	0.31	0.016	0.33	0.65	0.85	0.99
	2020-11	0.56	0.31	0.017	0.3	0.6	0.82	0.98
	2021-05	0.57	0.31	0.037	0.32	0.6	0.83	0.98
	Observations from all AEX waves	0.56	0.31	0.019	0.31	0.6	0.84	0.98
	2019-11 (Climate Change)	0.61	0.3	0.036	0.4	0.68	0.87	0.99
σ	2018-11	0.1	0.1	0.0011	0.015	0.083	0.15	0.3
	2019-05	0.097	0.1	0.0004	0.0088	0.075	0.14	0.29
	2019-11	0.097	0.094	0.0004	0.0094	0.073	0.15	0.29
	2020-05	0.11	0.11	0.0005	0.015	0.081	0.16	0.31
	2020-11	0.093	0.099	0.0003	0.0083	0.069	0.14	0.29
	2021-05	0.087	0.088	0.0004	0.0083	0.067	0.13	0.27
	Observations from all AEX waves	0.098	0.1	0.0005	0.009	0.075	0.14	0.29
	2019-11 (Climate Change)	0.1	0.1	0.0012	0.0085	0.081	0.15	0.31

Notes: This table replicates Table E.1 without restricting ℓ from below.

Table G.26. Predicting last three waves of ambiguity parameters with first three waves

		OLS	ORIV	
		(1)	(2)	(3)
$\alpha^{AEX}_{\text{last 3 waves}}$	Intercept	0.017^{***}	-0.0099^{***}	
		(0.0025)	(0.0038)	
	$\alpha^{AEX}_{\text{first 3 waves}}$	0.25^{***}	0.94^{***}	0.96^{***}
		(0.01)	(0.07)	(0.09)
	Adj. R^2	0.07		
	1st st. F		152	106
$\ell^{AEX}_{\text{last 3 waves}}$	Intercept	0.38^{***}	0.024	
		(0.0088)	(0.024)	
	$\ell^{AEX}_{\text{first 3 waves}}$	0.34^{***}	0.97^{***}	0.95^{***}
		(0.01)	(0.04)	(0.05)
	Adj. R^2	0.12		
	1st st. F		433	259
$\sigma^{AEX}_{\text{last 3 waves}}$	Intercept	0.068^{***}	-0.0026	
		(0.0024)	(0.0063)	
	$\sigma^{AEX}_{\text{first 3 waves}}$	0.28^{***}	0.99^{***}	1.00^{***}
		(0.02)	(0.06)	(0.10)
	Adj. R^2	0.075		
	1st st. F		94	38
Controls		No	No	Yes
N Subjects		1859	1859	1452

Notes: This table replicates the regressions shown in Table 4 without restricting ℓ from below.

Table G.27. Predicting climate ambiguity parameters with AEX parameters

		OLS	2SLS	
		(1)	(2)	(3)
$\alpha^{climate}_{2019-11}$	Intercept	-0.0029	-0.016^{***}	
		(0.0034)	(0.0039)	
	$\alpha^{AEX}_{2019-11}$	0.68^{***}	1.04^{***}	1.06^{***}
		(0.03)	(0.05)	(0.07)
	Adj. R^2	0.39		
	1st st. F		217	150
$\ell^{climate}_{2019-11}$	Intercept	0.42^{***}	0.27^{***}	
		(0.015)	(0.026)	
	$\ell^{AEX}_{2019-11}$	0.34^{***}	0.61^{***}	0.66^{***}
		(0.02)	(0.04)	(0.06)
	Adj. R^2	0.12		
	1st st. F		624	360
$\sigma^{climate}_{2019-11}$	Intercept	0.054^{***}	0.019^{***}	
		(0.0027)	(0.0051)	
	$\sigma^{AEX}_{2019-11}$	0.49^{***}	0.86^{***}	0.93^{***}
		(0.03)	(0.06)	(0.08)
	Adj. R^2	0.22		
	1st st. F		101	54
Controls		No	No	Yes
N Subjects		1843	1843	1411

Notes: This table replicates the regressions shown in Table 5 without restricting ℓ from below.

Tables and figures corresponding to Section 4

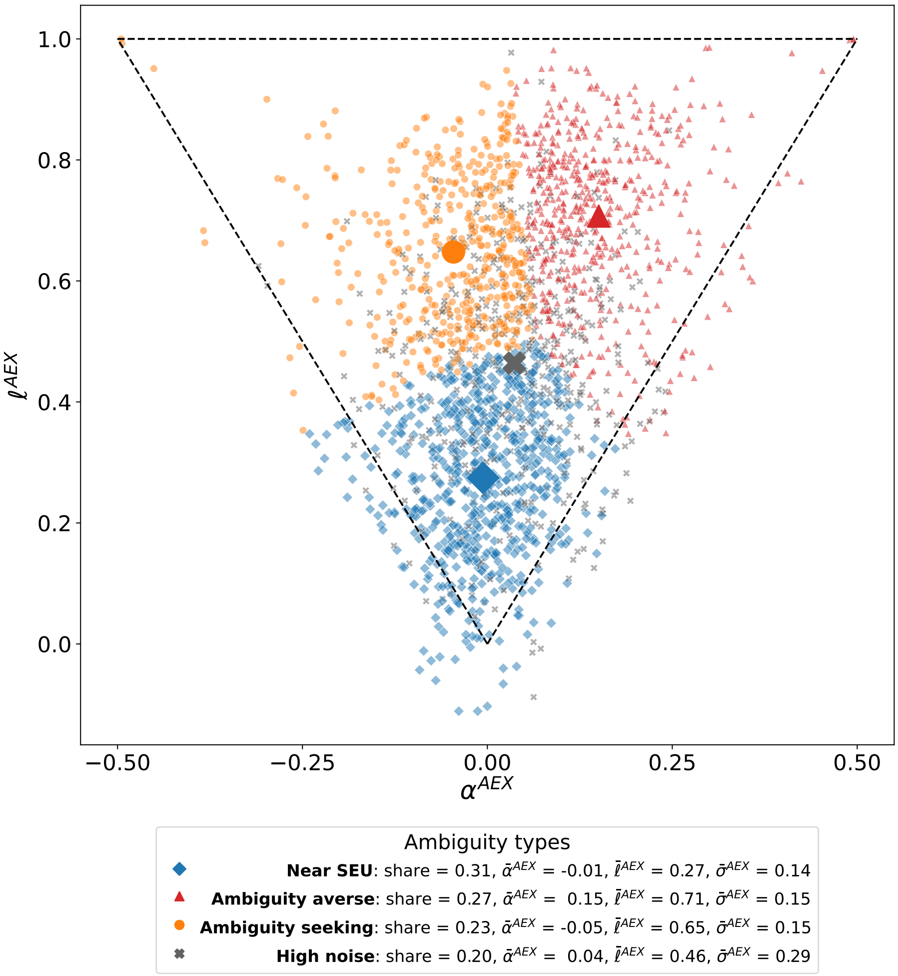


Figure G.6. Summarizing heterogeneity in ambiguity profiles with K=4 discrete groups

Notes: This figure replicates Figure 6 without restricting ℓ from below.

	Mean	Std. dev.	$q_{0.05}$	$q_{0.25}$	$q_{0.5}$	$q_{0.75}$	$q_{0.95}$
α^{AEX}	0.035	0.11	−0.13	−0.031	0.032	0.1	0.22
ℓ^{AEX}	0.51	0.23	0.13	0.34	0.53	0.69	0.85
σ^{AEX}	0.17	0.079	0.066	0.11	0.16	0.22	0.33

Table G.28. Example situations: Decision weights and choice probabilities for ambiguity types

				$\text{Pr}_{\text{subj}} = p = 0.25$		$\text{Pr}_{\text{subj}} = p = 0.5$		$\text{Pr}_{\text{subj}} = p = 0.75$	
				$W(E) - p$	Pr(choice $= AEX$)	$W(E) - p$	Pr(choice $= AEX$)	$W(E) - p$	Pr(choice $= AEX$)
Ambiguity type	α	ℓ	σ						
Near SEU	-0.0058	0.27	0.14	0.074	0.71	0.0058	0.52	−0.063	0.32
Ambiguity averse	0.15	0.71	0.15	0.026	0.57	−0.15	0.15	−0.33	0.012
Ambiguity seeking	-0.046	0.65	0.15	0.21	0.92	0.046	0.62	−0.12	0.21
High noise	0.036	0.46	0.29	0.08	0.61	−0.036	0.45	−0.15	0.3

Notes: This table replicates Table F.1 without restricting ℓ from below.

Table G.29. Average characteristics of group members

	Ambiguity types			
	Near SEU	Ambiguity averse	Ambiguity seeking	High noise
Share	0.31	0.27	0.23	0.2
α^{AEX}	−0.0058	0.15	−0.046	0.036
	(0.0026)	(0.0032)	(0.0038)	(0.0043)
ℓ^{AEX}	0.27	0.71	0.65	0.46
	(0.0048)	(0.0056)	(0.0055)	(0.0085)
σ^{AEX}	0.14	0.15	0.15	0.29
	(0.0017)	(0.0024)	(0.0024)	(0.0025)
Education: Lower secondary and below	0.12	0.3	0.26	0.43
	(0.013)	(0.019)	(0.02)	(0.024)
Education: Upper secondary	0.31	0.38	0.36	0.29
	(0.018)	(0.02)	(0.022)	(0.022)
Education: Tertiary	0.57	0.33	0.38	0.28
	(0.019)	(0.019)	(0.022)	(0.021)
Age	54	55	57	64
	(0.63)	(0.66)	(0.69)	(0.66)
Female	0.4	0.6	0.52	0.47
	(0.019)	(0.02)	(0.023)	(0.024)
Monthly hh net income (equiv., thousands)	2.5	2.1	2.2	2
	(0.042)	(0.039)	(0.048)	(0.042)
Total hh financial assets (equiv., thousands)	55	22	39	34
	(6.8)	(2.4)	(6)	(4.4)
Risk aversion index	−0.09	0.099	0.0096	−0.0053
	(0.035)	(0.042)	(0.048)	(0.053)
Numeracy index	0.63	−0.21	0.044	−0.72
	(0.024)	(0.038)	(0.041)	(0.056)

Notes: This table replicates Table 6 without restricting ℓ from below.

Table G.30. Predictors of groups, marginal effects

	Ambiguity types			
	Near SEU	Ambiguity averse	Ambiguity seeking	High noise
Age: $\in (35, 50]$	-0.035	-0.014	-0.03	0.079^{*}
	(0.037)	(0.038)	(0.039)	(0.041)
Age: $\in (50, 65]$	-0.058^{*}	-0.041	-0.0079	0.11^{***}
	(0.035)	(0.036)	(0.036)	(0.038)
Age: ≥ 65	-0.083^{**}	-0.078^{**}	-0.029	0.19^{***}
	(0.036)	(0.036)	(0.036)	(0.038)
Education: Upper secondary	0.078^{**}	-0.014	-0.028	-0.036
	(0.032)	(0.028)	(0.029)	(0.024)
Education: Tertiary	0.1^{***}	-0.061^{*}	-0.035	-0.0054
	(0.033)	(0.031)	(0.03)	(0.026)
Income: $\in (1.1, 1.6]$	-0.056^{*}	0.035	0.028	-0.0068
	(0.032)	(0.03)	(0.031)	(0.025)
Income: $\in (1.6, 2.2]$	-0.065^{**}	0.078^{**}	0.035	-0.047^{*}
	(0.032)	(0.032)	(0.033)	(0.028)
Income: ≥ 2.2	-0.098^{***}	0.066^{*}	0.039	-0.0068
	(0.033)	(0.036)	(0.034)	(0.029)
Financial assets: $\in (1.8, 11.2]$	0.095^{***}	-0.03	0.028	-0.093^{***}
	(0.035)	(0.029)	(0.032)	(0.027)
Financial assets: $\in (11.2, 32]$	0.15^{***}	-0.083^{***}	-0.036	-0.035
	(0.034)	(0.032)	(0.035)	(0.027)
Financial assets: ≥ 32	0.12^{***}	-0.11^{***}	0.0071	-0.011
	(0.034)	(0.036)	(0.035)	(0.029)
Female	0.0013	0.078^{***}	0.02	-0.099^{***}
	(0.022)	(0.022)	(0.022)	(0.019)
Risk aversion index	-0.015	0.02^{*}	-0.0055	0.0005
	(0.011)	(0.011)	(0.012)	(0.0088)
Numeracy index	0.23^{***}	-0.07^{***}	-0.032^{**}	-0.13^{***}
	(0.018)	(0.012)	(0.013)	(0.01)
Observations	1624	1624	1624	1624
Pseudo R^2	0.14	0.14	0.14	0.14

Notes: This table replicates Table F.2 without restricting ℓ from below.

Table G.31. Ambiguity attitudes and portfolio choice: Marginal effects

	Owns risky assets (Probit)		Share risky assets (Tobit)	
	(1)	(2)	(3)	(4)
Ambiguity averse type	−0.23***	−0.084***	−0.45***	−0.18***
	(0.024)	(0.023)	(0.06)	(0.055)
Ambiguity seeking type	−0.1***	−0.013	−0.15***	−0.015
	(0.028)	(0.024)	(0.05)	(0.046)
High noise type	−0.18***	−0.054**	−0.24***	−0.084
	(0.027)	(0.027)	(0.059)	(0.059)
Age: $\in (35, 50]$		−0.03		−0.025
		(0.034)		(0.067)
Age: $\in (50, 65]$		−0.0017		0.037
		(0.033)		(0.063)
Age: ≥ 65		−0.017		0.039
		(0.034)		(0.063)
Female		−0.026		−0.028
		(0.018)		(0.04)
Education: Upper secondary		0.017		0.062
		(0.026)		(0.059)
Education: Tertiary		0.037		0.13**
		(0.026)		(0.059)
Income: $\in (1.1, 1.6]$		0.018		0.072
		(0.027)		(0.063)
Income: $\in (1.6, 2.2]$		0.015		0.064
		(0.028)		(0.062)
Income: ≥ 2.2		0.078***		0.14**
		(0.029)		(0.062)
Financial assets: $\in (1.8, 11.2]$		0.044**		0.12
		(0.019)		(0.084)
Financial assets: $\in (11.2, 32]$		0.14***		0.34***
		(0.022)		(0.083)
Financial assets: ≥ 32		0.39***		0.68***
		(0.029)		(0.085)
Risk aversion index		−0.046***		−0.12***
		(0.0095)		(0.021)
Numeracy index		0.034**		0.068**
		(0.017)		(0.03)
Observations	1727	1624	1584	1502
Pseudo R^2	0.056	0.3	0.044	0.28
p-values for differences between				
Ambiguity averse, Ambiguity seeking	0	0.0051	0	0.0053
Ambiguity averse, High noise	0.033	0.27	0.0032	0.16
Ambiguity seeking, High noise	0.0051	0.15	0.14	0.25

Notes: This table replicates the regressions shown in Table 7 without restricting ℓ from below.

Appendix H Analysis with BBLW-indices

Baillon, Bleichrodt, Li, et al. (2021) propose estimating the ambiguity parameters with the following indices (notation adapted to our setting):

$$\hat{\alpha}_{\text{BBLW}} = \frac{1}{2} \cdot \left(1 - \frac{1}{3} \sum_{j=1}^{3} m(E_{j,C}^{AEX}) + m(E_j^{AEX}) \right) \tag{H.1}$$

$$\hat{\ell}_{\text{BBLW}} = 1 - \sum_{j=1}^{3} m(E_{j,C}^{AEX}) - m(E_j^{AEX}) \tag{H.2}$$

The approach has also been used for instance in Li (2017), Baillon, Huang, et al. (2018), and Anantanasuwong, Kouwenberg, Mitchell, and Peijnenburg (2020) Note that in other papers, α is defined on $[-1, 1]$ instead of the interval $[-0.5, 0.5]$ used here in order to have the same length of the scales of α and ℓ.

The indices do not include a stochastic component of choice and the researcher is left with a choice on how to deal with choice sequences that cannot be rationalized by the deterministic model. For example, when we run the analysis of Section 3.2 on the indices data, 37 % of person × wave observations violate the restrictions on α and ℓ. These deviations can be substantial; as shown in Table H.1, the 95$^{\text{th}}$ percentile of ℓ^{AEX} is 1.6, more than one standard deviation above its bound. We could either restrict ourselves to individuals with valid (α, ℓ)-pairs (e.g., Anantanasuwong et al., 2020) or keep all observations regardless of whether the estimated parameters make sense (e.g., Dimmock, Kouwenberg, Mitchell, and Peijnenburg, 2015; Dimmock, Kouwenberg, and Wakker, 2016). Not modelling decision errors explicitly has consequences for parameter stability: Comparing Tables E.7 and H.2 shows that correlations among the parameters from different waves drop substantially throughout the board. Unsurprisingly, the same is true for the OLS stability regressions in Tables H.3 (over time) and H.4 (across domains). The instrumental variables regressions are not affected much, so the indices do not introduce any systematic differences over time.

The question of how to deal with randomness in the choice data becomes more complicated for an analysis in the style of Section 3 of the paper, i.e., making use of multiple measurements per individual. There are good arguments for continuing to use the wave-by-wave indices or to calculate the indices based on data from all waves. Using the wave-by-wave data means that an individual would be classified in multiple ways; calculating the indices on all data at once makes it impossible to tell apart an individual with perfectly stable preference parameters from someone whose behavior changes erratically from one wave to the next, so long as their mean values for α and ℓ are the same. Section H.2 reports results corresponding to Section 4 when we classify individuals wave-by-wave. Section H.3 does the same for averaging the indices across waves.

Naturally, the estimated parameters are spread out much more when we use person × wave observations (Figure H.1) than if we do the same for mean indices (Figure H.2). An obvious consequence of reducing the dimensionality of the problem to the two dimensions plotted in the graph is that there are clear boundaries between the types. In both cases, instead of the “High Noise” type, we find “Monotonicity violators”, all situated above the triangle with valid parameters (in Figure H.2, this is not true for a very small subset). There is relatively little correspondence between the types we found in the main text (Section 4.1) and the two sets of classifications here. As is evident from Tables H.7 and H.13, there are only 49 % (wave-by-wave classification) and 58 % on the diagonal. While consistency is fairly high for the respective “Near SEU” types, it is very low for the “High Noise” types – the row distributions are not far from uniform. Not modelling decision errors explicitly thus leaves out an important dimension of individual behavior and wrongly subsumes it under preferences.

H.1 Tables and figures corresponding to Section 3

Table H.1. Marginal distributions of estimated parameters, wave by wave (BBLW-indices)

		Mean	Std. dev.	$q_{0.05}$	$q_{0.25}$	$q_{0.5}$	$q_{0.75}$	$q_{0.95}$
$\alpha^{AEX}_{\text{BBLW-Index}}$	2018-05	0.034	0.2	−0.31	−0.092	0.033	0.16	0.36
	2018-11	0.05	0.18	−0.25	−0.053	0.046	0.15	0.37
	2019-05	0.038	0.17	−0.24	−0.053	0.033	0.14	0.32
	2019-11	0.04	0.18	−0.24	−0.062	0.033	0.15	0.35
	2020-05	0.041	0.16	−0.22	−0.05	0.042	0.14	0.31
	2020-11	0.029	0.16	−0.22	−0.067	0.03	0.12	0.3
	Observations from all AEX waves	0.039	0.18	−0.25	−0.064	0.033	0.15	0.34
	2019-11 (Climate Change)	0.029	0.19	−0.3	−0.083	0.029	0.15	0.35
$\ell^{AEX}_{\text{BBLW-Index}}$	2018-05	0.85	0.55	0.005	0.56	0.9	1.1	1.8
	2018-11	0.79	0.51	0.005	0.5	0.83	1	1.6
	2019-05	0.81	0.48	0.01	0.5	0.9	1	1.5
	2019-11	0.81	0.48	0.051	0.52	0.85	1	1.6
	2020-05	0.82	0.5	0.01	0.51	0.9	1.1	1.6
	2020-11	0.78	0.45	0.03	0.5	0.8	1	1.5
	Observations from all AEX waves	0.81	0.5	0.01	0.5	0.88	1	1.6
	2019-11 (Climate Change)	0.86	0.49	0.055	0.6	0.9	1.1	1.7

Notes: Parameter estimates are based on the indices proposed by Baillon, Bleichrodt, Li, et al. (2021), calculated for each survey wave and individual.

Table H.2. Cross-wave correlations of parameters of BBLW-indices

		α	ℓ
2018-11	2019-05	0.25	0.16
	2019-11	0.20	0.16
	2020-05	0.15	0.16
	2020-11	0.22	0.16
	2021-05	0.18	0.14
2019-05	2019-11	0.32	0.19
	2020-05	0.31	0.16
	2020-11	0.33	0.23
	2021-05	0.30	0.20
2019-11	2020-05	0.27	0.17
	2020-11	0.33	0.18
	2021-05	0.25	0.19
2020-05	2020-11	0.31	0.18
	2021-05	0.24	0.15
2020-11	2021-05	0.44	0.22
Average		0.27	0.18

Notes: Sample: All waves meeting our inclusion criteria (i.e., there is variation across options and/or completion time is outside the fastest 15 %, see Section 2.3) for individuals with at least two such waves. Table shows Pearson correlations between parameter estimates across waves, with subscripts indicating the waves. Parameter estimates are based on the indices proposed by Baillon, Bleichrodt, Li, et al. (2021), calculated for each survey wave and individual.

Table H.3. Predicting last three waves of ambiguity parameters with first three waves (BBLW-indices)

		OLS	ORIV	
		(1)	(2)	(3)
$\alpha^{AEX}_{\text{last 3 waves}}$	Intercept	0.018^{***}	-0.011^{***}	
		(0.0026)	(0.0041)	
	$\alpha^{AEX}_{\text{first 3 waves}}$	0.24^{***}	0.95^{***}	0.99^{***}
		(0.01)	(0.07)	(0.10)
	Adj. R^2	0.065		
	1st st. F		138	92
$\ell^{AEX}_{\text{last 3 waves}}$	Intercept	0.66^{***}	0.052	
		(0.013)	(0.079)	
	$\ell^{AEX}_{\text{first 3 waves}}$	0.17^{***}	0.93^{***}	0.85^{***}
		(0.01)	(0.10)	(0.15)
	Adj. R^2	0.03		
	1st st. F		83	34
Controls		No	No	Yes
N Subjects		1859	1859	1452

Notes: Table shows OLS and ORIV regressions with the parameter estimates of the May 2020, November 2020, and May 2021 waves as dependent variables and the parameter estimates of the three earlier waves as potential independent variables and instruments. The table is split vertically, such that the first set of rows reports the regressions based on $\alpha^{AEX}_{\text{BBLW}}$ as dependent and independent variables. The second set of rows shows the results for ℓ^{AEX}_{BBLW}. Parameter estimates are based on the indices proposed by Baillon, Bleichrodt, Li, et al. (2021), calculated for each survey wave and individual. In line with the ORIV approach, we use a stacked data set in which all respective combinations of dependent, independent, and (for the ORIV regressions) instrumental variables enter as a separate observation. In all regressions, standard errors are clustered on the individual level. Controls are age dummies, gender, education, income and assets dummies, risk aversion, and numeracy. Robust standard errors in parentheses. Sample: All waves meeting our inclusion criteria (i.e., there is variation across options and/or completion time is outside the fastest 15 %, see Section 2.3) for individuals with at least two such waves in 2018/2019 and at least one such wave in 2020/2021 (This is required for ORIV regressions and we impose the same restriction for the OLS regression). $* - p < 0.1, ** - p < 0.05, *** - p < 0.01$.

Table H.4. Predicting climate ambiguity parameters with AEX parameters (BBLW-indices)

		OLS	2SLS	
		(1)	(2)	(3)
$\alpha^{climate}_{2019-11}$	Intercept	0.001	-0.014^{***}	
		(0.0035)	(0.0042)	
	$\alpha^{AEX}_{2019-11}$	0.67^{***}	1.06^{***}	1.10^{***}
		(0.03)	(0.06)	(0.07)
	Adj. R^2	0.37		
	1st st. F		204	140
$\ell^{climate}_{2019-11}$	Intercept	0.75^{***}	0.4^{***}	
		(0.027)	(0.076)	
	$\ell^{AEX}_{2019-11}$	0.14^{***}	0.57^{***}	0.57^{***}
		(0.03)	(0.10)	(0.16)
	Adj. R^2	0.019		
	1st st. F		124	46
Controls		No	No	Yes
N Subjects		1843	1843	1411

Notes: This table shows OLS and 2SLS regressions with the parameter estimates for the decisions about changes in climate (elicited in November 2019) as dependent variable and the parameter estimates for the decisions about the AEX elicited in November 2019 as independent variable. For the 2SLS regressions, the parameters of all other AEX waves are used as instruments. Parameter estimates are based on the indices proposed by Baillon, Bleichrodt, Li, et al. (2021), calculated for each survey wave and individual. For 2SLS, we use a stacked data set in which all instrumental variables enter as a separate observation and we cluster standard errors on the individual level. Controls are age dummies, gender, education, income and assets dummies, risk aversion, numeracy and indicators of self-assessed understanding and perceived threat of climate change. The latter two vary between 0 and 1. Robust standard errors in parentheses. Sample: All waves meeting our inclusion criteria (i.e., there is variation across options and/or completion time is outside the fastest 15 %, see Section 2.3) for individuals with at least two such waves.
$* - p < 0.1, ** - p < 0.05, *** - p < 0.01$.

H.2 Tables and figures corresponding to Section 4 (wave-by-wave estimates)

Table H.5. Predictors of marginal parameter estimates (BBLW-indices, wave-by-wave)

	α^{AEX}	ℓ^{AEX}
Intercept	0.057^{***}	0.8^{***}
	(0.012)	(0.025)
Age: $\in (35, 50]$	−0.0086	0.0005
	(0.0083)	(0.02)
Age: $\in (50, 65]$	−0.013	0.028
	(0.0081)	(0.02)
Age: ≥ 65	−0.012	0.072^{***}
	(0.0081)	(0.02)
Education: Upper secondary	−0.0079	0.001
	(0.0081)	(0.018)
Education: Tertiary	-0.016^{*}	-0.075^{***}
	(0.0089)	(0.019)
Income: $\in (1.1, 1.6]$	0.013	0.05^{***}
	(0.0083)	(0.018)
Income: $\in (1.6, 2.2]$	0.013	0.039^{**}
	(0.0086)	(0.018)
Income: ≥ 2.2	0.0042	0.064^{***}
	(0.0092)	(0.02)
Financial assets: $\in (1.8, 11.2]$	-0.018^{**}	-0.05^{***}
	(0.0084)	(0.018)
Financial assets: $\in (11.2, 32]$	−0.011	-0.063^{***}
	(0.0081)	(0.019)
Financial assets: ≥ 32	-0.027^{***}	-0.057^{***}
	(0.0087)	(0.021)
Female	0.0091	0.0085
	(0.0058)	(0.012)
Risk aversion index	0.0028	0.0055
	(0.0033)	(0.0064)
Numeracy index	−0.0058	-0.075^{***}
	(0.0036)	(0.0081)
Observations	8735	8735
Adj. R^2	0.01	0.043

Notes: This table reports OLS regressions with the estimated ambiguity and error parameters as dependent variable and several independent variables. Standard errors are clustered on the individual level and reported in parentheses. Income and financial assets are in thousands, pooled over partners and equivalized for couples. Risk aversion and numeracy are normalized to have mean zero and unit variance. Sample: All waves meeting our inclusion criteria (i.e., there is variation across options and/or completion time is outside the fastest 15 %, see Section 2.3) for individuals with at least two such waves.
$* - p < 0.1, ** - p < 0.05, *** - p < 0.01$.

Table H.6. Individual ambiguity parameters and portfolio choice: Marginal effects (BBLW-indices, wave-by-wave)

	Owns risky assets (Probit)		Share risky assets (Tobit)	
	(1)	(2)	(3)	(4)
α	-0.043^{***}	-0.024^{***}	-0.083^{***}	-0.044^{***}
	(0.0057)	(0.0053)	(0.0093)	(0.0085)
ℓ	-0.033^{***}	-0.0096^{**}	-0.058^{***}	-0.018^{**}
	(0.0052)	(0.0044)	(0.0087)	(0.0079)
Age: $\in (35, 50]$		-0.022		-0.0047
		(0.035)		(0.029)
Age: $\in (50, 65]$		0.0087		0.062^{**}
		(0.033)		(0.027)
Age: ≥ 65		-0.013		0.055^{**}
		(0.034)		(0.027)
Female		-0.027		-0.026
		(0.018)		(0.017)
Education: Upper secondary		0.022		0.07^{***}
		(0.026)		(0.025)
Education: Tertiary		0.047^{*}		0.15^{***}
		(0.027)		(0.025)
Income: $\in (1.1, 1.6]$		0.016		0.065^{**}
		(0.029)		(0.027)
Income: $\in (1.6, 2.2]$		0.0037		0.039
		(0.029)		(0.026)
Income: ≥ 2.2		0.069^{**}		0.12^{***}
		(0.03)		(0.026)
Financial assets: $\in (1.8, 11.2]$		0.046^{**}		0.12^{***}
		(0.019)		(0.035)
Financial assets: $\in (11.2, 32]$		0.15^{***}		0.35^{***}
		(0.023)		(0.035)
Financial assets: ≥ 32		0.4^{***}		0.68^{***}
		(0.03)		(0.035)
Risk aversion index		-0.05^{***}		-0.13^{***}
		(0.0096)		(0.0088)
Numeracy index		0.046^{***}		0.086^{***}
		(0.017)		(0.012)
Observations	9101	8735	8358	8081
Pseudo R^2	0.02	0.31	0.017	0.29

Notes: Parameter estimates are based on the indices proposed by Baillon, Bleichrodt, Li, et al. (2021). Marginal effects are calculated as a change from 0 to 1 for dummy variables, as a change from a category to the left-out category for categorical variables, and as an increase of a standard deviation for continuous variables. Standard errors are clustered on the individual level and reported in parentheses.
$* - p < 0.1, ** - p < 0.05, *** - p < 0.01$.

Ambiguity types with $k = 4$

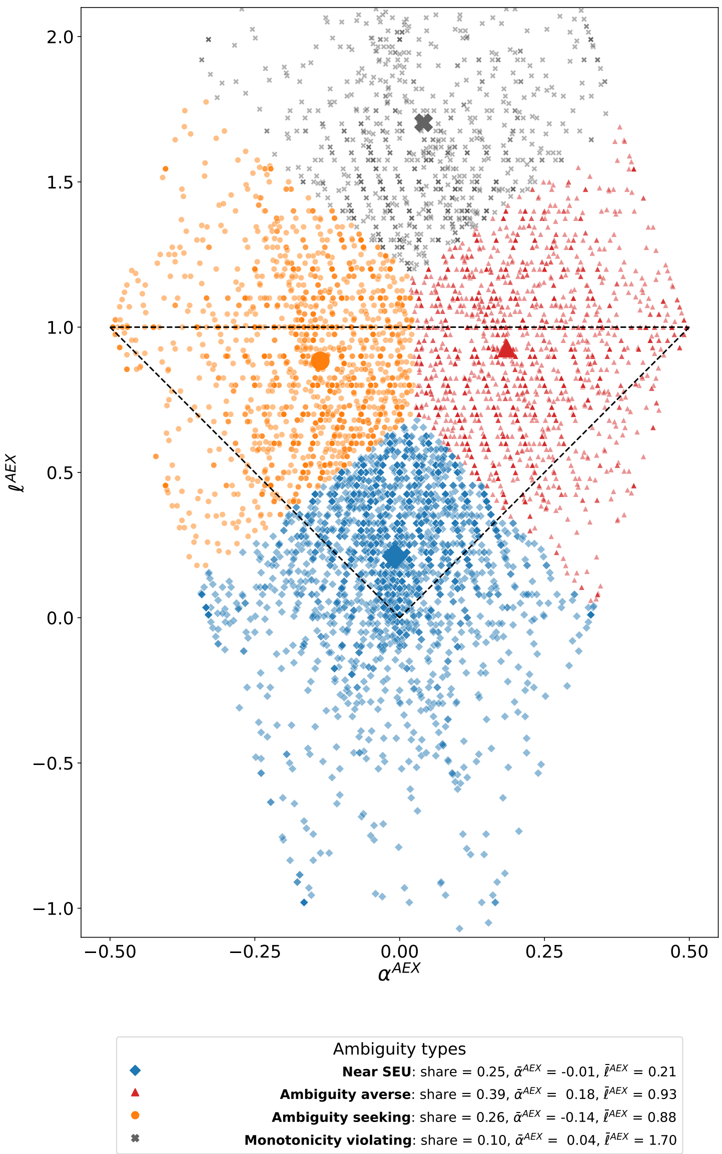


Figure H.1. Summarizing heterogeneity in ambiguity profiles with $k = 4$ discrete groups (BBLW-indices, wave-by-wave)

Notes: The small symbols depict individual preference parameter estimates $(\alpha_i^{AEX}, \ell_i^{AEX})$ based on the indices proposed by Baillon, Bleichrodt, Li, et al. (2021) (see page 96). The large symbols are group centers resulting from clustering individuals with the k-means algorithm on the two parameters into four groups. Sample: All waves meeting our inclusion criteria (i.e., there is variation across options and/or completion time is outside the fastest 15 %, see Section 2.3) for individuals with at least two such waves.

Table H.7. Cross-tabulation of group classification, main estimates vs. BBLW-indices, wave-by-wave

Type based on BBLW-index	Near SEU	Ambiguity averse	Ambiguity seeking	Monotonicity violating	All
Baseline: Near SEU	0.15	0.07	0.07	0.01	0.3
Baseline: Ambiguity averse	0.03	0.19	0.03	0.02	0.27
Baseline: Ambiguity seeking	0.04	0.06	0.11	0.02	0.23
Baseline: High noise	0.04	0.07	0.05	0.04	0.2
Baseline: All	0.25	0.39	0.26	0.1	1

Notes: The table shows the share of subjects which is assigned to the ambiguity group on the left based on main parameter estimates and to the ambiguity group on top based on the BBLW-indices. Sample: All waves meeting our inclusion criteria (i.e., there is variation across options and/or completion time is outside the fastest 15 %, see Section 2.3) for individuals with at least two such waves.

Table H.8. Average characteristics of group members (BBLW-indices, wave-by-wave)

	Ambiguity types			
	Near SEU	Ambiguity averse	Ambiguity seeking	Monotonicity violating
Share	0.25	0.39	0.26	0.1
α^{AEX}	−0.0083	0.18	−0.14	0.041
	(0.0019)	(0.0018)	(0.0024)	(0.0037)
ℓ^{AEX}	0.21	0.93	0.88	1.7
	(0.0057)	(0.0032)	(0.0043)	(0.012)
Education: Lower secondary and below	0.19	0.3	0.27	0.33
	(0.0073)	(0.0069)	(0.0082)	(0.014)
Education: Upper secondary	0.31	0.35	0.32	0.37
	(0.0086)	(0.0072)	(0.0087)	(0.014)
Education: Tertiary	0.51	0.34	0.4	0.3
	(0.0093)	(0.0071)	(0.0091)	(0.014)
Age	56	57	58	60
	(0.3)	(0.23)	(0.28)	(0.46)
Female	0.42	0.54	0.47	0.49
	(0.0092)	(0.0075)	(0.0093)	(0.015)
Monthly hh net income (equiv., thousands)	2.4	2.1	2.2	2.2
	(0.019)	(0.014)	(0.02)	(0.03)
Total hh financial assets (equiv., thousands)	51	32	46	38
	(3)	(1.6)	(2.9)	(3.5)
Risk aversion index	−0.049	0.072	−0.031	−0.0066
	(0.018)	(0.015)	(0.019)	(0.032)
Numeracy index	0.31	−0.13	0.033	−0.36
	(0.018)	(0.015)	(0.019)	(0.033)

Notes: The first row shows the share of individuals classified into a given group. For each group, the mean of several variables are shown. Parameter estimates are based on the indices proposed by Baillon, Bleichrodt, Li, et al. (2021). Income and financial assets are in thousands and equivalized for couples. We consider income of both partners. Total assets include assets kept in joint accounts and those assigned to the respondent (i.e., the person identifying as being most familiar with the household's finances). Risk aversion and numeracy are normalized to have mean zero and unit variance. Sample: All waves meeting our inclusion criteria (i.e., there is variation across options and/or completion time is outside the fastest 15 %, see Section 2.3) for individuals with at least two such waves.

Table H.9. Predictors of groups, marginal effects (BBLW-indices, wave-by-wave)

	Ambiguity types			
	Near SEU	Ambiguity averse	Ambiguity seeking	Monotonicity violating
Age: $\in (35, 50]$	-0.011	0.011	0.018	-0.018
	(0.021)	(0.026)	(0.023)	(0.013)
Age: $\in (50, 65]$	-0.035^{*}	0.015	0.025	-0.0057
	(0.02)	(0.025)	(0.022)	(0.012)
Age: ≥ 65	-0.06^{***}	0.019	0.024	0.018
	(0.02)	(0.025)	(0.021)	(0.013)
Education: Upper secondary	0.012	-0.017	-0.0035	0.0082
	(0.017)	(0.02)	(0.017)	(0.0088)
Education: Tertiary	0.059^{***}	-0.045^{**}	0.0097	-0.024^{**}
	(0.017)	(0.022)	(0.018)	(0.011)
Income: $\in (1.1, 1.6]$	-0.038^{**}	0.03	-0.0078	0.016^{*}
	(0.017)	(0.021)	(0.018)	(0.0094)
Income: $\in (1.6, 2.2]$	-0.03^{*}	0.034	-0.021	0.016
	(0.018)	(0.022)	(0.019)	(0.011)
Income: ≥ 2.2	-0.045^{**}	0.006	0.0089	0.03^{**}
	(0.019)	(0.025)	(0.02)	(0.012)
Financial assets: $\in (1.8, 11.2]$	0.048^{***}	-0.05^{**}	0.018	-0.017
	(0.018)	(0.021)	(0.018)	(0.01)
Financial assets: $\in (11.2, 32]$	0.064^{***}	-0.05^{**}	0.0004	-0.015
	(0.018)	(0.022)	(0.019)	(0.011)
Financial assets: ≥ 32	0.063^{***}	-0.089^{***}	0.032	-0.0062
	(0.019)	(0.024)	(0.02)	(0.012)
Female	-0.033^{***}	0.055^{***}	-0.013	-0.0097
	(0.012)	(0.015)	(0.013)	(0.0071)
Risk aversion index	-0.004	0.013^{*}	-0.0099	0.0013
	(0.0061)	(0.0074)	(0.0066)	(0.0036)
Numeracy index	0.068^{***}	-0.03^{***}	-0.0057	-0.032^{***}
	(0.0086)	(0.0089)	(0.0075)	(0.004)
Observations	8735	8735	8735	8735
Pseudo R^2	0.026	0.026	0.026	0.026

Notes: This table reports marginal effects of a multinomial logit regression that predicts the ambiguity type based on a set of individual characteristics. Parameter estimates are based on the indices proposed by Baillon, Bleichrodt, Li, et al. (2021). Reported are the average marginal effects over all observations. Dummy variables are treated as continuous. The groups are obtained from clustering individuals with the k-means algorithm on the parameters α^{AEX}, ℓ^{AEX} and σ^{AEX} into four groups. Standard errors are clustered on the individual level and reported in parentheses. Income and financial assets are in thousands, pooled over partners and equivalized for couples. Risk aversion and numeracy are normalized to have mean zero and unit variance. Sample: All waves meeting our inclusion criteria (i.e., there is variation across options and/or completion time is outside the fastest 15 %, see Section 2.3) for individuals with at least two such waves. $* - p < 0.1, ** - p < 0.05, *** - p < 0.01$.

Table H.10. Ambiguity attitudes and portfolio choice: Marginal effects (BBLW-indices, wave-by-wave)

	Owns risky assets (Probit)		Share risky assets (Tobit)	
	(1)	(2)	(3)	(4)
Ambiguity averse type	-0.15^{***}	-0.059^{***}	-0.28^{***}	-0.11^{***}
	(0.015)	(0.012)	(0.022)	(0.019)
Ambiguity seeking type	-0.044^{***}	-0.01	-0.06^{***}	-0.016
	(0.015)	(0.012)	(0.022)	(0.019)
Monotonicity violating type	-0.11^{***}	-0.024	-0.17^{***}	-0.039
	(0.019)	(0.017)	(0.032)	(0.029)
Age: $\in (35, 50]$		-0.019		-0.0003
		(0.035)		(0.029)
Age: $\in (50, 65]$		0.012		0.067^{**}
		(0.033)		(0.027)
Age: ≥ 65		-0.0092		0.061^{**}
		(0.034)		(0.027)
Female		-0.025		-0.022
		(0.018)		(0.017)
Education: Upper secondary		0.023		0.071^{***}
		(0.026)		(0.025)
Education: Tertiary		0.047^{*}		0.15^{***}
		(0.027)		(0.025)
Income: $\in (1.1, 1.6]$		0.014		0.061^{**}
		(0.029)		(0.026)
Income: $\in (1.6, 2.2]$		0.0022		0.037
		(0.03)		(0.026)
Income: ≥ 2.2		0.068^{**}		0.12^{***}
		(0.03)		(0.026)
Financial assets: $\in (1.8, 11.2]$		0.047^{**}		0.12^{***}
		(0.019)		(0.035)
Financial assets: $\in (11.2, 32]$		0.15^{***}		0.34^{***}
		(0.023)		(0.035)
Financial assets: ≥ 32		0.4^{***}		0.68^{***}
		(0.03)		(0.035)
Risk aversion index		-0.05^{***}		-0.13^{***}
		(0.0096)		(0.0087)
Numeracy index		0.045^{***}		0.085^{***}
		(0.017)		(0.012)
Observations	9101	8735	8358	8081
Pseudo R^2	0.025	0.31	0.023	0.29
p-values for differences between				
Ambiguity averse, Ambiguity seeking	0	0	0	0
Ambiguity averse, Monotonicity violating	0.0032	0.007	0.0007	0.01
Ambiguity seeking, Monotonicity violating	0	0.34	0.0008	0.43

Notes: The first two columns display Probit regressions where the dependent variables is a dummy indicating whether the subject holds any risky financial assets. In the last two columns, we run Tobit regressions with the share of risky financial assets of all financial assets as dependent variable. Marginal effects are calculated as a change from 0 to 1 for dummy variables, as a change from a category to the left-out category for categorical variables, and as an increase of a standard deviation for continuous variables. Standard errors are clustered on the individual level and reported in parentheses. Parameter estimates are based on the indices proposed by Baillon, Bleichrodt, Li, et al. (2021). Sample: All waves meeting our inclusion criteria (i.e., there is variation across options and/or completion time is outside the fastest 15 %, see Section 2.3) for individuals with at least two such waves. $* - p < 0.1$, $** - p < 0.05$, $*** - p < 0.01$

H.3 Tables and figures corresponding to Section 4 (mean over all AEX waves)

Table H.11. Predictors of marginal parameter estimates (BBLW-indices, mean over all AEX waves)

	α^{AEX}	ℓ^{AEX}
Intercept	0.055^{***}	0.79^{***}
	(0.012)	(0.026)
Age: $\in (35, 50]$	-0.0047	0.0098
	(0.0084)	(0.021)
Age: $\in (50, 65]$	-0.0083	0.033
	(0.0083)	(0.02)
Age: ≥ 65	-0.0096	0.075^{***}
	(0.0083)	(0.02)
Education: Upper secondary	-0.0075	0.0042
	(0.0081)	(0.018)
Education: Tertiary	-0.017^{*}	-0.073^{***}
	(0.0089)	(0.019)
Income: $\in (1.1, 1.6]$	0.01	0.046^{**}
	(0.0082)	(0.018)
Income: $\in (1.6, 2.2]$	0.0088	0.031
	(0.0087)	(0.019)
Income: ≥ 2.2	0.0015	0.059^{***}
	(0.0091)	(0.021)
Financial assets: $\in (1.8, 11.2]$	-0.015^{*}	-0.04^{**}
	(0.0086)	(0.019)
Financial assets: $\in (11.2, 32]$	-0.0085	-0.054^{***}
	(0.0081)	(0.02)
Financial assets: ≥ 32	-0.027^{***}	-0.048^{**}
	(0.009)	(0.022)
Female	0.01^{*}	0.0087
	(0.0058)	(0.013)
Risk aversion index	0.0026	0.0052
	(0.0033)	(0.0066)
Numeracy index	-0.0048	-0.075^{***}
	(0.0037)	(0.0083)
Observations	1624	1624
Adj. R^2	0.022	0.14

Notes: This table reports OLS regressions with the estimated ambiguity and error parameters as dependent variable and several independent variables. Robust standard errors in parentheses. Income and financial assets are in thousands, pooled over partners and equivalized for couples. Risk aversion and numeracy are normalized to have mean zero and unit variance. Sample: All waves meeting our inclusion criteria (i.e., there is variation across options and/or completion time is outside the fastest 15 %, see Section 2.3) for individuals with at least two such waves. * $- p < 0.1$, ** $- p < 0.05$, *** $- p < 0.01$.

Table H.12. Individual ambiguity parameters and portfolio choice: Marginal effects (BBLW-indices, mean over all AEX waves)

	Owns risky assets (Probit)		Share risky assets (Tobit)	
	(1)	(2)	(3)	(4)
α	-0.061^{***}	-0.038^{***}	-0.12^{***}	-0.073^{***}
	(0.0092)	(0.0088)	(0.023)	(0.021)
ℓ	-0.054^{***}	-0.018^{*}	-0.094^{***}	-0.036^{*}
	(0.0096)	(0.0094)	(0.021)	(0.02)
Age: $\in (35, 50]$		-0.034		-0.028
		(0.034)		(0.066)
Age: $\in (50, 65]$		-0.0065		0.033
		(0.033)		(0.063)
Age: ≥ 65		-0.021		0.038
		(0.034)		(0.063)
Female		-0.025		-0.027
		(0.018)		(0.04)
Education: Upper secondary		0.018		0.059
		(0.026)		(0.059)
Education: Tertiary		0.033		0.12^{**}
		(0.026)		(0.059)
Income: $\in (1.1, 1.6]$		0.023		0.082
		(0.027)		(0.063)
Income: $\in (1.6, 2.2]$		0.016		0.064
		(0.028)		(0.062)
Income: ≥ 2.2		0.078^{***}		0.14^{**}
		(0.029)		(0.062)
Financial assets: $\in (1.8, 11.2]$		0.043^{**}		0.11
		(0.019)		(0.084)
Financial assets: $\in (11.2, 32]$		0.14^{***}		0.34^{***}
		(0.023)		(0.082)
Financial assets: ≥ 32		0.38^{***}		0.68^{***}
		(0.029)		(0.084)
Risk aversion index		-0.046^{***}		-0.12^{***}
		(0.0095)		(0.021)
Numeracy index		0.038^{**}		0.073^{**}
		(0.016)		(0.029)
Observations	1727	1624	1584	1502
Pseudo R^2	0.051	0.31	0.043	0.29

Notes: Parameter estimates are based on the indices proposed by Baillon, Bleichrodt, Li, et al. (2021), pooled over all AEX waves per individual. Within each group, the first two columns display Probit regressions where the dependent variables is a dummy indicating whether the subject holds any risky financial assets and in the last two columns, we run Tobit regressions with the share of risky financial assets of all financial assets as dependent variable. Marginal effects are calculated as a change from 0 to 1 for dummy variables, as a change from a category to the left-out category for categorical variables, and as an increase of a standard deviation for continuous variables. $* - p < 0.1, ** - p < 0.05, *** - p < 0.01$.

Ambiguity types with $k = 4$

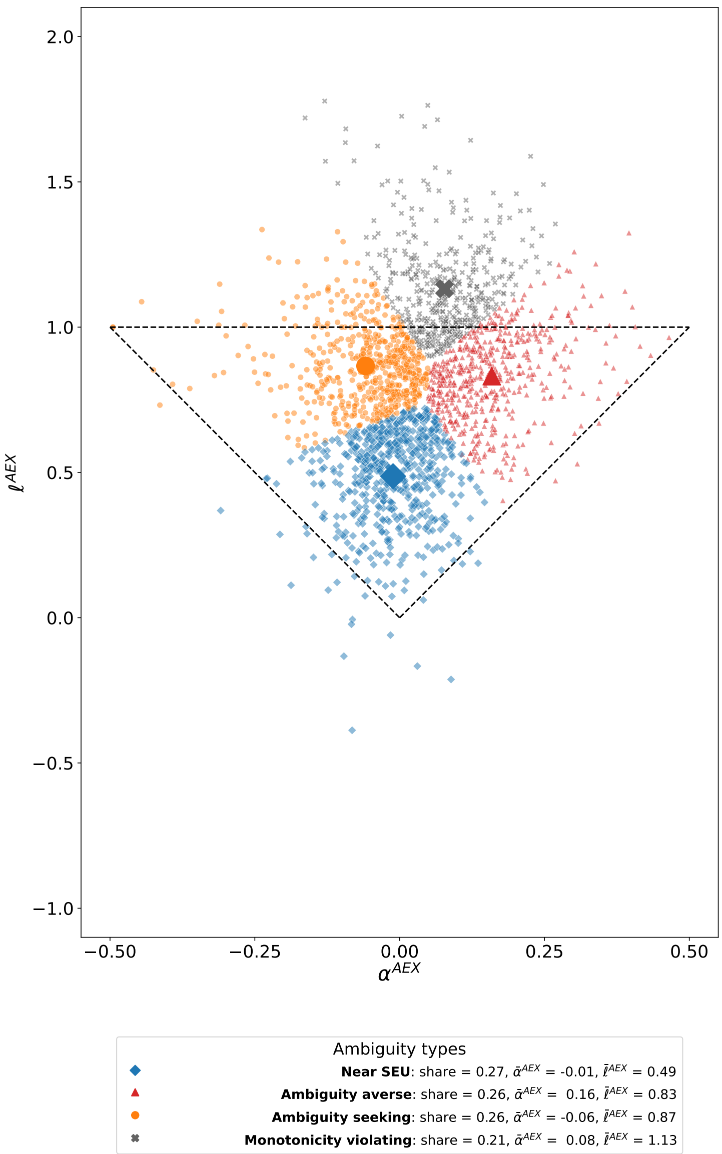


Figure H.2. Summarizing heterogeneity in ambiguity profiles with $k = 4$ discrete groups (BBLW-indices, mean over all AEX waves)

Notes: The small symbols depict individual preference parameter estimates $(\alpha_i^{AEX}, \ell_i^{AEX})$ based on the indices proposed by Baillon, Bleichrodt, Li, et al. (2021) (see page 96), pooled over all AEX waves per individual. The large symbols are group centers resulting from clustering individuals with the k-means algorithm on the two parameters into four groups. Sample: All waves meeting our inclusion criteria (i.e., there is variation across options and/or completion time is outside the fastest 15 %, see Section 2.3) for individuals with at least two such waves.

Table H.13. Cross-tabulation of group classification, main estimates vs. BBLW-indices, mean over all AEX waves

Type based on BBLW-index	Near SEU	Ambiguity averse	Ambiguity seeking	Monotonicity violating	All
Baseline: Near SEU	0.2	0.04	0.05	0.01	0.3
Baseline: Ambiguity averse	0.01	0.16	0.01	0.1	0.27
Baseline: Ambiguity seeking	0.04	0.01	0.15	0.03	0.23
Baseline: High noise	0.02	0.04	0.06	0.07	0.2
Baseline: All	0.27	0.26	0.26	0.21	1

Notes: The table shows the share of subjects which is assigned to the ambiguity group on the left based on main parameter estimates and to the ambiguity group on top based on the BBLW-indices. Sample: All waves meeting our inclusion criteria (i.e., there is variation across options and/or completion time is outside the fastest 15 %, see Section 2.3) for individuals with at least two such waves.

Table H.14. Average characteristics of group members (BBLW-indices, mean over all AEX waves)

	Ambiguity types			
	Near SEU	Ambiguity averse	Ambiguity seeking	Monotonicity violating
Share	0.27	0.26	0.26	0.21
α^{AEX}	−0.011	0.16	−0.059	0.078
	(0.0027)	(0.0032)	(0.0035)	(0.0029)
ℓ^{AEX}	0.49	0.83	0.87	1.1
	(0.0067)	(0.0061)	(0.0054)	(0.0082)
Education: Lower secondary and below	0.13	0.3	0.29	0.35
	(0.014)	(0.019)	(0.019)	(0.022)
Education: Upper secondary	0.28	0.34	0.36	0.38
	(0.019)	(0.02)	(0.02)	(0.023)
Education: Tertiary	0.59	0.36	0.36	0.27
	(0.02)	(0.02)	(0.02)	(0.021)
Age	54	56	59	60
	(0.7)	(0.68)	(0.63)	(0.7)
Female	0.41	0.57	0.49	0.52
	(0.02)	(0.021)	(0.021)	(0.023)
Monthly hh net income (equiv., thousands)	2.4	2.1	2.2	2.1
	(0.044)	(0.036)	(0.047)	(0.042)
Total hh financial assets (equiv., thousands)	54	31	43	23
	(7.6)	(3.5)	(5.5)	(2.5)
Risk aversion index	−0.07	0.1	−0.051	0.027
	(0.04)	(0.042)	(0.044)	(0.049)
Numeracy index	0.47	−0.16	−0.066	−0.33
	(0.036)	(0.041)	(0.045)	(0.047)

Notes: The first row shows the share of individuals classified into a given group. For each group, the mean of several variables are shown. Parameter estimates are based on the indices proposed by Baillon, Bleichrodt, Li, et al. (2021), pooled over all AEX waves per individual. Income and financial assets are in thousands and equivalized for couples. We consider income of both partners. Total assets include assets kept in joint accounts and those assigned to the respondent (i.e., the person identifying as being most familiar with the household's finances). Risk aversion and numeracy are normalized to have mean zero and unit variance. Sample: All waves meeting our inclusion criteria (i.e., there is variation across options and/or completion time is outside the fastest 15 %, see Section 2.3) for individuals with at least two such waves.

Table H.15. Predictors of groups, marginal effects (BBLW-indices, mean over all AEX waves)

	Ambiguity types			
	Near SEU	Ambiguity averse	Ambiguity seeking	Monotonicity violating
Age: $\in (35, 50]$	-0.035	-0.03	-0.012	0.078^{*}
	(0.036)	(0.038)	(0.042)	(0.04)
Age: $\in (50, 65]$	-0.049	-0.011	0.023	0.036
	(0.034)	(0.036)	(0.04)	(0.039)
Age: ≥ 65	-0.1^{***}	-0.05	0.037	0.11^{***}
	(0.034)	(0.036)	(0.04)	(0.038)
Education: Upper secondary	0.024	-0.024	-0.0054	0.0044
	(0.033)	(0.029)	(0.031)	(0.026)
Education: Tertiary	0.13^{***}	-0.016	-0.031	-0.081^{***}
	(0.033)	(0.032)	(0.032)	(0.03)
Income: $\in (1.1, 1.6]$	-0.071^{**}	-0.0094	0.001	0.079^{***}
	(0.034)	(0.03)	(0.032)	(0.028)
Income: $\in (1.6, 2.2]$	-0.047	0.0094	-0.023	0.06^{*}
	(0.033)	(0.033)	(0.035)	(0.031)
Income: ≥ 2.2	-0.07^{**}	-0.032	0.019	0.083^{**}
	(0.035)	(0.037)	(0.036)	(0.034)
Financial assets: $\in (1.8, 11.2]$	0.045	-0.018	0.017	-0.043
	(0.034)	(0.03)	(0.033)	(0.028)
Financial assets: $\in (11.2, 32]$	0.076^{**}	-0.014	-0.003	-0.058^{*}
	(0.035)	(0.032)	(0.036)	(0.031)
Financial assets: ≥ 32	0.072^{**}	-0.045	0.058	-0.086^{**}
	(0.036)	(0.035)	(0.036)	(0.035)
Female	-0.037^{*}	0.062^{***}	-0.014	-0.011
	(0.022)	(0.022)	(0.023)	(0.021)
Risk aversion index	-0.014	0.021^{*}	-0.012	0.0057
	(0.012)	(0.011)	(0.012)	(0.01)
Numeracy index	0.11^{***}	-0.022^{*}	-0.029^{**}	-0.06^{***}
	(0.018)	(0.013)	(0.014)	(0.012)
Observations	1624	1624	1624	1624
Pseudo R^2	0.06	0.06	0.06	0.06

Notes: This table reports marginal effects of a multinomial logit regression that predicts the ambiguity type based on a set of individual characteristics. Parameter estimates are based on the indices proposed by Baillon, Bleichrodt, Li, et al. (2021), pooled over all AEX waves per individual. Reported are the average marginal effects over all observations. Dummy variables are treated as continuous. The groups are obtained from clustering individuals with the k-means algorithm on the parameters α^{AEX}, ℓ^{AEX} and σ^{AEX} into four groups. Robust standard errors in parentheses. Income and financial assets are in thousands, pooled over partners and equivalized for couples. Risk aversion and numeracy are normalized to have mean zero and unit variance. Sample: All waves meeting our inclusion criteria (i.e., there is variation across options and/or completion time is outside the fastest 15 %, see Section 2.3) for individuals with at least two such waves. $* - p < 0.1, ** - p < 0.05, *** - p < 0.01.$

Table H.16. Ambiguity attitudes and portfolio choice: Marginal effects (BBLW-indices, mean over all AEX waves)

	Owns risky assets (Probit)		Share risky assets (Tobit)	
	(1)	(2)	(3)	(4)
Ambiguity averse type	-0.21^{***}	-0.1^{***}	-0.37^{***}	-0.18^{***}
	(0.026)	(0.024)	(0.059)	(0.054)
Ambiguity seeking type	-0.073^{**}	-0.013	-0.081^{*}	0.0019
	(0.029)	(0.024)	(0.048)	(0.044)
Monotonicity violating type	-0.21^{***}	-0.086^{***}	-0.4^{***}	-0.16^{***}
	(0.026)	(0.026)	(0.063)	(0.058)
Age: $\in (35, 50]$		-0.027		-0.016
		(0.034)		(0.067)
Age: $\in (50, 65]$		0.0006		0.044
		(0.033)		(0.063)
Age: ≥ 65		-0.013		0.05
		(0.034)		(0.063)
Female		-0.022		-0.023
		(0.017)		(0.04)
Education: Upper secondary		0.016		0.055
		(0.026)		(0.059)
Education: Tertiary		0.032		0.12^{**}
		(0.027)		(0.059)
Income: $\in (1.1, 1.6]$		0.019		0.072
		(0.027)		(0.063)
Income: $\in (1.6, 2.2]$		0.012		0.059
		(0.028)		(0.062)
Income: ≥ 2.2		0.075^{**}		0.13^{**}
		(0.029)		(0.062)
Financial assets: $\in (1.8, 11.2]$		0.043^{**}		0.11
		(0.019)		(0.084)
Financial assets: $\in (11.2, 32]$		0.14^{***}		0.34^{***}
		(0.023)		(0.082)
Financial assets: ≥ 32		0.38^{***}		0.68^{***}
		(0.03)		(0.084)
Risk aversion index		-0.045^{***}		-0.12^{***}
		(0.0095)		(0.021)
Numeracy index		0.038^{**}		0.075^{***}
		(0.016)		(0.029)
Observations	1727	1624	1584	1502
Pseudo R^2	0.055	0.31	0.046	0.29
p-values for differences between				
Ambiguity averse, Ambiguity seeking	0	0.0003	0	0.0009
Ambiguity averse, Monotonicity violating	0.73	0.52	0.71	0.81
Ambiguity seeking, Monotonicity violating	0	0.0054	0	0.0044

Notes: The first two columns display Probit regressions where the dependent variables is a dummy indicating whether the subject holds any risky financial assets. In the last two columns, we run Tobit regressions with the share of risky financial assets of all financial assets as dependent variable. Marginal effects are calculated as a change from 0 to 1 for dummy variables, as a change from a category to the left-out category for categorical variables, and as an increase of a standard deviation for continuous variables. Parameter estimates are based on the indices proposed by Baillon, Bleichrodt, Li, et al. (2021), pooled over all AEX waves per individual. Sample: All waves meeting our inclusion criteria (i.e., there is variation across options and/or completion time is outside the fastest 15 %, see Section 2.3) for individuals with at least two such waves. $* - p < 0.1$, $** - p < 0.05$, $*** - p < 0.01$

Appendix I Detailed placement of results in the literature

This section contains a more quantitative comparison of our results and those in prior literature than we could provide in the text. In order to do so, we mostly focus on comparing the numbers for the indices developed in Baillon, Bleichrodt, Li, et al. (2021), which have been employed by most of the recent literature.

The indices do not include a stochastic component of choice and the researcher is left with a choice on how to deal with choice sequences that cannot be rationalized by the deterministic model. For example, when we run the analysis of Section 3.2 on the indices data, 37 % of person × wave observations violate the restrictions on α and ℓ. These deviations can be substantial; the 95th percentile of ℓ^{AEX} is 1.6, more than one standard deviation above its bound. We could either restrict ourselves to individuals with valid (α, ℓ)-pairs (e.g., Anantanasuwong et al., 2020) or keep all observations regardless of whether the estimated parameters make sense (e.g., Dimmock, Kouwenberg, Mitchell, et al., 2015; Dimmock, Kouwenberg, and Wakker, 2016). Note that this issue is quantitatively negligible in typical laboratory samples, hence it has not been discussed too much in the literature.

The choice becomes more complicated for an analysis in the style of Section 3 of the paper, i.e., making use of multiple measurements per individual. There are good arguments for continuing to use the wave-by-wave indices or to calculate the indices based on data from all waves. Figure I.1 shows that this is consequential by plotting all estimated $(\alpha - \ell)$-pairs for both versions. The comparison shows that the wave-by-wave estimates in Panel a are spread out much more, while averaging across waves (unsurprisingly) brings everything closer to the mean values. However, in Panel b, it is impossible to tell apart an individual with perfectly stable preference parameters from someone whose behavior changes erratically from one wave to the next, so long as their mean values for α and ℓ are the same.

Again, one could argue for removing invalid index values, but in this panel setting, the order matters. Would one do so before or after averaging? Both versions are possible, each with different limitations. Below, we will mostly keep the entire sample and discuss some results when restricting ourselves to waves with valid index data.

All the basic stylized facts in Trautmann and van de Kuilen (2015) that apply to our design hold in our results. In particular, we find ambiguity aversion for high-likelihood gain events and ambiguity seeking for low-likelihood gain events – this is true on average and for the vast majority of people.[1] Trautmann and van de Kuilen (2015) compare various studies using the “ambiguity premium relative to

1. To some extent, we enforce it in our main specification with the exception of the special case of subjective expected utility maximization. However, when we allow for the reversed pattern in Online AppendixG.3, we find it to be relevant for only 18 % of person × wave observations or 8 % of individuals when imposing parameter stability over time.

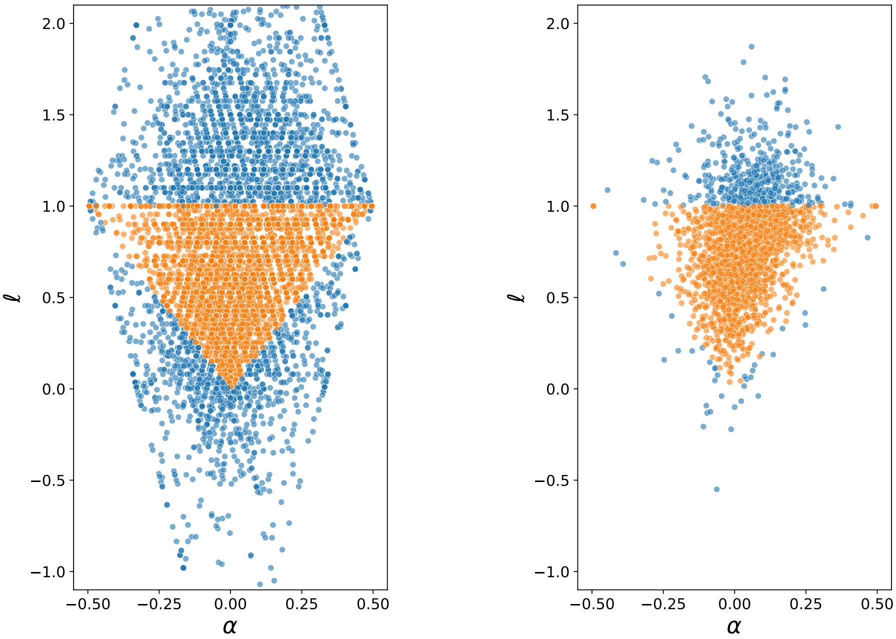


Figure I.1. Joint distribution of ambiguity parameters based on BBLW-indices

Notes: The figures depicts parameter estimates based on the indices proposed by Baillon, Bleichrodt, Li, et al. (2021) (see page 96). In Panel I.2a, indices are calculated for each AEX wave separately. In Panel I.2b, indices are for each subject averaged over all AEX waves. The blue dots are parameter values that violate the restrictions we impose in our main model. Values above the triangular indicate violations of set-monotonicity (26 % of the observations in the left panel and to 23 % of the observations in the right panel). Values below indicate hypersensitivity (11 % in the left panel and 1 % in the right panel). Sample: All waves meeting our inclusion criteria (i.e., there is variation across options and/or completion time is outside the fastest 15 %, see Section 2.3) for individuals with at least two such waves. The marginal parameter distributions are:

		Mean	Std. dev.	$q_{0.05}$	$q_{0.25}$	$q_{0.5}$	$q_{0.75}$	$q_{0.95}$
$\alpha^{AEX}_{\text{BBLW-Index}}$	Observations from all AEX waves	0.039	0.18	−0.25	−0.064	0.033	0.15	0.34
	Pooled estimation over all AEX waves	0.039	0.11	−0.13	−0.032	0.034	0.11	0.22
$\ell^{AEX}_{\text{BBLW-Index}}$	Observations from all AEX waves	0.81	0.5	0.01	0.5	0.88	1	1.6
	Pooled estimation over all AEX waves	0.81	0.27	0.34	0.63	0.83	0.99	1.2

risky choice”, i.e., the difference between the valuation of the risky and the ambiguous act, divided by the valuation of the risky act. For $\Pr_{\text{subj}}(E) = 0.5$—or averaging across subjective probabilities—this amounts to $2 \cdot \alpha^S$ in our framework. The values we have estimated are within the range of values reported in Trautmann and van de Kuilen (2015).

In general, our estimates of α are comparable to those from similar studies, though somewhat at the lower end. In an earlier elicitation in the LISS panel using Ellsberg urns as the source of uncertainty, Dimmock, Kouwenberg, and Wakker (2016) estimate an ambiguity aversion parameter of 0.06 with a standard deviation of 0.21, both of which are a bit above the values we find.[2] In a very similar data collection in the American Life Panel—which shares most characteristics with the LISS other than being run in the U.S.—Dimmock, Kouwenberg, Mitchell, et al. (2015) estimate $\alpha^{urn} = 0.025$ for a representative agent, very close to our mean values. Most closely related to our study, Anantanasuwong et al. (2020) estimate a median $\alpha^{AEX} = 0.05$ in a sample of Dutch investors along with a standard deviation of 0.24, both of which are slightly above our estimates. Using an index-based approach leaves the wave-by-wave estimates of α^{AEX} mostly unaffected. The median rises from 0.028 to 0.033, the change in the mean is similar, and the distribution is spread out slightly more with a standard deviation of 0.18 instead of 0.16. These values are very much in line with Dimmock, Kouwenberg, Mitchell, et al. (2015), Dimmock, Kouwenberg, and Wakker (2016), and Anantanasuwong et al. (2020).

In order to ease the comparison with prior studies, we regress α^{AEX} on a set of correlates (see Tables F.4 for our model, H.5 for BBLW-indices estimated on a wave-by-wave basis, and H.11 when estimating taking individual means of the BBLW-indices across waves). The most interesting relation concerns the relation of risk aversion and ambiguity attitudes. The mixed results of previous papers (Dimmock, Kouwenberg, and Wakker, 2016, and Delavande, Ganguli, and Mengel, 2019 find a negative relation; Dimmock, Kouwenberg, Mitchell, et al., 2015, and Anantanasuwong et al., 2020, a positive one) find their reflection in a zero conditional correlation in our data. In contrast, we found risk aversion to be a strong predictor of the ambiguity types in Table F.2. In terms of ambiguity aversion the implied relationship is nonlinear: The near-SEU types (α^{AEX} near zero) are clearly less risk averse on average than all other types, whose average α is larger (ambiguity averse and high noise types) or smaller (the ambiguity seeking). This result underscores the importance of considering the multidimensional nature of heterogeneity explicitly.

In line with Dimmock, Kouwenberg, Mitchell, et al. (2015), Dimmock, Kouwenberg, and Wakker (2016), and Anantanasuwong et al. (2020), we do not find financial numeracy to be a significant predictor of α^{AEX} when estimated based on the BBLW-indices. Conversely, based on our model estimates, we find a negative relation,

2. Where necessary, we convert all values from other studies to conform to the scale of our α parameter.

but the effect size is rather small: a one standard deviation increase in the numeracy index is associated with a decrease of α^{AEX} by 0.01 (Tables F.4).

For likelihood insensitivity, moving from our wave-by-wave estimates in Section 3 to an index-based approach, ℓ^{AEX} rises substantially (Table H.1). For example, the median increases from 0.6 to 0.88. This rise is a consequence of the fact that set-monotonicity errors are reflected in a more important random component when estimating (6) whereas they lead to $\ell^{AEX} > 1$ under the indices approach. When partitioning the sample into valid and invalid values of the indices, the mean of σ^{AEX} is 0.07 in the former and 0.16 in the latter. The stochastic component picks up other types of imprecisions as well – in the subsample with valid values of $(\alpha^{AEX}, \ell^{AEX})$, the index-based median estimate of ℓ^{AEX} is 0.8.

The values we estimate using indices are larger than urn-based estimates (both Dimmock, Kouwenberg, and Wakker (2016) and Dimmock, Kouwenberg, Mitchell, et al. (2015) find average values of ℓ^{urn} close to 0.4) and slightly below others for the stock market (Anantanasuwong et al., 2020, estimate the median of ℓ^{AEX} to be 1 when including all observations and 0.89 when conditioning on valid indices).

Looking at the correlates of marginal parameter estimates, ℓ falls in both education and numeracy, which is in line with Dimmock, Kouwenberg, and Wakker (2016) and Anantanasuwong et al. (2020) while Dimmock, Kouwenberg, Mitchell, et al. (2015) find a positive relation. While this holds true regardless of whether we use our model or the indices-based approach, the latter masks some interesting patterns. For example, the large positive correlation between ℓ^{AEX} and the oldest age group in the indices-based approach seems to be driven in equal parts by likelihood insensitivity and imprecisions: In Table F.4, the marginal effect of being in the highest age group compared to the lowest age group is 0.034 for ℓ^{AEX} and 0.05 for σ^{AEX} where only the latter is significant at the 0.05 level. Conversely, Table H.11 reveals that for the indices the marginal effect of the oldest age group is 0.075 and highly significant. Even more interesting, there does not seem to be a correlation between gender and likelihood insensitivity in the indices-based approach. Estimates from our model (Table F.4) show that this is due to women having a higher ℓ^{AEX} (0.032), but a smaller σ^{AEX} (-0.015). Those relations are hidden when only considering indices which can explain why Dimmock, Kouwenberg, and Wakker (2016) and Anantanasuwong et al. (2020) also do not find a relation of gender and likelihood insensitivity. Dimmock, Kouwenberg, Mitchell, et al. (2015), however, find a positive relation, as well.

While we are not aware of any studies estimating deviations from a benchmark model in the context of choice under ambiguity, several papers estimate parameters related to the standard deviation of σ^{AEX} in an expected utility context. Alekseev, Harrison, Lau, and Ross (2018) find subjects who are older, less educated, and have lower income, to have a larger measure for noise. Echenique, Imai, and Saito (2021) find younger and cognitively able subjects to come closer to expected utility behavior. Choi, Kariv, Müller, and Silverman (2014) find that deviations from utility maximizing behavior are by high age, low education, low income, and low wealth. The results line up well with ours: Table F.4 reports that older, less educated, and low numeracy subjects are associated with a higher σ^{AEX}. Increasing the numeracy measure by one standard deviation is related to a decrease in σ^{AEX} of 0.034. While we do not find a consistent relation to financial assets in Table F.4, we do so once we leave out the numeracy measure which Choi et al. (2014) also do not control for.

Our larger sample size helps add precision to suggestive prior findings on a negative relation of both α and ℓ on the one hand, and portfolio risk on the other hand. Anantanasuwong et al. (2020) predict risky investment shares in different asset classes (individual stock, MSCI World, Bitcoin) in a sample of investors. They find weak evidence that the respective ambiguity parameters predict investing in an asset class. Dimmock, Kouwenberg, and Wakker (2016) find also some evidence that both parameters predict low stock market participation rates. One standard deviation increase in ℓ is associated with a 2.8 percentage points lower likelihood to own any stocks or funds, but with all controls the relation is only significant at the 0.1-level. For the indices, Table H.6 reveals a smaller marginal effect (−0.0096) while we find a similar effect size for our model estimates (Table H.6), both coefficients being significant at the 0.05-level. For ambiguity aversion, Dimmock, Kouwenberg, and Wakker (2016) find a relation with stock participation only for subjects who perceive having a low competence with respect to stock returns. We find in the full sample a highly significant relation for both model estimates and the indices with marginal effects of −0.029 and −0.024, respectively. Also for shares invested in risky assets we find clearly negative coefficients for both ambiguity preferences. Bianchi and Tallon (2018) show that conditional on investing in a particular product class, ambiguity averse investors exhibit a form of home bias, causing them to take more risk. This is a subtle mechanism, which is consistent with our findings. Our results suggest that ambiguity averse individuals are less likely to invest in risky assets in the first place.

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