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The Distribution and Relevance of Ambiguity Attitudes

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This paper analyzes the stability and distribution of ambiguity attitudes using a broad population sample. Using six waves of data, a structural stochastic choice model yields three individual-level parameters: ambiguity aversion, ambiguity-induced insensitivity, and the magnitude of decision errors. These parameters are heterogeneous across individuals, but stable over time and across the domains of financial markets and climate change. We summarize heterogeneity using a discrete classification approach with four types. We label these types as being near ambiguity neutral, ambiguity-averse, ambiguity-seeking, or erratic. Observed characteristics vary between groups in plausible ways. Ambiguity types predict risky asset allocation, even after controlling for covariates.

Keywords: ambiguity attitudes; temporal stability; domain specificity; cluster analysis; household portfolio choice

JEL: D81, G41, C38, D14,

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. Ambiguity-induced insensitivity (α -insensitivity) measures how strongly decisions react to changes in subjective beliefs about the ambiguous event; an alternative interpretation of this parameter is the perceived degree of ambiguity. In ambiguous environments, decision-making under risk emerges as the special case where both parameters are irrelevant.

To what extent ambiguity aversion and α -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 more than 11,000 person \times 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. For 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*. The matching probability of an event makes an individual indifferent between receiving the prize with that probability and receiving it conditional on the event.

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 and non-complementary events exceeds the matching probability of their union. This is an indication of ambiguity-induced insensitivity, i.e., individuals underreact to changes in probabilities. On average they are, hence, ambiguity averse for high-probability events but ambiguity seeking for low-probability events. 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 individuals assess 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 α -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 \times wave observation separately. The stylized facts on matching probabilities are reflected in the marginal parameter distributions. On average, individuals are ambiguity averse. α -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 size of the stochastic component turns out to be a key feature for describing different individuals' choice sequences.

We show that all three parameters are largely stable over time and across domains. Over time, the stability of ambiguity aversion and α -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. Conversely, transferability for α -insensitivity is lower. These results suggest that ambiguity aversion is a domain-invariant preference parameter but that individuals might perceive a different level of ambiguity in different domains.

Imposing stability of ambiguity attitudes over time, 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 behaving just like under risk; ambiguity aversion and α -insensitivity play lim-

ited roles. For two groups, α -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 very similarly under ambiguity and under risk 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 for which ambiguity plays a limited role 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, 2024), 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, 2024) and show connections of ambiguity preferences with portfolio choices (Dimmock, Kouwenberg, Mitchell, and Peijnenburg, 2016; Anantanasuwong et al., 2024). We replicate many of these findings, unify several conflicting pieces of prior evidence, and go beyond them in various ways. Doing so is possible for three main reasons.

First, our data is very detailed and unusually large along both panel dimensions. Second, 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. Third, prior work looking at parameter heterogeneity and behavioral consequences has focused on marginal parameter distributions. However, the preference parameters in question 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. Modeling 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. This section also examines robustness to various specification choices and provides a detailed comparison with the literature. We discuss the findings in Section 5.

2 Measurement design and data

In this section, we sketch our design for measuring ambiguity attitudes and describe stylized facts in our data. These key facts will guide our framework and empirical strategy. Additionally, we briefly describe additional variables that will be important for our analyses.

2.1 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. Individuals make a series of choices, all of which are

between a bet on an uncertain event and a lottery with known probabilities.¹ Choices are incentivized and in case of a positive outcome, respondents would earn € 20 on top of regular compensation for participation. Our main source of uncertainty is the Amsterdam Exchange Index (AEX), the most widely known stock market index in the Netherlands. An exemplary uncertain event would be that a € 1000 investment into the AEX would be worth at least € 1100 after six months. The lottery is introduced as a wheel of fortune during the tutorial, which is spun to determine payoffs. The lottery starts with equal probabilities. Depending on a respondent’s choice between the AEX event and the lottery, the lottery will be made more or less attractive by adjusting the winning probability. In this chained design, subjects make three to four binary choices for each event. See Online Appendix A for a detailed documentation of the protocol.

To make the chained design incentive compatible, we let subjects start a random number generator for selecting the question to be paid out before they make any decisions (similar approaches have been suggested by Bardsley, 2000; Johnson, Baillon, Bleichrodt, Li, van Dolder, et al., 2021). 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 also makes it less likely that subjects hedge against the encountered ambiguity.²

We follow Baillon, Huang, et al. (2018) in partitioning 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 $E_3^{AEX} : Y_{t+6} \in [950, 1100]$. In the 1999-2019 period,

1. Since eliciting attitudes about ambiguous events is cognitively demanding for participants, we confront subjects with binary choices only. 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. 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.

2. See Baillon, Halevy, and Li (2022a) and Baillon, Halevy, and Li (2022b). Online Appendix B.4 provides a detailed discussion of evidence against meaningful amounts of hedging in our data.

empirical frequencies of the AEX' 6-month returns for this partition were 0.24, 0.28, and 0.48. We also include the complementary events $E_{1,C}^{AEX}, E_{2,C}^{AEX}, E_{3,C}^{AEX}$. Our elicitation starts with the most intuitive event $E_0^{AEX} : Y_{t+6} \in (1000, \infty]$ in order to make the start as smooth as possible for participants.

We implemented the elicitation in the LISS panel administered by CentER-data (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.

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. That wave would start by showing the screen selected for payment and the respondent's choice. 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"). Each participant whose choice turned out to be winning received € 20.

2.2 Data on ambiguity attitudes

In line with the domain of our application, we invited the financial deciders of households to participate. Invitations went out to 2,773 individuals, 2,407 of whom completed the questionnaire in at least one wave. In our main specification, we exclude 2 % of person \times wave observations where respondents seemingly did not engage with the contents of the questionnaire. This happens if she chose the same option (AEX or lottery) in all choices *and* her response

time was below the 15th percentile. 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. We summarize these data by looking at matching probabilities and set-monotonicity violations.

In a revealed preference setting, choices on each of our seven events yield data on an interval for the *matching probability* of length between 0.01 and 0.1. 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. They allow to abstract from risk attitudes and weighting of known probabilities (Dimmock, Kouwenberg, and Wakker, 2016). A core axiom of all theories of choice under ambiguity is set monotonicity. In our context, set monotonicity implies that if $E_j \subseteq E_k$, then $m(E_j) \leq m(E_k)$. Violations of set monotonicity are an important measure of individual rationality. In our design, eight superset-subset pairs of events bear the potential of such violations: $E_0^{AEX} \supset E_1^{AEX}$, $E_{1,C}^{AEX} \supset E_2^{AEX}$, $E_{1,C}^{AEX} \supset E_3^{AEX}$, $E_{2,C}^{AEX} \supset E_0^{AEX}$, $E_{2,C}^{AEX} \supset E_1^{AEX}$, $E_{2,C}^{AEX} \supset E_3^{AEX}$, $E_{3,C}^{AEX} \supset E_1^{AEX}$, and $E_{3,C}^{AEX} \supset E_2^{AEX}$. Summary statistics on matching probabilities (Table 1) and set-monotonicity errors (Table 2) reveal five salient features.

First, the sum of the average matching probabilities of an event and its complement is less than one. Similar to findings for Ellsberg (1961) urns (e.g., Dimmock, Kouwenberg, and Wakker, 2016) and in elicitation procedures more similar to ours (e.g., Anantanasuwong et al., 2024), this pattern is indicative of *ambiguity aversion*. This follows from the observation that matching probabilities add up to one for ambiguity-neutral decision makers, who behave identically under ambiguity and under risk.

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 *a-insensitive*, i.e., matching probabilities underreact to changes in subjective probabilities. The equivalent finding that subjects tend to be ambiguity seeking for low probability events and ambiguity averse for

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
$E_0^{AEX} : Y_{t+6} \in (1000, \infty)$	0.5	0.27	0.075	0.45	0.93	0.63	0.52
$E_1^{AEX} : Y_{t+6} \in (1100, \infty]$	0.36	0.25	0.03	0.35	0.65	0.24	0.31
$E_{1,C}^{AEX} : Y_{t+6} \in (-\infty, 1100]$	0.52	0.28	0.075	0.45	0.93	0.76	
$E_2^{AEX} : Y_{t+6} \in (-\infty, 950)$	0.36	0.25	0.03	0.35	0.75	0.28	0.22
$E_{2,C}^{AEX} : Y_{t+6} \in [950, \infty)$	0.56	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 A.3 for a visualization. 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 2.3). Judged frequencies are available for 1952 subjects in our sample. Online Appendix B.2 provides more statistics on matching probabilities including variation across waves. Sample restrictions as described in Section 2.2.

high probability events is very robust 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 0.62 and 0.86, with an average of 0.78. This fact reveals large heterogeneity in response patterns. Standard deviations in our sample range between 0.25 and 0.29, lining 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.³ The first 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,

3. In this and the subsequent paragraph, we refer to some numbers not contained in Table 2. These can be found in Online Appendix Table B.4.

Table 2. Judged historical frequencies and set-monotonicity violations

	Dependent variable: Set-monotonicity violation			
	(1)	(2)	(3)	(4)
Intercept	0.14*** (0.0024)	0.17*** (0.003)		
Judged frequencies (superset - subset)		−0.076*** (0.0055)	−0.044*** (0.0054)	−0.037*** (0.0059)
Superset-subset pair fixed effects	No	No	Yes	Yes
Individual fixed effects	No	No	No	Yes
Observations	15616	15616	15616	15616

Notes: OLS regressions on the subject \times 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 2.3 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 restrictions as described in Section 2.2. * – $p < 0.1$, ** – $p < 0.05$, *** – $p < 0.01$.

55 % of individuals violate set monotonicity at least once. While substantial, such frequencies are anything but uncommon in general subject pools (see, for example, Dimmock, Kouwenberg, and Wakker (2016) and Anantanasuwong et al. (2024) for ambiguity attitudes or Gaudecker, Soest, and Wengström (2011) for risky choices). We view violations of set monotonicity as *prima facie* evidence for decision errors. That is, they are unlikely to reflect preferences.

Fifth, set-monotonicity errors are highest when individuals think that the event forming the subset has occurred almost as frequently as the superset. In May 2019, we asked individuals to state the empirical frequency of the events we also use during elicitation of ambiguity attitudes. Columns 2-4 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/or for 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,

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
Feels threatened by climate change	1936	0.55	0.22	0.4	0.6	0.6

Notes: Income and financial assets are in thousands and equivalized for couples. The variables concerning climate change are normalized such that they vary between 0 and 1. Sample restrictions as described in Section 2.2.

from Table 1 we see the average judged 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 $E_{1,C}^{AEX} \supset E_3^{AEX}$.

The first four stylized facts are also present in the data collected with climate change as the source of uncertainty; we did not ask about historical frequencies and cannot check the fifth.

2.3 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.

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.

Risky asset holdings. 20 % of our sample directly hold risky assets, which include, among others, individual stocks, funds, and bonds. Conditional on owning risky assets, the average share is 35 %.

Risk Aversion. We measure households’ risk aversion using the preference survey module developed by Falk, Becker, Dohmen, Huffman, and Sunde (2022) which includes a general risk question and a quantitative component. 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).

Numeracy. We measure three dimensions of numeracy based on established survey modules: basic numeracy; financial numeracy; and probabilistic numeracy. 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., Rooij, Lusardi, and Alessie, 2011; Hudomiet, Hurd, and Rohwedder, 2018).

Knowledge of and concern about climate change. To help analyze ambiguity attitudes toward climate change, we asked subjects in November 2019 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.

3 Framework, marginal parameter distributions, and stability

We set up a stochastic model of choice under ambiguity that is guided by the stylized facts we described above. After describing the distributions of wave-by-wave estimates of parameters in Section 3.2, we examine transferability of ambiguity attitudes across time and domains.

3.1 Framework and empirical strategy

Baillon, Bleichrodt, Li, et al. (2021) propose estimating ambiguity aversion α and α -insensitivity ℓ using the following indices:⁴

$$\alpha_{\text{BBLW}}^S = \frac{1}{2} \cdot \left(1 - \frac{1}{3} \sum_{j=1}^3 m(E_j^S) - \frac{1}{3} \sum_{j=1}^3 m(E_{j,C}^S) \right) \quad (1)$$

$$\ell_{\text{BBLW}}^S = 1 - \sum_{j=1}^3 m(E_{j,C}^S) + \sum_{j=1}^3 m(E_j^S) \quad (2)$$

These indices formalize the intuition from above. α_{BBLW}^S measures how strongly the sum of matching probabilities for an event and its complement deviate from one. ℓ_{BBLW}^S measures sub-additivity by comparing the sum of complementary events to the sum of single events. Some multiple-prior models of ambiguity admit an interpretation of ℓ_{BBLW}^S as the perceived level of ambiguity (e.g. Ghirardato, Maccheroni, and Marinacci, 2004). Each single event appears in two composite events. Hence, both α_{BBLW}^S and ℓ_{BBLW}^S are zero for an ambiguity neutral agent. The indices are valid for decision sequences satisfying set monotonicity. We use a different estimation strategy because of the large number of violations we see in our data. Section 4.3 reports results for the BBLW-indices.

Our approach puts more structure on $m(E)$ by assuming that observed individual-level matching probabilities consist of a deterministic part $m^*(E)$ and a random error. Because set-monotonicity violations increase in the perceived similarity of two events in the past, we use an additive error term, also known as a Fechner error (e.g. Loomes and Sugden, 1995). Assuming it to be normally distributed, we have

$$m(E) = m^*(E) + \varepsilon \quad \text{with } \varepsilon \sim \mathcal{N}\left(0, (\sigma^S)^2\right). \quad (3)$$

4. We define α to lie on $[-0.5, 0.5]$ so that the scales of α and ℓ have the same length.

We further assume that $m^*(E)$ depends on a subjective, additive probability measure $\Pr_{\text{subj}}(E)$ ⁵ and follows the *neo-additive* model (Chateauneuf, Eichberger, and Grant, 2007):

$$m^*(E) = \begin{cases} 0, & \text{if } \Pr_{\text{subj}}(E) = 0 \\ \tau_0^S + \tau_1^S \cdot \Pr_{\text{subj}}(E), & \text{if } \Pr_{\text{subj}}(E) \in (0, 1) \\ 1, & \text{if } \Pr_{\text{subj}}(E) = 1 \end{cases} \quad (4)$$

$$0 \leq \tau_1^S, 0 \leq \tau_0^S \leq 1 - \tau_1^S.$$

Neo stands for “non-extreme outcome”, i.e., the deterministic component of matching probabilities is zero (one) for events the decision-maker considers impossible (certain); it is linear in $\Pr_{\text{subj}}(E)$ in between.⁶ How these translate into matching probabilities may depend on the source of uncertainty S . We chose this functional form because of its tractability and good empirical performance (Li et al., 2018). The ambiguity indices are calculated based on the deterministic component of matching probabilities:

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

Restricting $\tau_1^S \geq 0$ means that set-monotonicity violations must be generated by decision errors. $0 \leq \tau_0^S \leq 1 - \tau_1^S$ excludes overreaction to changes in subjective probabilities. Whether the latter restriction is useful can be debated; we drop it in robustness checks. Whenever the restrictions do not bite, our estimates will closely align with the BBLW indices. If they do, our estimation strategy adds clarity by enforcing theoretical restrictions on the ambiguity parameters,

5. Subjective probabilities might be influenced by probability weighting induced by risk. Baillon, Bleichrodt, Li, et al. (2021) introduce the more precise term *a*-neutral probabilities, interpreting them as the beliefs of an ambiguity-neutral twin of the decision-maker.

6. The general reasoning does not depend on the functional form assumption. For decision sequences satisfying set monotonicity, condition (ii) in Proposition 24 of Baillon, Bleichrodt, Li, et al. (2021) guarantees that the BBLW-indices are equivalent to least squares estimates of a neo-additive matching probability function. Their condition (iii) ensures that under set monotonicity, the ambiguity indices remain valid if $m^*(\cdot)$ does not have the neo-additive structure, but the subjective probabilities are the best fit to $m^*(\cdot)$.

attributing deviations from the best-fitting deterministic model to the random component of the matching probability in (3).

Under these assumptions, we can write down the likelihood for the data of individual i in wave t . Let $m_{\text{lb}}^{\text{ub}}(E) := \{m(E) \mid \text{lb}(E) \leq m(E) \leq \text{ub}(E)\}$ be the interval identified by the choice sequence for event E . The likelihood that the actual matching probability falls into the interval becomes:

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

With $\theta := [\tau_0^S, \tau_1^S, \sigma^S, \Pr_{\text{subj}}(E_0), \Pr_{\text{subj}}(E_1), \Pr_{\text{subj}}(E_2)]$, the likelihood of observing individual i 's data in wave t becomes:

$$\mathcal{L}(\theta_{i,t}) = \prod_{E \in \{E_0^S, \dots, E_{3,C}^S\}} \Pr(m(E; \theta_{i,t}) \in (m_{\text{lb}}^{\text{ub}}(E))_{i,t}), \quad (5)$$

which we estimate subject to the constraints on τ_0^S and τ_1^S given in (4) and $\Pr_{\text{subj}}(\cdot)$ being proper probabilities. Online Appendix C has more details on the estimation procedure.

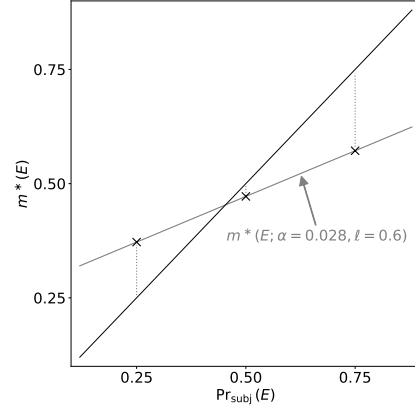
3.2 Marginal parameter distributions

Figure 1a summarizes the marginal distribution of our parameters of interest across the AEX waves. There is substantial variation in all estimated parameters. The $[0.05, 0.95]$ -range covers a large portion of the ambiguity parameters' respective support. Ambiguity aversion prevails at both the mean and at the median; we estimate ambiguity seeking behavior at the first quartile. The degree of a -insensitivity is substantial; the mean and median are both close to 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 95th percentile.

We illustrate these numbers with choice behavior in an environment similar to a task in our design. A decision maker decides between a lottery yielding x with probability p and a bet on an event E with $\Pr_{\text{subj}}(E) = p$ which pays out x if event E occurs and nothing otherwise. The probability to choose the bet on

	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 individual \times wave observation; Panel a displays the estimates over all waves. Sample restrictions as described in Section 2.2. Panel b illustrates $m^*(E)$ at the median parameter estimates from Panel a. The gray line shows the neo-additive function $m^*(E)(Pr_{subj}(E); \alpha, \ell)$. The dotted vertical lines depict the difference between $m^*(E)$ and $Pr_{subj}(E)$ with these probabilities fixed at 0.25, 0.5, and 0.75 respectively.

Figure 1. Marginal distributions of estimated parameters

the ambiguous event obtains as $\Phi\left(\frac{m^*(E)-p}{\sigma^{AEX}}\right)$ with Φ denoting the standard normal cumulative distribution function. The gray line in Figure 1b depicts $m^*(E)$. For $Pr_{subj}(E) = p \in \{0.25, 0.5, 0.75\}$, the dotted vertical lines show $|m^*(E) - p|$. Online Appendix Tables D.1–D.3 contain choice probabilities when varying parameters along the quantiles shown in Figure 1a.

For $p = Pr_{subj} = 0.5$, α -insensitivity does not impact choices because $m^*(E) - p = -\alpha^{AEX}$. At the median value of σ^{AEX} , the probability to choose the ambiguous option would be 36 %, which is substantially below 50 %. Hence, the seemingly small value $\alpha^{AEX} = 0.028$ can lead to sizable deviations from choice under risk, even at the point where α -insensitivity does not play a role. Changing α^{AEX} shifts the line $m^*(E)(Pr_{subj}(E); \alpha^{AEX}, \ell^{AEX})$; the value at the first quartile of α^{AEX} implies ambiguity seeking behavior for $p = Pr_{subj} = 0.5$.

For the other two choices singled out in Figure 1b, the probabilities to choose the bet on the ambiguous event amount to 0.95 ($p = 0.25$) and 0.01 ($p = 0.75$) indicating ambiguity seeking behavior for small probability events. When α -insensitivity changes, the line for $m^*(E; \cdot)$ rotates in the point

$(0.5, m^*(0.5; \cdot))$. Increasing it thus makes both choice probabilities even more extreme; decreasing it brings $m^*(E) - p$ 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 the bet with probability 0.46.

These results illustrate two facts. First, there is rich heterogeneity in the parameters. Second, the model makes sharp predictions for a wide range of estimated values of σ^{AEX} . The marginal distributions considered in this section are, however, of limited value because they do not capture co-variation of the three parameters. We address this in Section 4 below, where we also assume temporal stability of the three parameters. We now establish that there is no systematic variation in individual parameters over time.

3.3 Parameter stability over time

Figure 2 depicts the same quantiles of the parameter estimates' distributions as Figure 1a, but separately for each wave. The shapes of all three parameters' distributions look broadly similar for the AEX waves. Nevertheless, there are statistically significant differences; Table D.5 and Figure D.1 in the Online Appendix show the complete set. 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 the difference between the 54th and 48th percentiles in the pooled data. There are no significant changes in average α -insensitivity between the early and the late waves. For the standard deviation of Fechner errors, 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 an extremely volatile AEX episode, associated with the onset of the Covid-19 pandemic. The overall pattern is consistent with a moderate amount of learn-

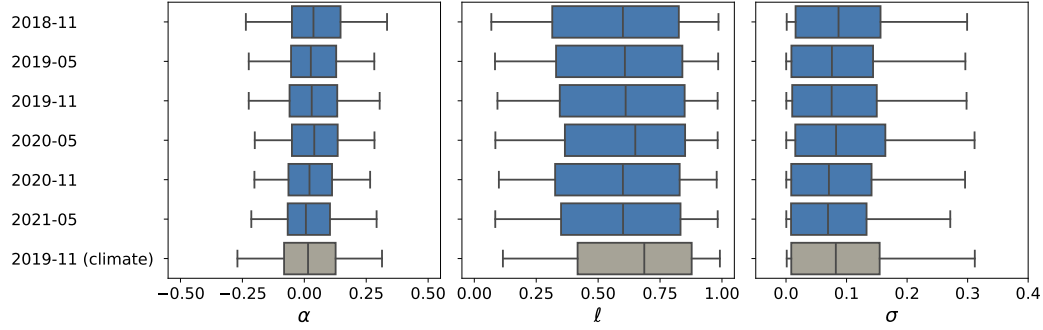


Figure 2. Marginal distributions of estimated parameters, wave by wave

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 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 restrictions as described in Section 2.2. Online Appendix Table D.4 contains the underlying numbers.

ing—except for α -insensitivity—and a transitory shock associated with the uncertainty during the initial phase of the pandemic. Magnitudes of all changes are small in economic terms.

From the perspective of our paper, a 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. The 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} . These coefficients can be interpreted as correlations since the variance of the parameters is stable over time. They are similar in magnitude to temporal correlations of risk aversion coefficients: Chuang and Schechter (2015) survey that literature and report correlations between 0.13 and 0.48 for large-scale studies with at least one month between elicitations.⁷

7. Alternatively, Table D.7 reports correlations between parameter estimates for all pairs of survey waves. The correlation coefficients are slightly decreasing in the distance between survey waves. Again, they are slightly lower for the wave in May 2020.

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

		OLS	ORIV	
		(1)	(2)	(3)
$\alpha_{\text{last 3 waves}}^{AEX}$	Intercept	0.017*** (0.0025)	−0.0097** (0.0038)	
	$\alpha_{\text{first 3 waves}}^{AEX}$	0.25*** (0.01)	0.95*** (0.07)	0.98*** (0.09)
	Adj. R ²	0.07		
	1st st. F		148	101
$\ell_{\text{last 3 waves}}^{AEX}$	Intercept	0.37*** (0.0087)	0.024 (0.022)	
	$\ell_{\text{first 3 waves}}^{AEX}$	0.36*** (0.01)	0.97*** (0.04)	0.95*** (0.05)
	Adj. R ²	0.14		
	1st st. F		512	294
$\sigma_{\text{last 3 waves}}^{AEX}$	Intercept	0.066*** (0.0019)	−0.0012 (0.0054)	
	$\sigma_{\text{first 3 waves}}^{AEX}$	0.32*** (0.01)	0.99*** (0.05)	0.97*** (0.08)
	Adj. R ²	0.082		
	1st st. F		250	130
Controls		No	No	Yes
N Subjects		1859	1859	1452

Notes: 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 top set of rows reports the regressions based on α^{AEX} as dependent and independent variables. The middle (bottom) set of rows shows the results for ℓ^{AEX} (σ^{AEX}). 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 are reported in Table D.8. Sample: All waves meeting our inclusion criteria (see Section 2.2) for individuals with at least two such waves in 2018/2019 and at least one such wave in 2020/2021. * – $p < 0.1$, ** – $p < 0.05$, *** – $p < 0.01$.

It is well known that estimated risk aversion parameters are subject to large measurement error. 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 again partition the data so that we predict parameters in waves 4-6 with parameters from waves 1-3. 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. Whether we control for a large set of variables or not, all coefficients of interest are between 0.95 and 0.99. None of them is statistically different from 1. In the first stage regressions, all F-statistics for joint significance of the instruments exceed 100. These 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. We compare our AEX results with the same design, but using climate as the source of uncertainty (see Section 2.1). Estimation is identical to estimation for one wave of the AEX data.

The last row in Figure 2 shows the distribution of the estimated parameters. On average, ambiguity aversion is slightly lower in the climate data than in the AEX data. α -insensitivity regarding temperature changes is notably greater than for the AEX data; the average difference amounts to 0.05. The standard deviation of the Fechner errors is very similar in both domains.

Once more, parameter stability at the individual level is the more interesting question from our perspective. Table 5 shows regressions for each param-

eter in the climate domain on parameters from the financial domain elicited in the same wave. The first column OLS-based 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, OLS estimates may well be biased. Beyond attenuation due to classical measurement, spurious *positive* correlation because the two elicitations took place in the same session. We address this issue by running 2SLS 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 will be eliminated if estimation errors are uncorrelated across waves. The last two columns in Table 4 report our results. Again, the coefficients of interest are very similar across specifications with and without covariates.

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. Our OLS coefficients are comparable to results from Anantanasuwong et al. (2024) for different sources of ambiguity within the financial domain. In line with our 2SLS results, Anantanasuwong et al. (2024) conclude from a factor analysis 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 coefficients of 0.6 are 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. (2024) also find weaker dependence across domains for ℓ with correlation coefficients of 0.16 or 0.45, depending on whether they keep subjects with set-monotonicity violations in the sample. Correcting for measurement error, we find a substantially higher common component. 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 other values.

Table 5. Predicting climate ambiguity parameters with AEX parameters

		OLS	2SLS	
		(1)	(2)	(3)
$\alpha_{2019-11}^{climate}$	Intercept	−0.003 (0.0033)	−0.016*** (0.0039)	
	$\alpha_{2019-11}^{AEX}$	0.69*** (0.03)	1.04*** (0.05)	1.06*** (0.07)
	Adj. R ²	0.39		
	1st st. F		215	148
$\ell_{2019-11}^{climate}$	Intercept	0.43*** (0.015)	0.28*** (0.024)	
	$\ell_{2019-11}^{AEX}$	0.35*** (0.02)	0.60*** (0.04)	0.63*** (0.05)
	Adj. R ²	0.13		
	1st st. F		735	408
$\sigma_{2019-11}^{climate}$	Intercept	0.053*** (0.0027)	0.022*** (0.005)	
	$\sigma_{2019-11}^{AEX}$	0.51*** (0.03)	0.83*** (0.05)	0.88*** (0.07)
	Adj. R ²	0.23		
	1st st. F		92	51
Controls		No	No	Yes
N Subjects		1843	1843	1411

Notes: 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. The top set of rows reports the regressions based on α^S as dependent and independent variables. The middle (bottom) set of rows shows the results for ℓ^S (σ^S). For 2SLS, we use a stacked data set in which each instrumental variable enters 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 are reported in Table D.12. Sample restrictions as described in Section 2.2.

* – $p < 0.1$, ** – $p < 0.05$, *** – $p < 0.01$.

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 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. 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

We have established that all three parameters α^{AEX} , ℓ^{AEX} , and σ^{AEX} are very heterogeneous across individuals, but remarkably stable within individuals over time. Due to the non-separable nature of the choice model, the marginal distributions are not directly informative for decision behavior. For example, individuals who fully trust their probability judgments necessarily have an ambiguity aversion parameter of zero. This is even clearer in the perception-of-ambiguity interpretation of ℓ : When a situation is perceived to be free of ambiguity, taste for it cannot play a role. In general, ℓ bounds how much α can matter through the constraints in (4), which implies $|\alpha| \leq \ell/2$. In a similar vein, both preference parameters hardly matter for choice probabilities if σ takes on very high values.

In this section, we classify individuals into discrete types characterized by our three parameters of interest, without imposing restrictions on their dependence. We find that four types capture much of the observed heterogeneity. These types relate to socio-demographic characteristics and help predict real-

world financial behavior. In Section 4.3, we compare our results to alternative specifications and to prior literature.

4.1 Describing heterogeneity in attitudes and error propensities

In a first step, we re-estimate (5), imposing that $\tau_{0,i}^{AEX}$, $\tau_{1,i}^{AEX}$, and σ_i^{AEX} do not vary across waves. Doing so changes the interpretation of σ_i^{AEX} because, in addition to the previous types of inconsistencies, it will also capture behavior that cannot be explained by time-constant preference parameters. Estimates of σ_i^{AEX} will thus be larger than our previously-reported estimates of $\sigma_{i,t}^{AEX}$. We then apply the k -means algorithm (e.g. Bonhomme and Manresa, 2015) to classify individuals into a discrete set of groups.

We report results for $k = 4$ types, striking a balance between qualifying as a summary and not merging types with economically meaningful choice behaviors. With results at hand, we explain this choice in more detail at the end of this section. Figure 3 shows the distribution of ambiguity profiles in the (α, ℓ) -space with large symbols indicating group means and small symbols indicating individual profiles. We list the group means of σ in the legend.

At 30%, the largest share of all subjects is estimated to have an ambiguity aversion parameter $\alpha^{AEX} = -0.0002$, α -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 ambiguity-neutral decision makers who do not make any errors would have a zero for each parameter, we label it the “near ambiguity neutral” type. For the examples we used in the Section 3.2—binary choices between a lottery yielding € x with probability p and a bet on an event E with $\Pr_{\text{subj}}(E) = p \in (0.25, 0.5, 0.75)$ —we obtain choice probabilities for the bet of 0.7, 0.5, and 0.31. That is, the probability of choosing the ambiguous outcome strongly decreases in the probability of the high risky outcome.⁸

8. The numbers on choice probabilities by ambiguity groups can be found in Online Appendix Table E.1.

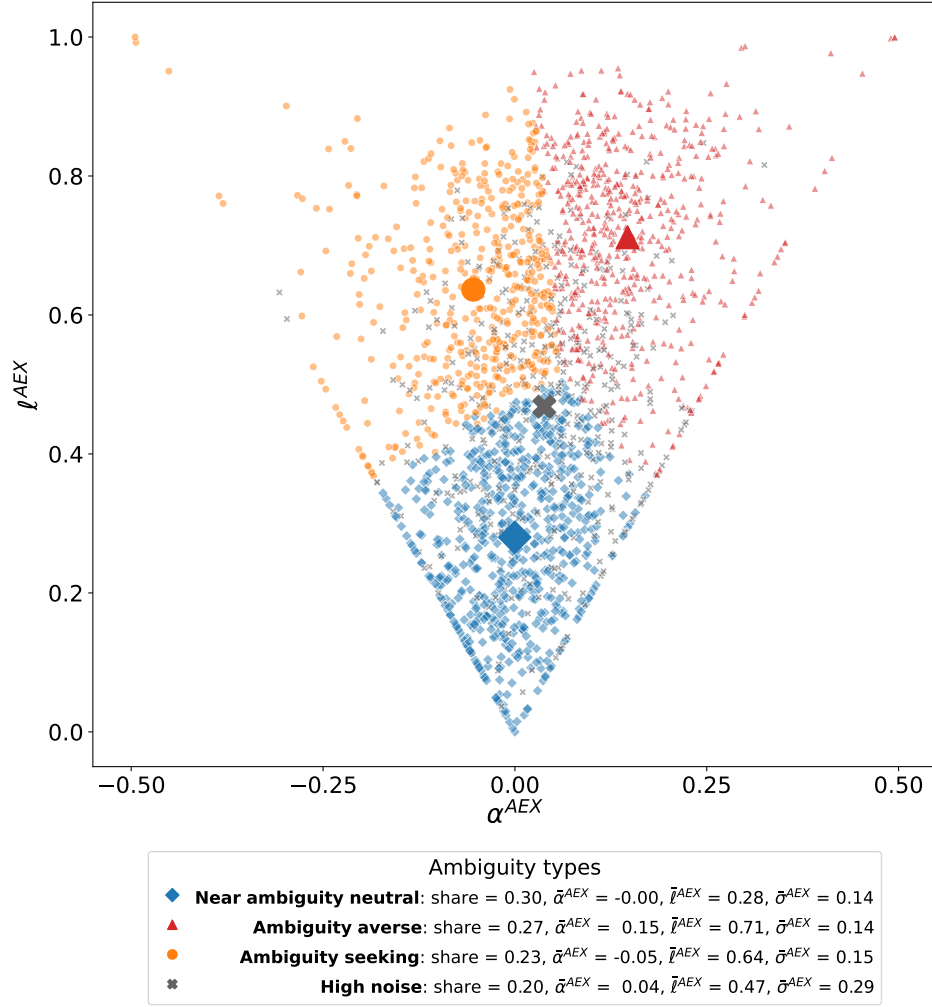


Figure 3. Summarizing heterogeneity in ambiguity profiles with $k = 4$ discrete groups

Notes: The small symbols depict individual preference parameter estimates $(\alpha_i^{AEX}, \ell_i^{AEX})$ obtained from estimating (5) 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. We display summary statistics on marginal distributions in the table below. Sample restrictions as described in Section 2.2.

	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

We label the second-largest group, comprising 27 % of the sample, the “Ambiguity averse”. This group is estimated to have an ambiguity aversion parameter $\alpha^{AEX} = 0.15$, α -insensitivity $\ell^{AEX} = 0.71$, and a standard deviation of the Fechner errors $\sigma^{AEX} = 0.14$. Ambiguity aversion is reflected in the choice probabilities of our example, which are 58 %, 15 % and 1 % at $p = 0.25$, $p = 0.5$, and $p = 0.75$, respectively.

A third group is associated with a α -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 probabilities for the ambiguous prospect are 93 %, 64 %, and 24 %.

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 (α, ℓ) -space in Figure 3 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 3. 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.

Choice probabilities in the example are 60 %, 45 %, and 30 %; reacting much less to changes in subjective probabilities. This is not due to the source function being particularly close to the 45°-line, but because the random component in (3) 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 $m(E) = m^*(E) + \varepsilon$ will occur with a substantially positive probability. At 25 % of superset-subset pairs, we find the largest fraction of set-monotonicity errors in this group. This is about twice as often as for the other groups. 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 Table E.2). Hence, 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 $k = 4$. We have also estimated ambiguity types for $k \in$

$\{2, 3, \dots, 15\}$ and compare different cluster evaluation methods in Online Appendix E.2. $k = 4$ comes in second for the Silhouette Score, which favors $k = 3$. However, reducing k to 3 distributes the group we classified as ambiguity seeking across the other three groups. Most individuals go into the *near ambiguity neutral* group, which comprises almost 40 % of the sample and, thus, covers a very wide range of behavior. The Davies-Bouldin Index yields the best cluster performance for $k = 14$, which is far too large for our purposes. Among all number of clusters not exceeding eight $k = 4$ is the favorite.

In Online Appendix Sections E.3–E.5, we report results for $k \in \{3, 5, 8\}$. Increasing k to 5 leaves the near ambiguity neutral 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. Even when doubling k to 8, there are no groups with clearly different choice behavior from the four types considered here. The four original groups do move somewhat more toward the respective extremes. 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 of our main specification 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 3. 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 3, adding the (very small) standard errors.

Table 6. Average characteristics of group members

	Ambiguity types			
	Near ambiguity neutral	Ambiguity averse	Ambiguity seeking	High noise
Share	0.3	0.27	0.23	0.2
α^{AEX}	-0.0002 (0.0024)	0.15 (0.0032)	-0.054 (0.0039)	0.038 (0.0043)
ℓ^{AEX}	0.28 (0.0045)	0.71 (0.0054)	0.64 (0.0056)	0.47 (0.0079)
σ^{AEX}	0.14 (0.0018)	0.14 (0.0023)	0.15 (0.0024)	0.29 (0.0025)
Education: Lower secondary and below	0.13 (0.013)	0.29 (0.019)	0.26 (0.02)	0.42 (0.024)
Education: Upper secondary	0.31 (0.018)	0.38 (0.02)	0.36 (0.022)	0.3 (0.022)
Education: Tertiary	0.56 (0.019)	0.33 (0.019)	0.38 (0.022)	0.28 (0.022)
Age	54 (0.64)	55 (0.65)	57 (0.69)	65 (0.65)
Female	0.4 (0.019)	0.6 (0.02)	0.52 (0.023)	0.47 (0.024)
Monthly hh net income (equiv., thousands)	2.5 (0.04)	2.1 (0.038)	2.2 (0.05)	2 (0.042)
Total hh financial assets (equiv., thousands)	55 (6.9)	23 (2.6)	39 (5.9)	34 (4.4)
Risk aversion index	-0.1 (0.035)	0.094 (0.041)	0.012 (0.049)	0.0094 (0.053)
Numeracy index	0.63 (0.024)	-0.2 (0.038)	0.047 (0.042)	-0.72 (0.056)

Notes: The first row shows the share of individuals classified into a given group. Below, the mean of several variables for each group are shown. We display standard deviations in parentheses. Income and financial assets are in thousands and equivalized for couples. Risk aversion and numeracy are normalized to have mean zero and unit variance. Sample restrictions as described in Section 2.2.

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 E.3.

Near ambiguity neutral 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 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 ambiguity neutrality being a benchmark of rationality, from which near ambiguity neutral subjects fall short the least.

In most cases, subjects classified to be of the high noise type are found at the opposite extreme. They are the least educated and oldest on average, and their income is among the lowest. The female share is similar to the overall mean, financial assets are in between those of the other groups. The numeracy index is -0.72 on average, which corresponds to the 22nd percentile in the overall sample. The fact that subjects in the high-noise group score lower on dimensions associated with performance in cognitively demanding tasks clearly support an interpretation of decision errors stemming from erratic behavior rather than inappropriate functional form assumptions.

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 ambiguity neutral 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 ambiguity neutral and high noise types for income. 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.

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 on additional control variables, including other potential determinants of financial decisions like risk aversion and numeracy

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*** (0.024)	−0.083*** (0.023)	−0.44*** (0.059)	−0.17*** (0.055)
Ambiguity seeking type	−0.099*** (0.029)	−0.016 (0.024)	−0.15*** (0.05)	−0.026 (0.046)
High noise type	−0.18*** (0.027)	−0.054* (0.028)	−0.24*** (0.059)	−0.085 (0.059)
Controls	No	Yes	No	Yes
Observations	1727	1624	1584	1502
Pseudo R ²	0.055	0.3	0.042	0.28
<i>p</i> -values for differences between				
Ambiguity averse, Ambiguity seeking	0	0.0072	0	0.012
Ambiguity averse, High noise	0.043	0.28	0.0051	0.19
Ambiguity seeking, High noise	0.0041	0.17	0.14	0.33

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 ambiguity neutral) 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 are reported in Table E.5. Sample restrictions as described in Section 2.2.

* – $p < 0.1$, ** – $p < 0.05$, *** – $p < 0.01$.

(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 ambiguity neutral-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 invest the smallest share into them. Almost all differences between groups are significant in the unconditional specifications. 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 ambiguity neutral and ambiguity averse types. Differences between the ambiguity averse on the one hand and near ambiguity neutral 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 Table E.7, are very similar to those reported in Table 7. In particular, the same conclusions hold for unconditional and conditional differences between the ambiguity averse on the one hand, and near ambiguity neutral 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 a positive correlation of erratic response behavior in our survey and underreporting of assets.

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 Villevall (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. Within our estimation approach, we discuss four alternative specifications. We then explore differences between our estimation strategy and using the indices-based approach of Baillon, Bleichrodt, Li, et al. (2021) directly. Finally, we provide a detailed comparison with prior literature.

The four alternative specifications are (1) including all possible observations, (2) requiring a balanced panel, (3) dropping E_0 from the estimation, and (4) allowing for hypersensitivity to subjective probabilities. We highlight the main results in the text; longer descriptions and all relevant tables and figures are in Online Appendices F.1–F.4.

Including all data instead of requiring two waves meeting minimal quality standards increases the number of individuals by 10 %. Doing so does not lead to any substantive changes in the parameter distributions or the clustering outcomes. Coefficients for portfolio choice behavior attenuate slightly toward zero, but all comparisons we have highlighted in the previous section remain significant.

The opposite strategy is to require a balanced panel, i.e., six waves of reasonable data. The number of individuals in the sample drops 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 individual time series lead to more sharply identified differences in types' portfolio choice behavior – most point estimates remain similar, but p-values for group differences are even smaller than what we report in the main text.

Third, estimating the model without using the matching probabilities for the event E_0 hardly affects the results. Both the distributions of estimated parameters and of the ambiguity types remain almost unchanged. At the individual level, 93 % are assigned to the same type as with our main estimates. This means that breaking the belief hedge property (Baillon, Bleichrodt, Li, et al., 2021) does not have empirical consequences in our setup.

Fourth, we drop the restriction $0 \leq \tau_0^S \leq 1 - \tau_1^S$ in (4) so that individuals' choices may react in a hypersensitive fashion to changes in subjective probabilities. The downside is that ℓ cannot be interpreted as the perceived level of ambiguity anymore. Graphically, points can now fall below the triangle that bounds the parameter space in Figure 3. This asymmetry is reflected in the results – the only noticeable change is a drop in the estimated value of ℓ by

about 0.01. In the clustering approach, the average characteristics of near ambiguity neutral and ambiguity averse types change slightly; within individuals, 97 % are assigned the same type as in our main specification.

All these results use our maximum likelihood estimation approach, which explicitly models random choices and the interval nature of our data. An alternative is to employ the indices of Baillon, Bleichrodt, Li, et al. (2021) using least squares estimation, working with the midpoints of the identified intervals. Least squares estimation using the indices is equivalent to our approach when dropping all parameter restrictions and using interval midpoints instead of the ranges. See Online Appendix G for the procedure and detailed results. Five patterns emerge.

First, all estimates align almost perfectly at the individual level for person \times wave observations that satisfy set monotonicity and do not exhibit hypersensitivity. In general, the marginal distributions of α and σ are fairly similar to our main results. However, some restriction is binding for the majority of our sample, which makes some of the index-based results hard to interpret. For example, ℓ exceeds one for a quarter of the sample. For four out of ten person \times wave observations, one of the estimated subjective probabilities lies outside the unit interval. When working with index-based estimates of ambiguity parameters, a researcher is, hence, left with a choice of either restricting the sample to individuals with valid ambiguity parameters (e.g., Anantanasuwong et al., 2024) or keeping all observations regardless of whether the estimated parameters make sense (e.g., Dimmock, Kouwenberg, Mitchell, et al., 2015; Dimmock, Kouwenberg, and Wakker, 2016).

Second, index-based parameter estimates of ℓ are less stable across time and domains. The OLS coefficient predicting ℓ in the last three waves based on its value in the first three waves drops from 0.36 (Table 4) to 0.17. Across domains, the change is from 0.35 (Table 5) to 0.14. The two sets of instrumental variables regressions are not affected much, indicating that the indices do not introduce any systematic differences over time.

Third, the reason behind the previous two results is that our main approach is better able to disentangle decision error and ambiguity attitudes. For

instance, in the index-based estimation, ℓ and σ exhibit a substantial correlation of 0.3, whereas we do not find any such relation based on our main estimates. Intuitively, set-monotonicity errors are reflected in a higher random component in our main estimation whereas they directly lead to a higher ℓ under the indices approach.

Fourth, our main approach leads to better out-of-sample choice predictions. We make use of the choices that subjects make at the end of each questionnaire if they have not previously answered the question selected for payment. The predictive quality is substantially better for our main approach, particularly for those with high values of ℓ in the index-based approach.

Fifth, the classification procedure remains remarkably robust. At the individual level, 80% of subjects are assigned to the same ambiguity type as with our main estimates. Differences emerge in the shares of near ambiguity neutral and ambiguity averse types, the latter rise at the expense of the former. Average values of ℓ are substantially higher in the index-based approach for all types. Relations of the types to predictors and to portfolio choice behavior are similar to our main results.

Because of the multidimensional nature of our model, we have not attempted to compare results to prior literature when describing our results in this section. We do so now, providing much more detail in Online Appendix H.

Our estimates of α are comparable to those from similar studies, though somewhat at the lower end. In order to ease the comparison with prior studies, we regress α^{AEX} on a set of correlates. The most interesting relation concerns the relation of risk aversion and ambiguity attitudes. Prior studies reported diverging results. Dimmock, Kouwenberg, and Wakker (2016) and Delavande, Ganguli, and Mengel (2022) find a negative relation; Dimmock, Kouwenberg, Mitchell, et al. (2015) and Anantanasuwong et al. (2024) a positive one. Our data exhibits a conditional correlation of zero. In contrast, we found risk aversion to be a strong predictor of the ambiguity types in Table 6. For ambiguity aversion the implied relationship is nonlinear: The near ambiguity neutral types (α^{AEX} near zero) are clearly less risk averse on average than all other types. For ambiguity averse and high noise types, the average α is larger; for

the ambiguity seeking it is smaller. This result underscores the importance of considering the multidimensional nature of heterogeneity explicitly.

For α -insensitivity, the values we estimate using indices (median 0.82) 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, partly driven by a substantial share of hypersensitive individuals with negative ℓ) and slightly below others for the stock market (Anantanasuwong et al., 2024, 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. (2024) whereas Dimmock, Kouwenberg, Mitchell, et al. (2015) find a positive relation with education.

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: higher age, lower education, and lower numeracy are associated with larger decision noise (Gaudecker, Soest, and Wengström, 2011; Choi, Kariv, Müller, and Silverman, 2014; Chapman, Dean, Ortoleva, Snowberg, and Camerer, 2023; Echenique, Imai, and Saito, 2023).

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 \times wave-level have yielded a triplet of ambiguity aversion, α -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. Our IV approach has shown the absence of any systematic changes.

Our core analysis has thus focused on estimating individual-level parameters while imposing their stability over time. 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. Choice predictions differ sharply across these groups. The way the groups vary 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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