Online Appendix Accompanying: The Distribution and Relevance of Ambiguity Attitudes

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Appendix A Questionnaire

This section documents our questionnaires. Individuals make a series of choices, all of which share the structure shown in Figure A.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 A.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.

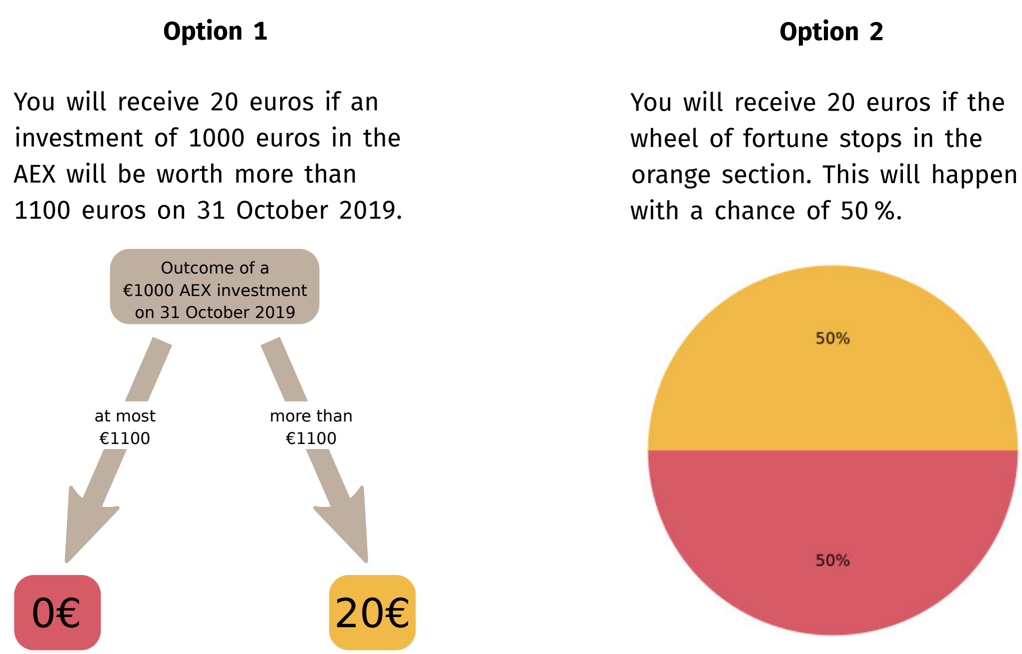


Figure A.1. Exemplary binary choice situation

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

A typical wave 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 paid 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.

A.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.

A.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].*

A.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.

A.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, and Wakker (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 A.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 ….*

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

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

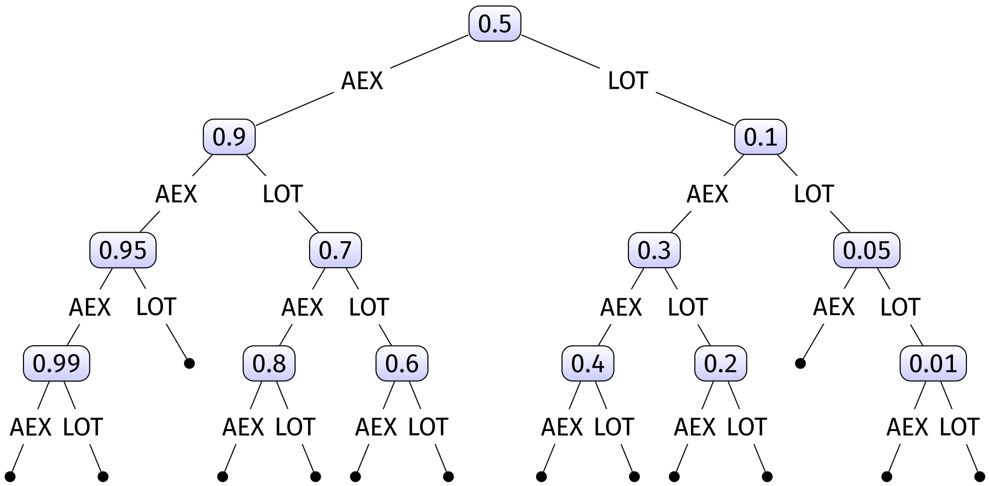


Figure A.2. Iterative sequence of lottery probabilities for any AEX event. Nodes display the probability for winning 20 € in the lottery task.

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

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

$E^{AEX}_{3,C}$ *...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 A.2 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: $E^{AEX}_1 : Y_{t+6} \in (1100, \infty]$, $E^{AEX}_2 : Y_{t+6} \in [0, 950)$, and $E^{AEX}_3 : Y_{t+6} \in [950, 1100]$, see Figure A.3. 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 $E^{AEX}_0 : Y_{t+6} \in (1000, \infty]$. This is

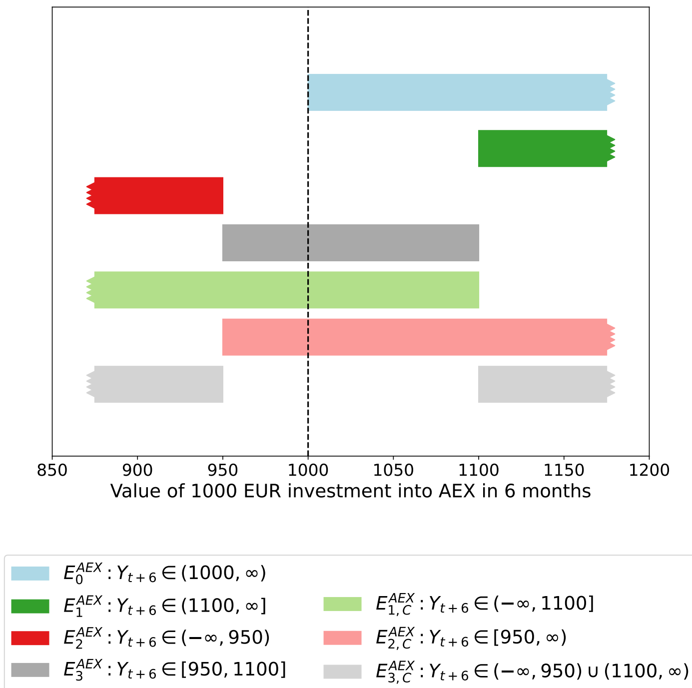


Figure A.3. Events of AEX performance used in the experiment

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.

A.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.

A.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 B.5, 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 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 (2022). 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?*

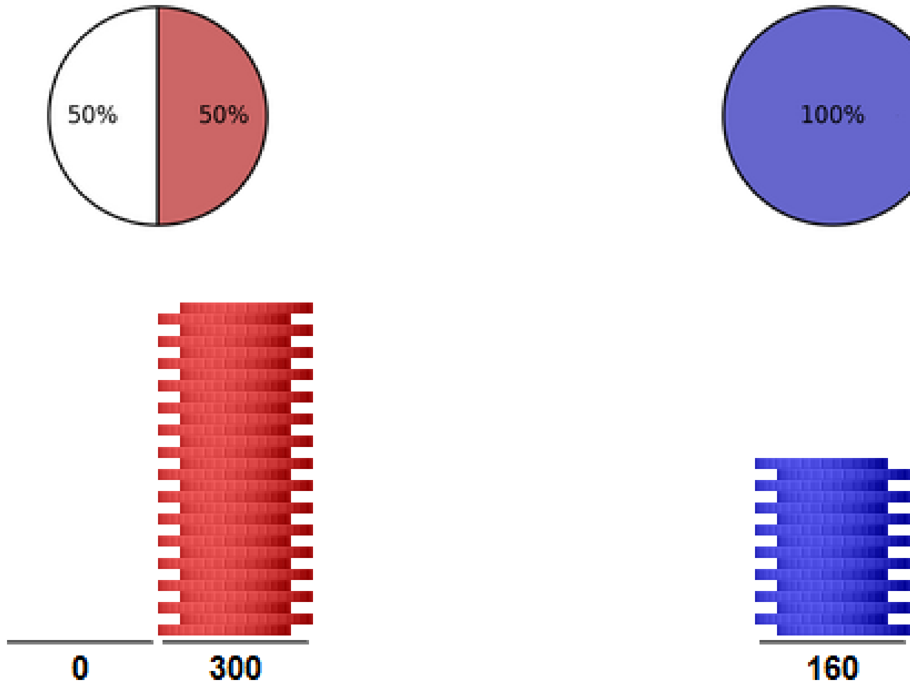


Figure A.4. Exemplary visualization for the elicitation of quantitative risk aversion

Notes:

Each choice is accompanied by a visualization for which an example is shown in Figure A.4. 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.

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 B Data

B.1 Sample

Table B.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 B.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: 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 chose 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.

B.2 Matching probabilities

Table B.2. Average matching probabilities by wave

	2018-11	2019-05	2019-11	2020-05	2020-11	2021-05
$E_0^{AEX} : Y_{t+6} \in (1000, \infty)$	0.51	0.52	0.49	0.43	0.52	0.55
$E_1^{AEX} : Y_{t+6} \in (1100, \infty]$	0.35	0.37	0.36	0.33	0.35	0.42
$E_{1,C}^{AEX} : Y_{t+6} \in (-\infty, 1100]$	0.5	0.52	0.52	0.51	0.54	0.52
$E_2^{AEX} : Y_{t+6} \in (-\infty, 950)$	0.35	0.34	0.35	0.43	0.36	0.34
$E_{2,C}^{AEX} : Y_{t+6} \in [950, \infty)$	0.54	0.56	0.56	0.51	0.58	0.59
$E_3^{AEX} : Y_{t+6} \in [950, 1100]$	0.55	0.57	0.57	0.53	0.59	0.58
$E_{3,C}^{AEX} : Y_{t+6} \in (-\infty, 950) \cup (1100, \infty)$	0.41	0.41	0.4	0.45	0.41	0.43

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 restrictions as described in Section 2.2.

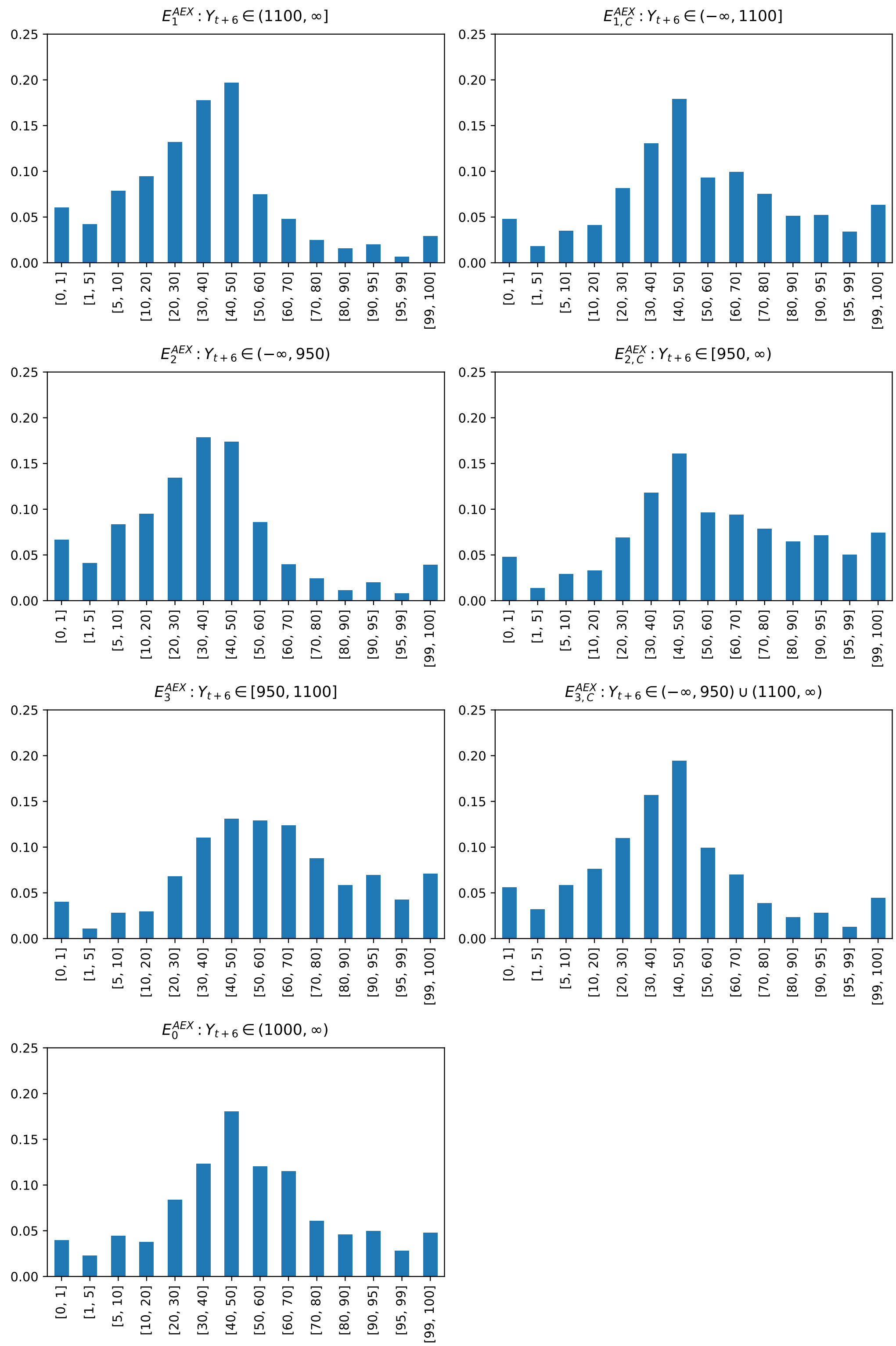


Figure B.1. Distribution of matching probabilities averaged across waves

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 restrictions as described in Section 2.2.

Table B.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 restrictions as described in Section 2.2.

B.3 Set-monotonicity violations

During the elicitation of matching probabilities, the responses of subjects can violate set monotonicity for eight pairs of events. Table B.4 presents the share of subjects which violates set monotonicity for each of these events. While 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 B.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 B.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 restrictions as described in Section 2.2.

Table B.5. Average set-monotonicity violations by superset-subset pair (matching probabilities set to midpoints of intervals)

		Rate of set-monotonicity violations	
		AEX	climate
$E^S_{1,C}$	E^S_2	0.18	0.18
	E^S_3	0.38	0.24
$E^S_{2,C}$	E^S_1	0.15	0.28
	E^S_3	0.3	0.3
$E^S_{3,C}$	E^S_1	0.28	0.31
	E^S_2	0.26	0.24
E^S_0	E^S_1	0.14	0.19
$E^S_{2,C}$	E^S_0	0.25	0.36
Any violation	excluding E^S_0	0.7	0.67
	including E^S_0	0.77	0.75

Notes: The first column reports the rates of set-monotonicity violations for each pair of events when we set matching probabilities to the midpoints of estimated intervals. Then, set monotonicity is violated if the lower bound of the interval elicited for the matching probability of the subset is **weakly** larger than the upper bound of the corresponding interval of the superset. For instance, if the interval for the matching probability of the subset is $[0.4, 0.5]$ and the interval for the matching probability of the superset is $[0.3, 0.4]$, set monotonicity in this stricter sense is violated. In contrast, in Table B.4, we do not treat this pattern as a set-monotonicity violation as the choices can be rationalized with a matching probability of 0.4. The second to last row shows the share of subjects with at least one such 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 restrictions as described in Section 2.2.

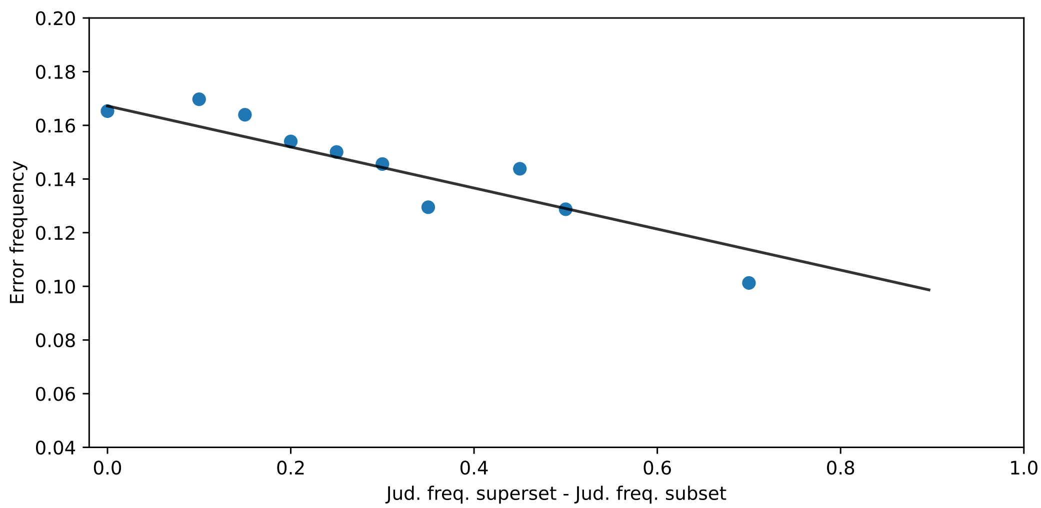


Figure B.2. Set-monotonicity violations and difference in judged historical frequencies (binscatter)

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 restrictions as described in Section 2.2.

B.4 Do people engage in hedging?

Baillon, Halevy, and Li (2022b) argue that subjects might engage in hedging when facing a series of ambiguous choices when the question that is paid out is chosen at random. They show that this can lead to a substantial underestimation of ambiguity aversion.

This is much less of a concern in our data because there is no direct hedge for the event E_0^{AEX}. Any strategy integrating the seven different events in a way that would yield a perfect hedge against ambiguity would require substantial cognitive effort. As proposed by Baillon, Halevy, and Li (2022a), we pre-select the choice to be paid out which makes the option to hedge against the encountered ambiguity even less salient.

Indeed we do not find any evidence for hedging in our questionnaire. To test for hedging, we compare the final binary choice of the questionnaire that subjects are asked if they have not encountered the pay-out relevant choice situation to the expected choice based on the responses in the main part of the elicitation (e.g. if a subject chose the lottery option for $p = 0.5$, we would expect her to also choose the lottery option for $p > 0.5$ for a given AEX event). When responding to the final choice situation, subjects know for sure that (only) the response to this question will be paid out 6 months later. Hence, they clearly cannot hedge against the encountered uncertainty. In case hedging occurs in the main part of the elicitation, we would expect subjects to show more ambiguity aversion in the last choice situation and, hence, choose the lottery option more frequently. Conversely, we find if anything the opposite pattern: 8% of the subjects choose the AEX option while we expect the lottery option and only 5% deviate in the other direction. This pattern is very stable across education groups, numeracy groups, and elicitation waves.

B.5 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 whether 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 (only very few subjects are affected who report negative safe or risky financial assets).

Risk aversion index Elicited ourselves (see Online Appendix A) based on the preference survey module developed by Falk et al. (2022). We take the mean over all elicitations for each subject (one or two). We use the experimentally validated weights by Falk et al. (2022) 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 A). We measure three dimensions of numeracy: First, a basic numeracy component that is, e.g., used in the English Longitudinal Study of Ageing (Steptoe et al., 2013); second, a financial numeracy component that involves interest rates and inflation (a subset of the questions of Rooij, Lusardi, and Alessie (2011)); third, a probabilistic 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.[1]

Knowledge of and concern about 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. We normalize the variables such that they vary between 0 and 1.

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

1. As documented in Section A.6, we have elicited risk aversion and basic numeracy in January 2019 and November 2020 while financial numeracy and probability numeracy have been elicited in November 2018 and November 2020. For all those measures, we take the mean over all elicitations (one or two for each subject).

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 value in 2018 or 2020 or the mean of those values if we observe both. For age, gender, and education, we use the first observation between 2018 and 2021.

Table B.6. Relation of risk aversion and numeracy with characteristics

	Risk aversion index	Numeracy index
Intercept	-0.4^{***}	-0.55^{***}
	(0.1)	(0.098)
Age: $\in (35, 50]$	0.26^{***}	-0.17^{**}
	(0.079)	(0.075)
Age: $\in (50, 65]$	0.31^{***}	-0.15^{**}
	(0.076)	(0.073)
Age: ≥ 65	0.33^{***}	-0.42^{***}
	(0.075)	(0.072)
Female	0.3^{***}	-0.35^{***}
	(0.049)	(0.041)
Education: Tertiary	-0.089	0.61^{***}
	(0.073)	(0.061)
Education: Upper secondary	-0.085	0.34^{***}
	(0.07)	(0.061)
Income: $\in (1.1, 1.6]$	0.017	0.13^{**}
	(0.076)	(0.066)
Income: $\in (1.6, 2.2]$	-0.034	0.3^{***}
	(0.074)	(0.06)
Income: ≥ 2.2	-0.22^{***}	0.18^{***}
	(0.077)	(0.069)
Financial assets: $\in (1.8, 11.2]$	0.053	0.57^{***}
	(0.073)	(0.067)
Financial assets: $\in (11.2, 32]$	0.23^{***}	0.66^{***}
	(0.074)	(0.065)
Financial assets: ≥ 32	0.043	0.8^{***}
	(0.076)	(0.067)
Observations	1624	1624
Adj. R^2	0.053	0.34
Note:	$^{***}p<0.01$; $^{**}p<0.05$; $^{*}p<0.1$	

Notes: Sample restrictions as described in Section 2.2.

Appendix C Details of the estimation

C.1 Estimation of ambiguity parameters

We estimate the neo-additive model at the individual level, which allows us to match average levels of ambiguity aversion and a-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
- $\text{Pr}_{\text{subj}}(E_0)$
- $\text{Pr}_{\text{subj}}(E_1)$
- $\text{Pr}_{\text{subj}}(E_2)$

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:

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

For the estimation in which we pool observations 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. $\text{Pr}_{\text{subj}}(E_0)^{\text{2018-11}}, \text{Pr}_{\text{subj}}(E_0)^{\text{2019-05}}, \ldots$).

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).

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).

C.2 The k-means algorithm

We use the k-means clustering algorithm (e.g., Bonhomme and Manresa, 2015) to classify individuals into a discrete set of groups based on their estimated parameters. The algorithm partitions individual observations, represented as feature vectors $x_i := [\alpha_i^{AEX}, \ell_i^{AEX}, \sigma_i^{AEX}]$, into groups g by minimizing within-group variance. Specifically, it assigns each observation to a group such that the sum of squared distances to the respective group mean is minimized:

$$\sum_i ||x_i - c_{g(i)}||^2$$

where c_g denote group means:

$$c_g = \frac{1}{N_g} \sum_{i \in g} x_i$$

The number of groups is chosen in advance, and different choices can be evaluated using various cluster performance metrics, as discussed in Section E.2. The algorithm iteratively updates group assignments and centroids until convergence.

To ensure equal weighting of all components in the clustering process, we follow standard practice and normalize each element of x_i to have a mean of 0 and a standard deviation of 1 in the cross-section. This standardization prevents features with larger numerical ranges from disproportionately influencing the clustering outcome.

The k-means method is widely used in machine learning and statistical analysis for uncovering latent group structures in data. We implement it using the *scikit-learn* library in Python (Pedregosa, Varoquaux, Gramfort, Michel, Thirion, et al., 2011), which provides an efficient and well-optimized version of the algorithm.

Appendix D Additional tables and figures for Section 3

D.1 Marginal distributions

Table D.1. Deterministic matching probabilities and choice probabilities for different ambiguity parameters (σ=0.076)

		$\text{Pr}_{\text{subj}} = p = 0.25$		$\text{Pr}_{\text{subj}} = p = 0.5$		$\text{Pr}_{\text{subj}} = p = 0.75$	
α	ℓ	$m^*(E) - p$	Pr(choice $= AEX$)	$m^*(E) - p$	Pr(choice $= AEX$)	$m^*(E) - p$	Pr(choice $= AEX$)
-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

Notes: Over the rows, we vary α and ℓ along the five quantiles $q_{0.05}$, $q_{0.5}$, $q_{0.75}$, and $q_{0.95}$ of their estimated marginal distributions while σ is set to the estimated $q_{0.5}$ quantile. We consider a decision maker who chooses between a lottery yielding €x with probability p and a bet on an event E 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 deterministic matching probabilities and subjective probabilities and the choice probability to choose the ambiguous option.

Table D.2. Deterministic matching probabilities and choice probabilities for different ambiguity parameters (σ=0.15)

		$\text{Pr}_{\text{subj}} = p = 0.25$		$\text{Pr}_{\text{subj}} = p = 0.5$		$\text{Pr}_{\text{subj}} = p = 0.75$	
α	ℓ	$m^*(E) - p$	$\text{Pr}(\text{choice} = AEX)$	$m^*(E) - p$	$\text{Pr}(\text{choice} = AEX)$	$m^*(E) - p$	$\text{Pr}(\text{choice} = AEX)$
-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

Notes: Over the rows, we vary α and ℓ along the five quantiles $q_{0.05}$, $q_{0.5}$, $q_{0.75}$, and $q_{0.95}$ of their estimated marginal distributions while σ is set to the estimated $q_{0.75}$ quantile. We consider a decision maker who chooses between a lottery yielding €x with probability p and a bet on an event E 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 deterministic matching probabilities and subjective probabilities and the choice probability to choose the ambiguous option.

Table D.3. Deterministic matching probabilities and choice probabilities for different ambiguity parameters (σ=0.3)

		$\text{Pr}_{\text{subj}} = p = 0.25$		$\text{Pr}_{\text{subj}} = p = 0.5$		$\text{Pr}_{\text{subj}} = p = 0.75$	
		$m^*(E)-p$	Pr(choice $= AEX$)	$m^*(E)-p$	Pr(choice $= AEX$)	$m^*(E)-p$	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

Notes: Over the rows, we vary α and ℓ along the five quantiles $q_{0.05}$, $q_{0.5}$, $q_{0.75}$, and $q_{0.95}$ of their estimated marginal distributions while σ is set to the estimated $q_{0.95}$ quantile. We consider a decision maker who chooses between a lottery yielding €x with probability p and a bet on an event E 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 deterministic matching probabilities and subjective probabilities and the choice probability to choose the ambiguous option.

Table D.4. Marginal distributions of estimated parameters, wave by wave

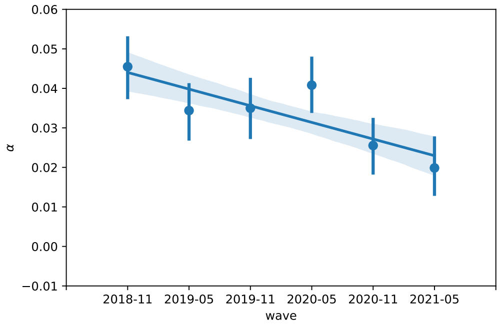
		Mean	Std. dev.	$q_{0.05}$	$q_{0.25}$	$q_{0.5}$	$q_{0.75}$	$q_{0.95}$
α	2018-11	0.045	0.17	−0.24	−0.05	0.037	0.15	0.33
	2019-05	0.034	0.16	−0.22	−0.053	0.026	0.13	0.28
	2019-11	0.035	0.16	−0.22	−0.06	0.03	0.13	0.3
	2020-05	0.041	0.15	−0.2	−0.05	0.04	0.13	0.28
	2020-11	0.026	0.15	−0.2	−0.064	0.021	0.11	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 2 for a graphical representation. The rows labelled "Observations from all AEX waves" are the same as the columns in Panel a of Figure 1.

Table D.5. Parameter estimates regressed on wave dummies and controls

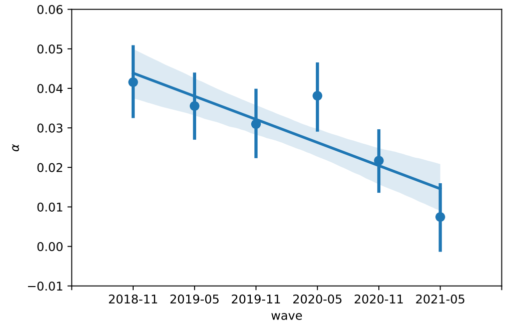
	α			ℓ			σ		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	0.045***	0.065***	0.074***	0.57***	0.55***	0.55***	0.11***	0.11***	0.11***
	(0.0038)	(0.011)	(0.014)	(0.0066)	(0.02)	(0.028)	(0.0022)	(0.0065)	(0.0081)
2019-05	−0.011**	−0.0074	−0.0042	0.011	0.018**	0.011	−0.0099***	−0.014***	−0.015***
	(0.0046)	(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	0.0081	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: $\in (35, 50]$		−0.014*	−0.026**		0.019	0.02		0.0044	0.0042
		(0.0082)	(0.011)		(0.017)	(0.025)		(0.0041)	(0.0054)
Age: $\in (50, 65]$		−0.016**	−0.032***		0.03*	0.025		0.013***	0.011*
		(0.0077)	(0.0096)		(0.016)	(0.023)		(0.0045)	(0.0055)
Age: ≥ 65		−0.011	−0.017*		0.049***	0.043*		0.027***	0.028***
		(0.0077)	(0.0095)		(0.016)	(0.023)		(0.0046)	(0.0055)
Female		0.0036	−0.0033		0.03***	0.028**		−0.014***	−0.014***
		(0.0053)	(0.0064)		(0.01)	(0.013)		(0.0032)	(0.0039)
Education: Tertiary		−0.013*	−0.011		−0.055***	−0.047**		−0.0057	−0.0045
		(0.008)	(0.0095)		(0.015)	(0.018)		(0.0048)	(0.0058)
Education: Upper secondary		−0.0042	0.0001		−0.016	−0.014		−0.0007	0.0025
		(0.0074)	(0.0088)		(0.013)	(0.016)		(0.0048)	(0.0057)
Income: $\in (1.1, 1.6]$		0.012	0.014		0.032**	0.049***		−0.0028	−0.0044
		(0.0076)	(0.0088)		(0.014)	(0.017)		(0.0049)	(0.006)
Income: $\in (1.6, 2.2]$		0.01	0.012		0.031**	0.038**		−0.01**	−0.011*
		(0.0079)	(0.0094)		(0.015)	(0.019)		(0.0046)	(0.0057)
Income: ≥ 2.2		0.0075	0.01		0.041**	0.042**		−0.0052	−0.0057
		(0.0084)	(0.01)		(0.016)	(0.02)		(0.005)	(0.006)
Financial assets: $\in (1.8, 11.2]$		−0.02***	−0.029***		−0.021	−0.019		0.0003	−0.0026
		(0.0076)	(0.0095)		(0.014)	(0.018)		(0.0047)	(0.006)
Financial assets: $\in (11.2, 32]$		−0.012	−0.015		−0.065***	−0.061***		0.0091*	0.0061
		(0.0075)	(0.0092)		(0.015)	(0.019)		(0.0047)	(0.006)
Financial assets: ≥ 32		−0.025***	−0.027***		−0.056***	−0.044**		0.0083	0.0033
		(0.0082)	(0.0098)		(0.016)	(0.02)		(0.0052)	(0.0063)
Risk aversion index		0.0026	0.0055*		0.009*	0.008		−0.0028*	−0.0038*
		(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)	(0.0086)		(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	0.078	0.071	0.0032	0.08	0.08

Notes: 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 2.2) 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. $* - p < 0.1, ** - p < 0.05, *** - p < 0.01$.

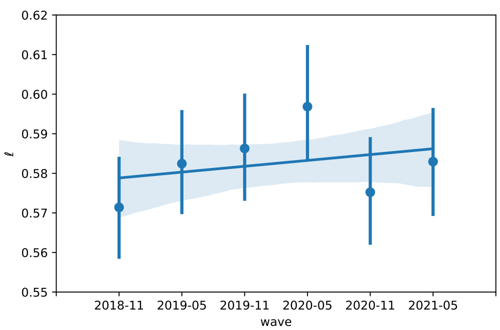


heterogeneity in ambiguity profiles with K=4 discrete groups

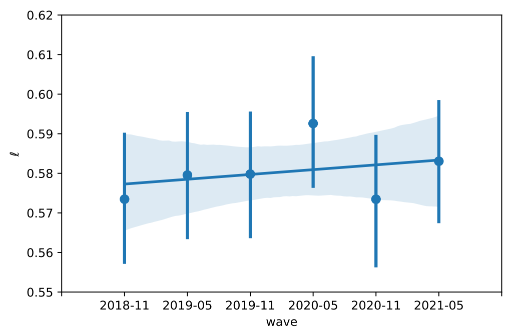
(a) α^{AEX}, baseline sample



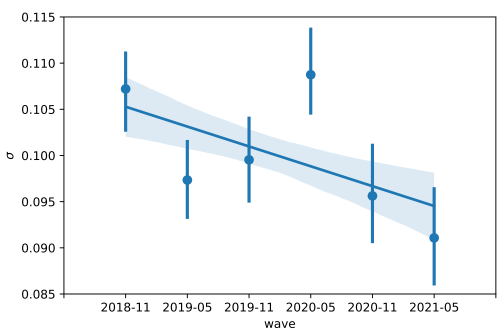
(b) α^{AEX}, balanced sample



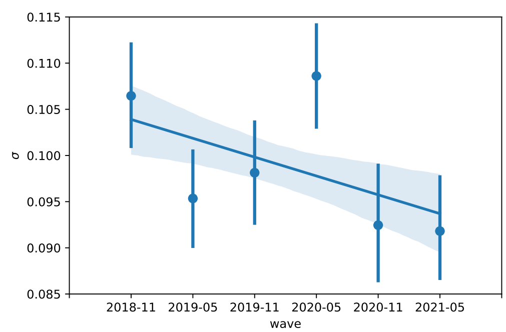
(c) ℓ^{AEX}, baseline sample



(d) ℓ^{AEX}, balanced sample



(e) σ^{AEX}, baseline sample



(f) σ^{AEX}, balanced sample

Figure D.1. Average parameter estimates by wave

Notes: Controling for age groups, gender, education, income and assets groups, risk aversion, and numeracy. See Table D.4 for the underlying regressions.

Table D.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^{***}	0.063^{***}	0.58^{***}	0.56^{***}	0.55^{***}	0.1^{***}	0.098^{***}	0.098^{***}
	(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: $\in (35, 50]$		-0.013	-0.024^{**}		0.027^{*}	0.029		0.0041	0.005
		(0.0083)	(0.011)		(0.016)	(0.024)		(0.0041)	(0.0053)
Age: $\in (50, 65]$		-0.016^{**}	-0.031^{***}		0.038^{**}	0.034		0.011^{**}	0.011^{**}
		(0.0078)	(0.0098)		(0.015)	(0.022)		(0.0044)	(0.0053)
Age: ≥ 65		-0.011	-0.015		0.056^{***}	0.051^{**}		0.025^{***}	0.028^{***}
		(0.0078)	(0.0097)		(0.015)	(0.022)		(0.0045)	(0.0053)
Female		0.0012	-0.0059		0.03^{***}	0.031^{**}		-0.013^{***}	-0.013^{***}
		(0.0054)	(0.0065)		(0.0096)	(0.012)		(0.0032)	(0.0038)
Education: Tertiary		-0.015^{*}	-0.011		-0.053^{***}	-0.043^{**}		-0.0049	-0.0051
		(0.0082)	(0.0097)		(0.014)	(0.017)		(0.0047)	(0.0057)
Education: Upper secondary		-0.0042	-0.0011		-0.016	-0.013		-0.0003	0.002
		(0.0076)	(0.0089)		(0.012)	(0.015)		(0.0046)	(0.0056)
Income: $\in (1.1, 1.6]$		0.012	0.015^{*}		0.033^{**}	0.052^{***}		-0.0031	-0.0044
		(0.0078)	(0.009)		(0.013)	(0.016)		(0.0048)	(0.0058)
Income: $\in (1.6, 2.2]$		0.013	0.013		0.03^{**}	0.037^{**}		-0.01^{**}	-0.0089
		(0.0081)	(0.0095)		(0.014)	(0.018)		(0.0046)	(0.0057)
Income: ≥ 2.2		0.01	0.012		0.039^{**}	0.039^{**}		-0.0049	-0.0042
		(0.0085)	(0.01)		(0.016)	(0.019)		(0.0049)	(0.0059)
Financial assets: $\in (1.8, 11.2]$		-0.019^{**}	-0.029^{***}		-0.022^{*}	-0.02		0.0007	-0.0023
		(0.0078)	(0.0096)		(0.013)	(0.018)		(0.0046)	(0.0059)
Financial assets: $\in (11.2, 32]$		-0.0095	-0.015		-0.06^{***}	-0.053^{***}		0.0082^{*}	0.0039
		(0.0077)	(0.0094)		(0.015)	(0.019)		(0.0047)	(0.0059)
Financial assets: ≥ 32		-0.023^{***}	-0.026^{***}		-0.055^{***}	-0.042^{**}		0.0071	0.0015
		(0.0083)	(0.0099)		(0.016)	(0.019)		(0.0051)	(0.0062)
Risk aversion index		0.0025	0.0058^{*}		0.0095^{*}	0.0089		-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^{***}	-0.025^{***}
		(0.0033)	(0.0039)		(0.0061)	(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	0.019	0.0036	0.074	0.069	0.0002	0.072	0.073

Notes: 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 2.2) 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. $* - p < 0.1, ** - p < 0.05, *** - p < 0.01$.

D.2 Correlations of parameters and alternative ORIV regressions

Table D.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: 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 separately for each survey wave and individual. The last row shows the average correlation coefficient over all pairs of waves. Sample restrictions as described in Section 2.2.

Table D.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	-0.0057	-0.0033
	(0.015)	(0.037)	(0.011)
AEX parameter first 3 waves	0.98^{***}	0.95^{***}	0.97^{***}
	(0.09)	(0.05)	(0.079)
Age: $\in (35, 50]$	-0.006	0.032	-0.0022
	(0.011)	(0.02)	(0.0061)
Age: $\in (50, 65]$	-0.0049	0.043^{**}	-0.0058
	(0.011)	(0.02)	(0.0062)
Age: ≥ 65	0.0003	0.032	-0.0003
	(0.012)	(0.02)	(0.0065)
Female	0.011	0.0076	0.0013
	(0.0067)	(0.011)	(0.0046)
Education: Tertiary	-0.0062	-0.019	0.016^{**}
	(0.01)	(0.016)	(0.0062)
Education: Upper secondary	0.0033	-0.022	0.011^{*}
	(0.0095)	(0.015)	(0.0065)
Income: $\in (1.1, 1.6]$	-0.0048	0.021	-0.0001
	(0.0096)	(0.016)	(0.0069)
Income: $\in (1.6, 2.2]$	0.011	0.03^{*}	-0.0039
	(0.0096)	(0.016)	(0.0063)
Income: ≥ 2.2	0.001	0.017	-0.0058
	(0.01)	(0.018)	(0.0072)
Financial assets: $\in (1.8, 11.2]$	0.0046	0.015	0.0032
	(0.0099)	(0.016)	(0.0071)
Financial assets: $\in (11.2, 32]$	0.02^{**}	0.019	-0.0025
	(0.01)	(0.016)	(0.0061)
Financial assets: ≥ 32	0.015	-0.013	-0.0025
	(0.011)	(0.017)	(0.0064)
Risk aversion index	-0.0064^{*}	-0.001	0.0037
	(0.0036)	(0.0057)	(0.0023)
Numeracy index	-0.012^{**}	-0.011	-0.0029
	(0.0046)	(0.0076)	(0.0039)
N Subjects	1452	1452	1452
1st st. F	101	294	130

Notes: The full list of coefficients for the regressions reported in Table 4.

Table D.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	127
$\sigma^{AEX}_{\text{last 4 waves}}$	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: This table replicates Table 4 with the parameter estimates of the last four waves as dependent variables and the parameter estimates of the two earlier waves as potential independent variables and instruments.

Table D.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	387
$\sigma^{AEX}_{\text{last 2 waves}}$	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	174
Controls		No	No	Yes
N Subjects		1833	1833	1433

Notes: This table replicates Table 4 with the parameter estimates of the last two waves as dependent variables and the parameter estimates of the four earlier waves as potential independent variables and instruments.

Table D.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	495
$\sigma^{AEX}_{2021-05}$	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: This table replicates Table 4 with the parameter estimates of the last wave as dependent variables and the parameter estimates of the five earlier waves as potential independent variables and instruments.

Table D.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	0.22^{***}	0.0042
	(0.021)	(0.053)	(0.017)
AEX parameter 2019-11	1.1^{***}	0.63^{***}	0.88^{***}
	(0.067)	(0.052)	(0.074)
Age: $\in (35, 50]$	0.0093	0.075^{***}	-0.0024
	(0.011)	(0.027)	(0.0085)
Age: $\in (50, 65]$	0.0059	0.067^{***}	-0.0079
	(0.011)	(0.025)	(0.0082)
Age: ≥ 65	0.0074	0.061^{**}	-0.015^{*}
	(0.012)	(0.026)	(0.0087)
Female	-0.0019	-0.0039	0.011^{*}
	(0.0086)	(0.016)	(0.0059)
Education: Tertiary	-0.011	-0.0017	0.0044
	(0.012)	(0.023)	(0.0083)
Education: Upper secondary	0.0015	0.008	0.004
	(0.012)	(0.021)	(0.0077)
Income: $\in (1.1, 1.6]$	-0.0023	0.031	-0.0017
	(0.012)	(0.022)	(0.0081)
Income: $\in (1.6, 2.2]$	0.022^{*}	0.022	-0.003
	(0.012)	(0.023)	(0.0078)
Income: ≥ 2.2	0.024^{*}	-0.0018	0.0007
	(0.012)	(0.024)	(0.0085)
Financial assets: $\in (1.8, 11.2]$	0.0033	-0.022	0.0018
	(0.012)	(0.022)	(0.008)
Financial assets: $\in (11.2, 32]$	0.011	0.013	-0.0092
	(0.013)	(0.023)	(0.0083)
Financial assets: ≥ 32	0.011	-0.0088	-0.0072
	(0.013)	(0.025)	(0.0088)
Risk aversion index	-0.0095^{**}	0.0006	0.0026
	(0.0043)	(0.0079)	(0.0028)
Numeracy index	-0.0025	0.016	0.0005
	(0.0057)	(0.011)	(0.0041)
Understands climate change	-0.045^{**}	-0.053	0.032^{**}
	(0.02)	(0.037)	(0.013)
Feels threatened by climate change	0.0066	0.0006	0.0044
	(0.019)	(0.035)	(0.013)
N Subjects	1411	1411	1411
1st st. F	148	408	51

Notes: The full list of coefficients for the regressions reported in Table 5.

Appendix E Additional tables and figures for Section 4

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

Table E.1. Deterministic matching probabilities and choice probabilities for ambiguity types

				$\text{Pr}_{\text{subj}} = p = 0.25$		$\text{Pr}_{\text{subj}} = p = 0.5$		$\text{Pr}_{\text{subj}} = p = 0.75$	
Ambiguity type	α	ℓ	σ	$m^*(E) - p$	$\text{Pr}(\text{choice} = AEX)$	$m^*(E) - p$	$\text{Pr}(\text{choice} = AEX)$	$m^*(E) - p$	$\text{Pr}(\text{choice} = AEX)$
Near ambiguity neutral	-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	0.59	−0.15	0.15	−0.32	0.012
Ambiguity seeking	-0.054	0.64	0.15	0.21	0.93	0.054	0.64	−0.1	0.24
High noise	0.038	0.47	0.29	0.079	0.61	−0.038	0.45	−0.16	0.3

Notes: For this table we consider a decision maker who chooses between a lottery yielding €x with probability p and a bet on an event E 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 deterministic matching probabilities and subjective probabilities and the choice probability to choose the ambiguous option for each of the estimated ambiguity types.

Table E.2. Average within subject standard deviation of wave-by-wave parameters by ambiguity type

	α^{AEX}	ℓ^{AEX}	σ^{AEX}
Near ambiguity neutral	0.084	0.21	0.06
	(0.0016)	(0.0038)	(0.0014)
Ambiguity averse	0.11	0.18	0.062
	(0.0021)	(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: 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 separately for each survey wave and individual. Standard errors are reported in parentheses. Sample restrictions as described in Section 2.2. $* - p < 0.1, ** - p < 0.05, *** - p < 0.01$.

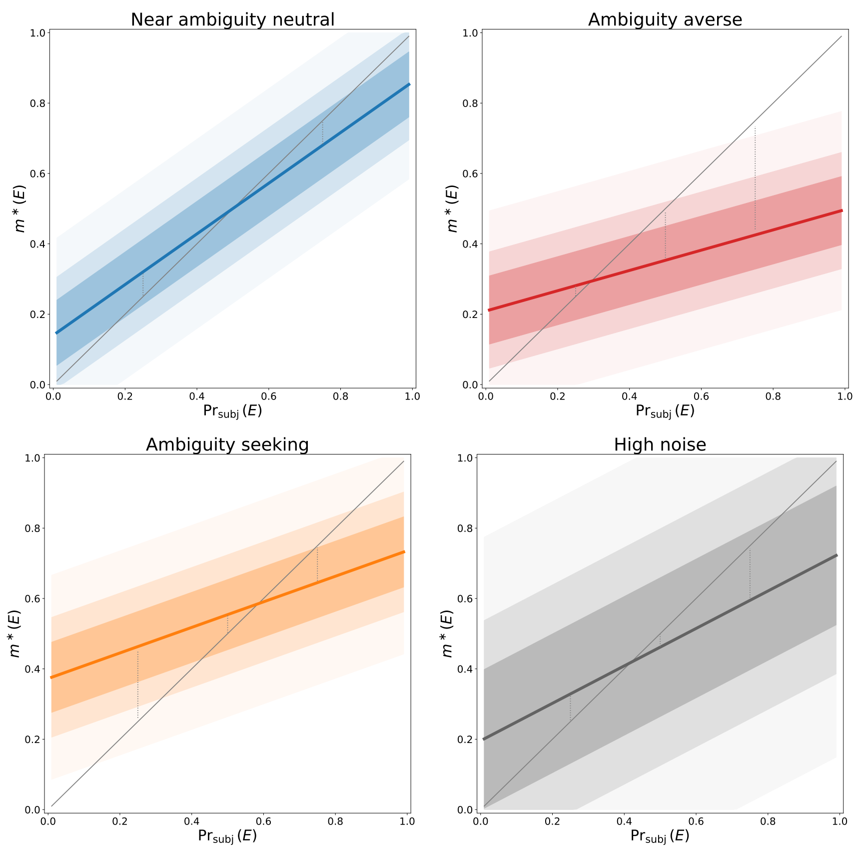


Figure E.1. Matching probabilities as a function of subjective probabilities, by group

Notes: The solid lines plot the deterministic matching probabilities $m^{*}(E)$ 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 restrictions as described in Section 2.2.

Table E.3. Predictors of groups, marginal effects

	Ambiguity types			
	Near ambiguity neutral	Ambiguity averse	Ambiguity seeking	High noise
Age: $\in (35, 50]$	-0.034	-0.026	-0.013	0.073^{*}
	(0.037)	(0.038)	(0.038)	(0.041)
Age: $\in (50, 65]$	-0.038	-0.054	-0.02	0.11^{***}
	(0.035)	(0.036)	(0.037)	(0.039)
Age: ≥ 65	-0.069^{*}	-0.095^{***}	-0.031	0.2^{***}
	(0.035)	(0.036)	(0.036)	(0.038)
Female	0.0041	0.074^{***}	0.018	-0.096^{***}
	(0.022)	(0.022)	(0.022)	(0.019)
Education: Tertiary	0.082^{**}	-0.05	-0.033	0.0015
	(0.033)	(0.032)	(0.03)	(0.027)
Education: Upper secondary	0.063^{*}	-0.0079	-0.031	-0.025
	(0.032)	(0.029)	(0.029)	(0.024)
Income: $\in (1.1, 1.6]$	-0.05	0.037	0.018	-0.0055
	(0.033)	(0.03)	(0.032)	(0.024)
Income: $\in (1.6, 2.2]$	-0.05	0.065^{**}	0.028	-0.043
	(0.032)	(0.032)	(0.033)	(0.028)
Income: ≥ 2.2	-0.079^{**}	0.055	0.023	0.001
	(0.034)	(0.036)	(0.035)	(0.03)
Financial assets: $\in (1.8, 11.2]$	0.086^{**}	-0.022	0.024	-0.088^{***}
	(0.035)	(0.03)	(0.031)	(0.027)
Financial assets: $\in (11.2, 32]$	0.15^{***}	-0.068^{**}	-0.049	-0.034
	(0.034)	(0.032)	(0.035)	(0.027)
Financial assets: ≥ 32	0.099^{***}	-0.1^{***}	0.021	-0.016
	(0.034)	(0.037)	(0.035)	(0.029)
Risk aversion index	-0.017	0.023^{**}	-0.0082	0.0025
	(0.011)	(0.011)	(0.012)	(0.0088)
Numeracy index	0.23^{***}	-0.072^{***}	-0.03^{**}	-0.13^{***}
	(0.017)	(0.012)	(0.013)	(0.01)
Observations	1624	1624	1624	1624
Pseudo R^2	0.13	0.13	0.13	0.13

Notes: 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 restrictions as described in Section 2.2. $* - p < 0.1, ** - p < 0.05, *** - p < 0.01$.

Table E.4. Predictors of marginal parameter estimates

	α^{AEX}	ℓ^{AEX}	σ^{AEX}
Intercept	0.052^{***}	0.5^{***}	0.17^{***}
	(0.012)	(0.022)	(0.0071)
Age: $\in (35, 50]$	−0.0095	0.013	0.014^{***}
	(0.0087)	(0.018)	(0.0049)
Age: $\in (50, 65]$	−0.012	0.022	0.022^{***}
	(0.0084)	(0.017)	(0.005)
Age: ≥ 65	−0.01	0.032^{*}	0.049^{***}
	(0.0082)	(0.017)	(0.0053)
Female	0.0058	0.033^{***}	-0.014^{***}
	(0.0055)	(0.011)	(0.0036)
Education: Tertiary	−0.013	-0.048^{***}	-0.012^{**}
	(0.0083)	(0.016)	(0.0056)
Education: Upper secondary	−0.0048	−0.0019	-0.0099^{*}
	(0.0078)	(0.015)	(0.0052)
Income: $\in (1.1, 1.6]$	0.012	0.031^{**}	−0.0043
	(0.008)	(0.015)	(0.0054)
Income: $\in (1.6, 2.2]$	0.0071	0.029^{*}	-0.011^{**}
	(0.0084)	(0.016)	(0.0054)
Income: ≥ 2.2	0.0058	0.039^{**}	−0.0065
	(0.0088)	(0.018)	(0.0056)
Financial assets: $\in (1.8, 11.2]$	-0.015^{*}	−0.014	-0.0097^{*}
	(0.0083)	(0.016)	(0.0051)
Financial assets: $\in (11.2, 32]$	−0.0099	-0.058^{***}	−0.0008
	(0.0078)	(0.017)	(0.0054)
Financial assets: ≥ 32	-0.024^{***}	-0.056^{***}	0.0003
	(0.0085)	(0.018)	(0.0058)
Risk aversion index	0.0011	0.0094	−0.0014
	(0.0031)	(0.0057)	(0.002)
Numeracy index	-0.0098^{***}	-0.048^{***}	-0.034^{***}
	(0.0035)	(0.0069)	(0.0023)
Observations	1624	1624	1624
Adj. R^2	0.025	0.11	0.28

Notes: 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 restrictions as described in Section 2.2. $* - p < 0.1, ** - p < 0.05, *** - p < 0.01$.

Table E.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^{***}	-0.083^{***}	-0.44^{***}	-0.17^{***}
	(0.024)	(0.023)	(0.059)	(0.055)
Ambiguity seeking type	-0.099^{***}	-0.016	-0.15^{***}	-0.026
	(0.029)	(0.024)	(0.05)	(0.046)
High noise type	-0.18^{***}	-0.054^{*}	-0.24^{***}	-0.085
	(0.027)	(0.028)	(0.059)	(0.059)
Age: $\in (35, 50]$		-0.023		-0.01
		(0.033)		(0.067)
Age: $\in (50, 65]$		0.0036		0.048
		(0.032)		(0.063)
Age: ≥ 65		-0.016		0.042
		(0.033)		(0.063)
Education: Tertiary		0.043		0.14^{**}
		(0.027)		(0.059)
Education: Upper secondary		0.016		0.061
		(0.026)		(0.059)
Female		-0.027		-0.029
		(0.018)		(0.04)
Income: $\in (1.1, 1.6]$		0.022		0.082
		(0.029)		(0.063)
Income: $\in (1.6, 2.2]$		0.0046		0.043
		(0.027)		(0.062)
Income: ≥ 2.2		0.074^{**}		0.13^{**}
		(0.029)		(0.062)
Numeracy index		0.034^{**}		0.067^{**}
		(0.017)		(0.031)
Risk aversion index		-0.046^{***}		-0.12^{***}
		(0.0094)		(0.021)
Financial assets: $\in (1.8, 11.2]$		0.043^{**}		0.12
		(0.019)		(0.084)
Financial assets: $\in (11.2, 32]$		0.14^{***}		0.35^{***}
		(0.022)		(0.083)
Financial assets: ≥ 32		0.39^{***}		0.69^{***}
		(0.029)		(0.085)
Observations	1727	1624	1584	1502
Pseudo R^2	0.055	0.3	0.042	0.28
p-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 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 E.6. Ambiguity attitudes and portfolio choice (OLS)

	Owns risky financial assets		Share risky financial assets	
	(1)	(2)	(3)	(4)
Intercept (left-out type: Near ambiguity neutral)	0.31^{***}	0.09^{**}	0.11^{***}	-0.011
	(0.02)	(0.036)	(0.009)	(0.018)
Ambiguity averse type	-0.23^{***}	-0.1^{***}	-0.071^{***}	-0.032^{***}
	(0.024)	(0.023)	(0.011)	(0.011)
Ambiguity seeking type	-0.099^{***}	-0.032	-0.03^{**}	-0.0092
	(0.029)	(0.026)	(0.013)	(0.013)
High noise type	-0.18^{***}	-0.071^{**}	-0.041^{***}	-0.017
	(0.027)	(0.028)	(0.015)	(0.014)
Age: $\in (35, 50]$		-0.0048		0.019
		(0.031)		(0.014)
Age: $\in (50, 65]$		0.026		0.034^{**}
		(0.03)		(0.013)
Age: ≥ 65		-0.003		0.038^{***}
		(0.03)		(0.014)
Female		-0.04^{**}		-0.0027
		(0.017)		(0.009)
Education: Tertiary		0.042^{*}		0.038^{***}
		(0.024)		(0.012)
Education: Upper secondary		0.0014		0.0084
		(0.021)		(0.0099)
Income: $\in (1.1, 1.6]$		0.002		0.011
		(0.021)		(0.011)
Income: $\in (1.6, 2.2]$		-0.012		0.0044
		(0.024)		(0.013)
Income: ≥ 2.2		0.091^{***}		0.024
		(0.029)		(0.015)
Financial assets: $\in (1.8, 11.2]$		0.01		-0.0046
		(0.017)		(0.0093)
Financial assets: $\in (11.2, 32]$		0.11^{***}		0.019
		(0.023)		(0.012)
Financial assets: ≥ 32		0.39^{***}		0.13^{***}
		(0.029)		(0.016)
Risk aversion index		-0.042^{***}		-0.027^{***}
		(0.0085)		(0.0047)
Numeracy index		0.022^{**}		0.0083
		(0.0098)		(0.0053)
Mean dependent variable	0.2	0.2	0.074	0.074
Observations	1727	1624	1584	1502
R^2	0.053	0.29	0.022	0.18
Adj. R^2	0.051	0.28	0.02	0.17

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

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

Table E.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)	(0.0095)	(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^{**}	-0.015
	(0.0095)	(0.01)	(0.022)	(0.023)
Age: $\in (35, 50]$		-0.024		-0.01
		(0.033)		(0.067)
Age: $\in (50, 65]$		0.0024		0.045
		(0.032)		(0.063)
Age: ≥ 65		-0.011		0.048
		(0.033)		(0.065)
Education: Tertiary		0.04		0.14^{**}
		(0.027)		(0.059)
Education: Upper secondary		0.016		0.059
		(0.026)		(0.059)
Female		-0.026		-0.027
		(0.018)		(0.04)
Income: $\in (1.1, 1.6]$		0.024		0.089
		(0.029)		(0.063)
Income: $\in (1.6, 2.2]$		0.0036		0.042
		(0.027)		(0.062)
Income: ≥ 2.2		0.074^{**}		0.14^{**}
		(0.029)		(0.062)
Numeracy index		0.03^{*}		0.062^{**}
		(0.016)		(0.031)
Risk aversion index		-0.047^{***}		-0.12^{***}
		(0.0094)		(0.021)
Financial assets: $\in (1.8, 11.2]$		0.043^{**}		0.12
		(0.019)		(0.084)
Financial assets: $\in (11.2, 32]$		0.14^{***}		0.35^{***}
		(0.023)		(0.083)
Financial assets: ≥ 32		0.39^{***}		0.68^{***}
		(0.029)		(0.085)
Observations	1727	1624	1584	1502
Pseudo R^2	0.068	0.31	0.053	0.29

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 restrictions as described in Section 2.2.

E.2 Cluster evaluation metrics by number of ambiguity types

While we focus on the case with four ambiguity types in the main text ($k = 4$), we have also estimated ambiguity types for all k between 2 and 15. In this subsection, we compare cluster evaluation metrics over different k and report more specific results on specific numbers of groups in the next sections.

We make use of the following three metrics to evaluate the optimal number of groups.

Within group sum of squared distances. We calculate within group sum of squared distances from each point to its assigned cluster centroid as

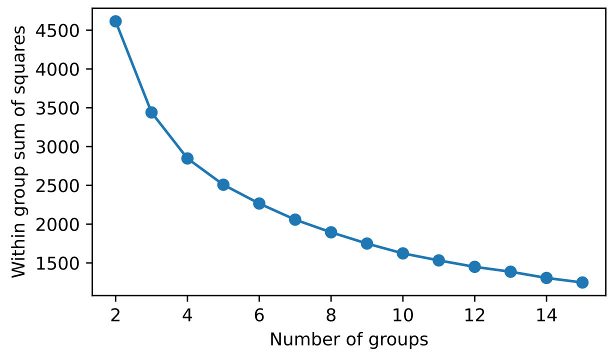
$$\text{Sum of squared distances} = \sum_{i=1}^{k} \frac{1}{|C_i|} \sum_{x \in C_i} ||x - \mu_i||^2 \tag{E.1}$$

where C_i is a cluster, μ_i is the centroid of cluster C_i, and $||x - \mu_i||^2$ is the squared Euclidean distance between a point x and its centroid. The optimal number of clusters based on this metric is at the 'elbow' point, where the decrease in the sum of squares starts to slow down. Figure E.2a shows the sum of squared distances for numbers of groups ranging from two to fifteen. As expected, the within cluster sum of squared distances monotonically decreases in the number of groups. While there is no unambiguous 'elbow' point, after $k = 4$ the slope becomes substantially flatter than before.

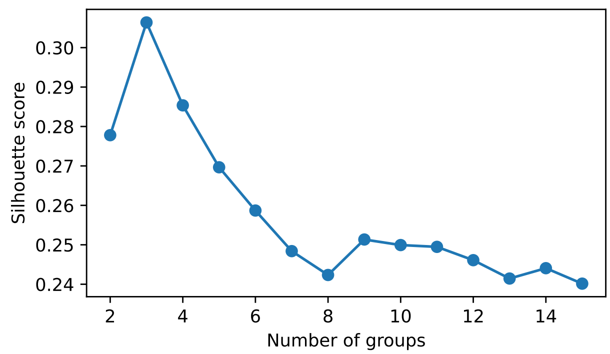
Silhouette Score. We next turn to the Silhouette Score which measures how similar an object is to its own cluster compared to other clusters (Rousseeuw, 1987). It ranges from -1 to 1, where a higher score indicates better-defined clusters. The average Silhouette Score is defined as:

$$\text{Silhouette Score} = \frac{1}{n} \sum_{i=1}^{n} \frac{b(i) - a(i)}{\max(a(i), b(i))} \tag{E.2}$$

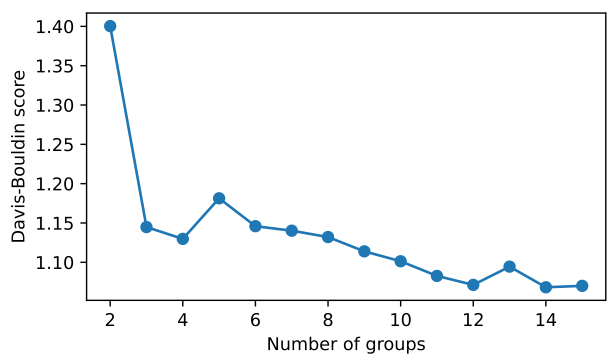
where n is the number of data points, $a(i)$ is the average distance between point i and other points in the same cluster, and $b(i)$ is the average distance between point i and points in the nearest other cluster. Figure E.2b reveals that the Silhouette Score is highest for $k = 3$ and second highest for $k = 4$.



(a) Within group sum of squared distances



(b) Silhouette Score



(c) Davies-Bouldin Index

Figure E.2. Cluster evaluation metrics by number of groups

Davies-Bouldin Index. Finally, the Davies-Bouldin Index quantifies the compactness and separation of clusters (Davies and Bouldin, 1979). A lower value indicates better clustering performance, where each cluster is compact and well separated from others. For a set of k clusters, the index is given by:

$$\text{Davies-Bouldin Index} = \frac{1}{k}\sum_{i=1}^{k}\max_{i\neq j}\left(\frac{s_i + s_j}{d_{ij}}\right) \tag{E.3}$$

where s_i is the average distance between points in cluster i and its centroid, and d_{ij} is the distance between the centroids of clusters i and j. A lower value indicates more compact, well-separated clusters. Figure E.2c shows that the Davies-Bouldin Index for $k = 4$ is lower than for the classifications with any k not exceeding eight. For nine or more groups, however the index is even lower, bottoming out at $k = 14$.

While the three metrics do not agree on the optimal number of clusters, we choose $k = 4$ as a good middle ground. Like in our case, it is typical that the Davies-Bouldin Index suggests more clusters than the Silhouette Score as the former puts more weight on compactness of clusters. In particular, the Davies-Bouldin Index indicates that there is still substantial heterogeneity within groups. For our purpose, we are looking for a good way to summarize observed heterogeneity while maintaining interpretability of the results. We find that $k = 4$ provides the optimal balance between these two objectives, but report results for other k in the following subsections.[2]

E.3 Ambiguity types with $k = 3$

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

This distributes the group we classified as ambiguity seeking across the other three groups. Most individuals go into the near ambiguity neutral group,

2. The estimated groups for k ranging from two to fifteen are available in the replication package for use in other applications that require a smaller or greater number of groups.

which comprises almost 40 % of the sample. It covers a very wide range of behavior. Both individuals whose behavior is indistinguishable from choice under risk and the subjects at the top left tip of the triangle in Figure 3, i.e., behavior that is most distant from choice under risk while consistent, are put in this group. This is not a grouping that makes much sense from a behavioral perspective.

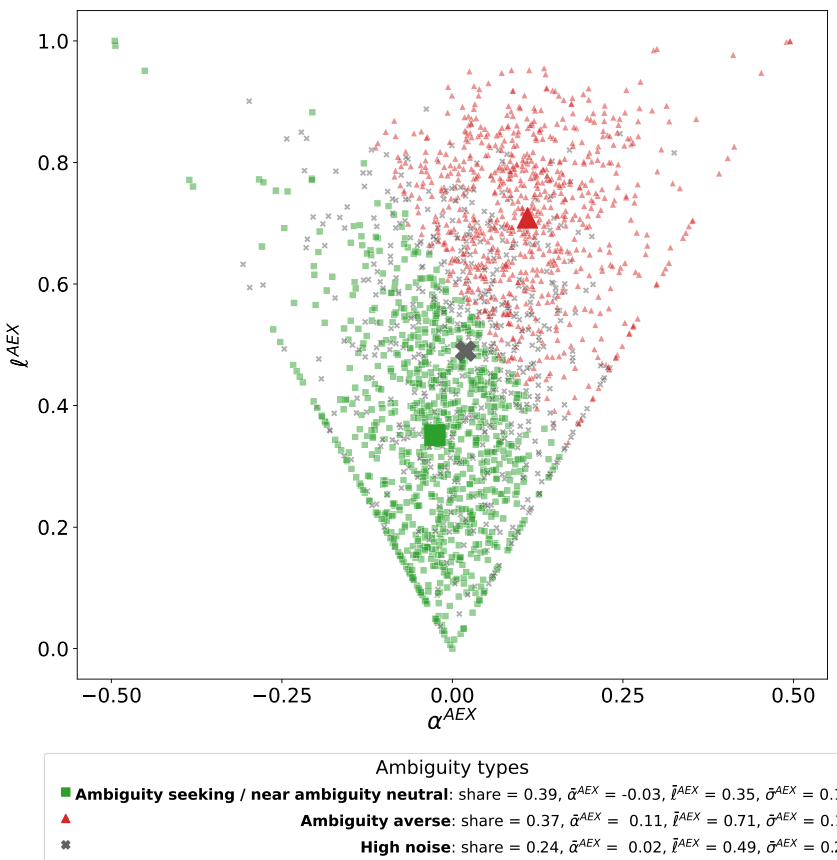


Figure E.3. Summarizing heterogeneity in ambiguity profiles with $k = 3$ discrete groups

Notes: This figure replicates Figure 3 when we classify individuals into three ambiguity groups instead of four.

Table E.9. Deterministic matching probabilities and choice probabilities for ambiguity types (3 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	$m^*(E) - p$	$\text{Pr}(\text{choice} = AEX)$	$m^*(E) - p$	$\text{Pr}(\text{choice} = AEX)$	$m^*(E) - p$	$\text{Pr}(\text{choice} = AEX)$
Ambiguity seeking / near ambiguity neutral	-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: This table replicates Table E.1 when we classify individuals into three ambiguity groups instead of four.

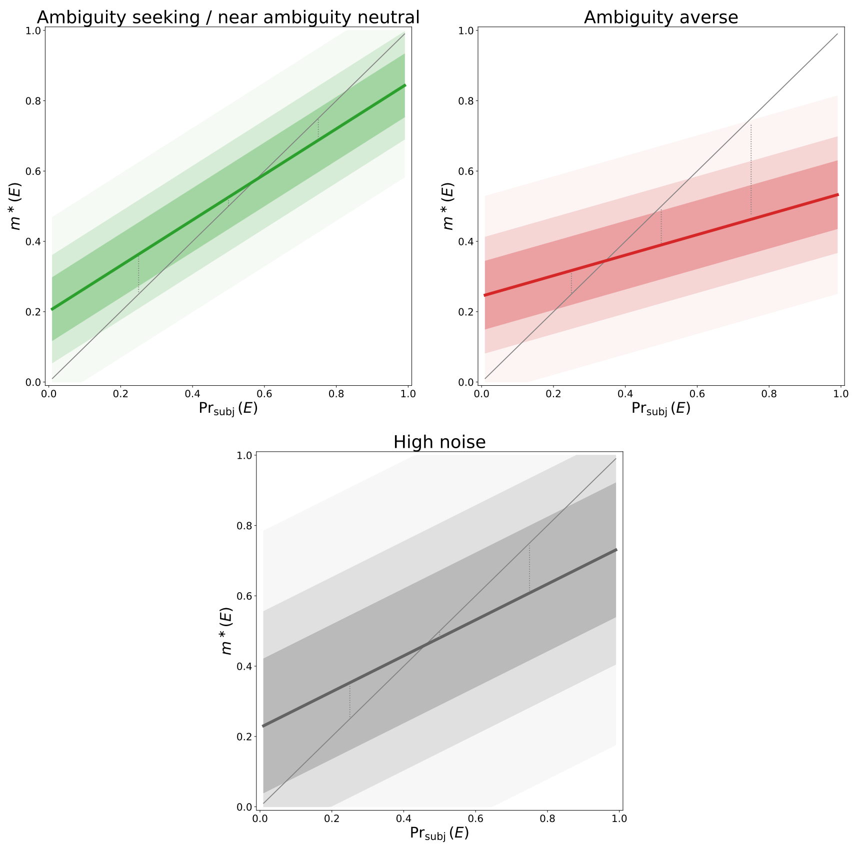


Figure E.4. Matching probabilities as a function of subjective probabilities, by group (3 groups)

Notes: This figure replicates Figure E.1 when we classify individuals into three ambiguity groups instead of four.

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

	Ambiguity types		
	Ambiguity seeking / near ambiguity neutral	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: This table replicates Table 6 when we classify individuals into three ambiguity groups instead of four.

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

	Ambiguity types		
	Ambiguity seeking / near ambiguity neutral	Ambiguity averse	High noise
Age: $\in (35, 50]$	-0.028	-0.05	0.078^{*}
	(0.038)	(0.043)	(0.042)
Age: $\in (50, 65]$	-0.067^{*}	-0.056	0.12^{***}
	(0.036)	(0.041)	(0.039)
Age: ≥ 65	-0.14^{***}	-0.076^{*}	0.21^{***}
	(0.037)	(0.04)	(0.038)
Female	-0.0087	0.1^{***}	-0.096^{***}
	(0.023)	(0.023)	(0.02)
Education: Tertiary	0.064^{*}	-0.062^{*}	-0.0014
	(0.032)	(0.034)	(0.028)
Education: Upper secondary	0.018	0.0098	-0.028
	(0.032)	(0.031)	(0.026)
Income: $\in (1.1, 1.6]$	-0.07^{**}	0.071^{**}	-0.0007
	(0.033)	(0.033)	(0.026)
Income: $\in (1.6, 2.2]$	-0.022	0.077^{**}	-0.055^{*}
	(0.033)	(0.036)	(0.029)
Income: ≥ 2.2	-0.068^{**}	0.066^{*}	0.0026
	(0.035)	(0.039)	(0.031)
Financial assets: $\in (1.8, 11.2]$	0.1^{***}	-0.03	-0.071^{**}
	(0.035)	(0.034)	(0.028)
Financial assets: $\in (11.2, 32]$	0.12^{***}	-0.082^{**}	-0.04
	(0.034)	(0.036)	(0.028)
Financial assets: ≥ 32	0.12^{***}	-0.1^{***}	-0.02
	(0.035)	(0.039)	(0.031)
Risk aversion index	-0.01	0.012	-0.0021
	(0.012)	(0.012)	(0.0094)
Numeracy index	0.23^{***}	-0.085^{***}	-0.15^{***}
	(0.016)	(0.014)	(0.011)
Observations	1624	1624	1624
Pseudo R^2	0.17	0.17	0.17

Notes: This table replicates Table E.3 when we classify individuals into three ambiguity groups instead of four.

Table E.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^{***}	-0.06^{***}	-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	0.88	0.14	0.64

Notes: This table replicates the regressions shown in Table 7 when we classify individuals into three ambiguity groups instead of four. The left-out type is 'Ambiguity seeking / near ambiguity neutral'.

E.4 Ambiguity types with $k = 5$

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

This 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. Decision behavior is fairly close to the near ambiguity neutral-type with $k = 4$, but somewhat more erratic.

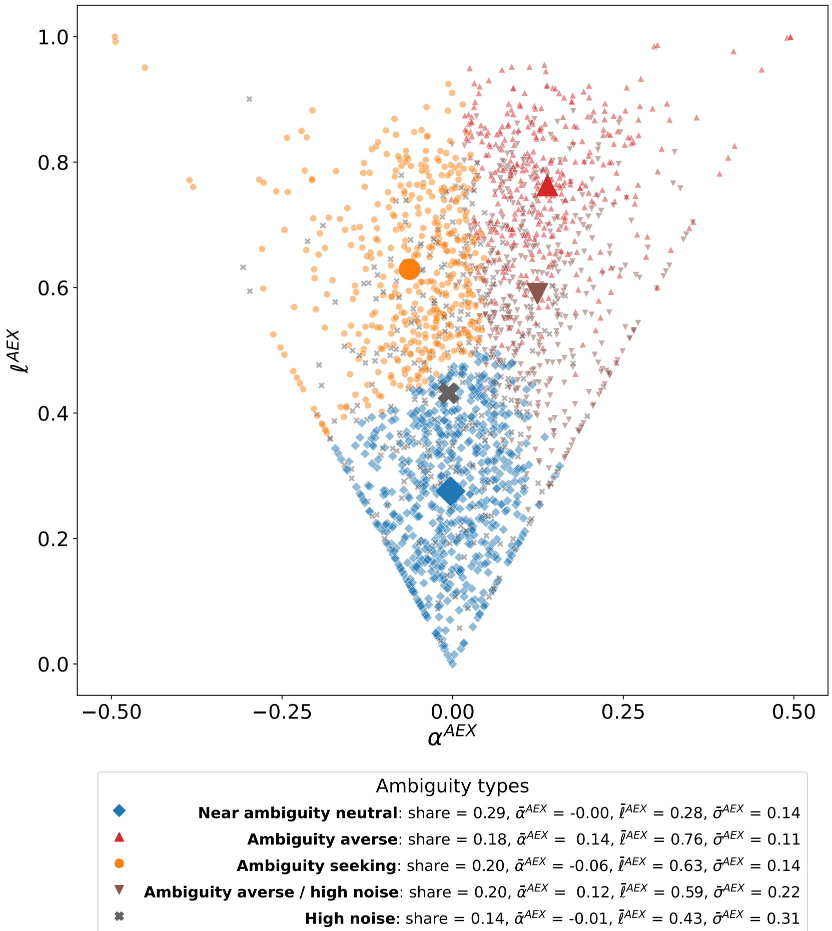


Figure E.5. Summarizing heterogeneity in ambiguity profiles with $k = 5$ discrete groups

Notes: This figure replicates Figure 3 when we classify individuals into five ambiguity groups instead of four.

Table E.13. Deterministic matching probabilities and choice probabilities for ambiguity types (5 groups)

				$\Pr_{subj} = p = 0.25$		$\Pr_{subj} = p = 0.5$		$\Pr_{subj} = p = 0.75$	
Ambiguity type	α	ℓ	σ	$m^*(E) - p$	Pr(choice $= AEX$)	$m^*(E) - p$	Pr(choice $= AEX$)	$m^*(E) - p$	Pr(choice $= AEX$)
Near ambiguity neutral	-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: This table replicates Table E.1 when we classify individuals into five ambiguity groups instead of four.

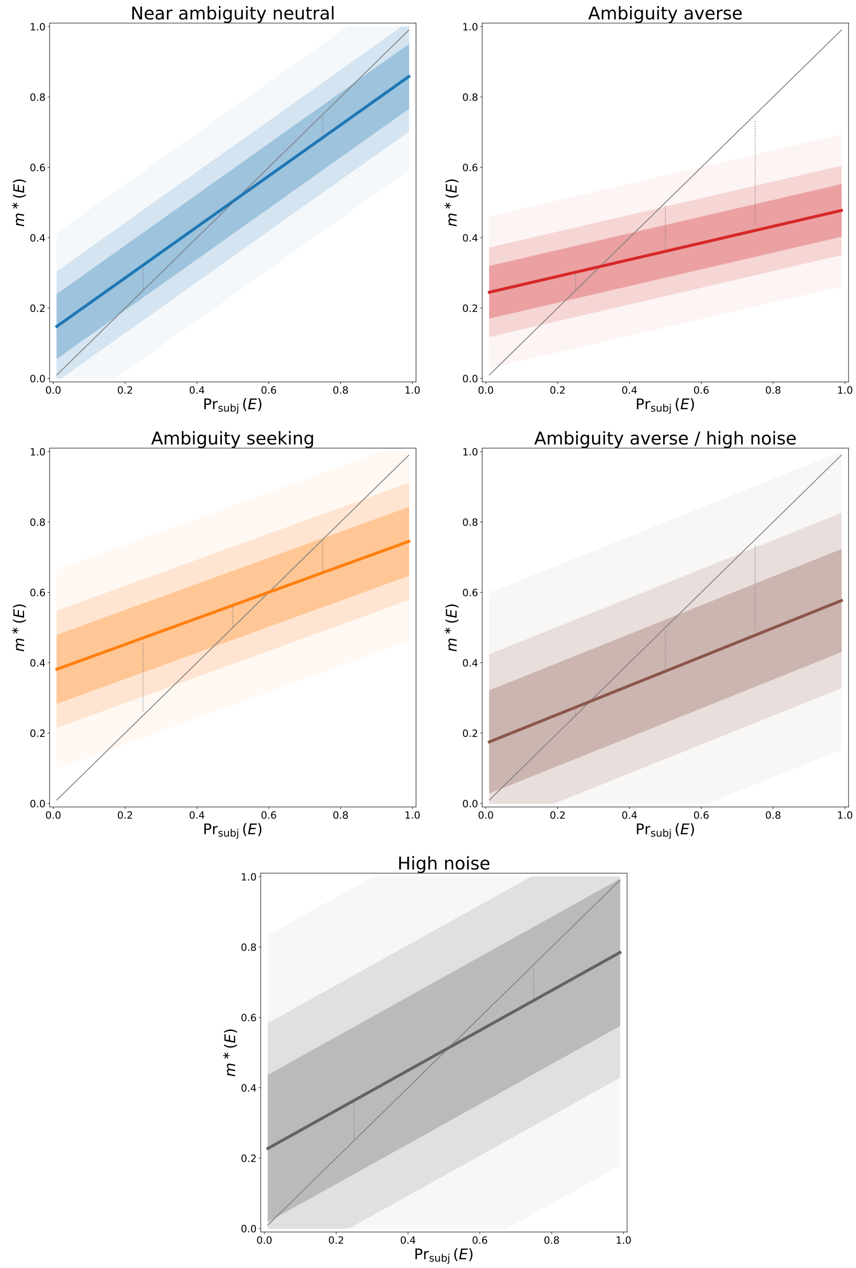


Figure E.6. Matching probabilities as a function of subjective probabilities, by group (5 groups)

Notes: This figure replicates Figure E.1 when we classify individuals into five ambiguity groups instead of four.

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

	Ambiguity types				
	Near ambiguity neutral	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	0.36	0.29
	(0.019)	(0.025)	(0.023)	(0.023)	(0.026)
Education: Tertiary	0.57	0.35	0.4	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: This table replicates Table 6 when we classify individuals into five ambiguity groups instead of four.

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

	Ambiguity types				
	Near ambiguity neutral	Ambiguity averse	Ambiguity seeking	Ambiguity averse / high noise	High noise
Age: $\in (35, 50]$	-0.024	-0.019	-0.0004	0.016	0.028
	(0.036)	(0.031)	(0.036)	(0.038)	(0.036)
Age: $\in (50, 65]$	-0.034	-0.018	-0.0089	-0.018	0.079^{**}
	(0.034)	(0.03)	(0.034)	(0.036)	(0.033)
Age: ≥ 65	-0.062^{*}	-0.066^{**}	-0.037	0.028	0.14^{***}
	(0.034)	(0.031)	(0.035)	(0.035)	(0.033)
Female	-0.005	0.066^{***}	0.015	-0.0098	-0.066^{***}
	(0.022)	(0.019)	(0.021)	(0.02)	(0.016)
Education: Tertiary	0.088^{***}	-0.0051	-0.014	-0.095^{***}	0.026
	(0.032)	(0.028)	(0.029)	(0.028)	(0.023)
Education: Upper secondary	0.07^{**}	0.012	-0.038	-0.033	-0.012
	(0.032)	(0.025)	(0.028)	(0.025)	(0.021)
Income: $\in (1.1, 1.6]$	-0.045	0.03	0.0026	0.047^{*}	-0.034
	(0.032)	(0.027)	(0.03)	(0.027)	(0.021)
Income: $\in (1.6, 2.2]$	-0.057^{*}	0.057^{**}	0.013	0.025	-0.038
	(0.032)	(0.028)	(0.031)	(0.03)	(0.024)
Income: ≥ 2.2	-0.081^{**}	0.041	0.0019	0.066^{**}	-0.029
	(0.034)	(0.032)	(0.033)	(0.033)	(0.027)
Financial assets: $\in (1.8, 11.2]$	0.077^{**}	-0.055^{**}	0.031	0.017	-0.069^{***}
	(0.034)	(0.026)	(0.03)	(0.027)	(0.024)
Financial assets: $\in (11.2, 32]$	0.14^{***}	-0.071^{**}	-0.048	-0.0073	-0.011
	(0.034)	(0.028)	(0.034)	(0.029)	(0.023)
Financial assets: ≥ 32	0.097^{***}	-0.097^{***}	0.015	-0.029	0.014
	(0.034)	(0.032)	(0.033)	(0.032)	(0.025)
Risk aversion index	-0.014	0.015^{*}	-0.0091	0.019^{**}	-0.011
	(0.011)	(0.0093)	(0.011)	(0.0097)	(0.0078)
Numeracy index	0.23^{***}	-0.038^{***}	-0.024^{*}	-0.067^{***}	-0.1^{***}
	(0.017)	(0.0098)	(0.013)	(0.011)	(0.0088)
Observations	1624	1624	1624	1624	1624
Pseudo R^2	0.12	0.12	0.12	0.12	0.12

Notes: This table replicates Table E.3 when we classify individuals into five ambiguity groups instead of four.

Table E.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^{***}	-0.0056	-0.13^{**}	-0.0043
	(0.03)	(0.025)	(0.052)	(0.047)
Ambiguity averse / high noise type	-0.18^{***}	-0.044	-0.29^{***}	-0.092
	(0.028)	(0.027)	(0.059)	(0.056)
High noise type	-0.18^{***}	-0.054^{*}	-0.24^{***}	-0.092
	(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	0.14
Ambiguity averse, High noise	0.011	0.062	0.0009	0.036
Ambiguity seeking, High noise	0.0079	0.14	0.15	0.2
Ambiguity averse / high noise, High noise	0.9	0.75	0.51	1

Notes: This table replicates the regressions shown in Table 7 when we classify individuals into five ambiguity groups instead of four. The left-out type is 'Near ambiguity neutral'.

E.5 Ambiguity types with $k = 8$

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

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.

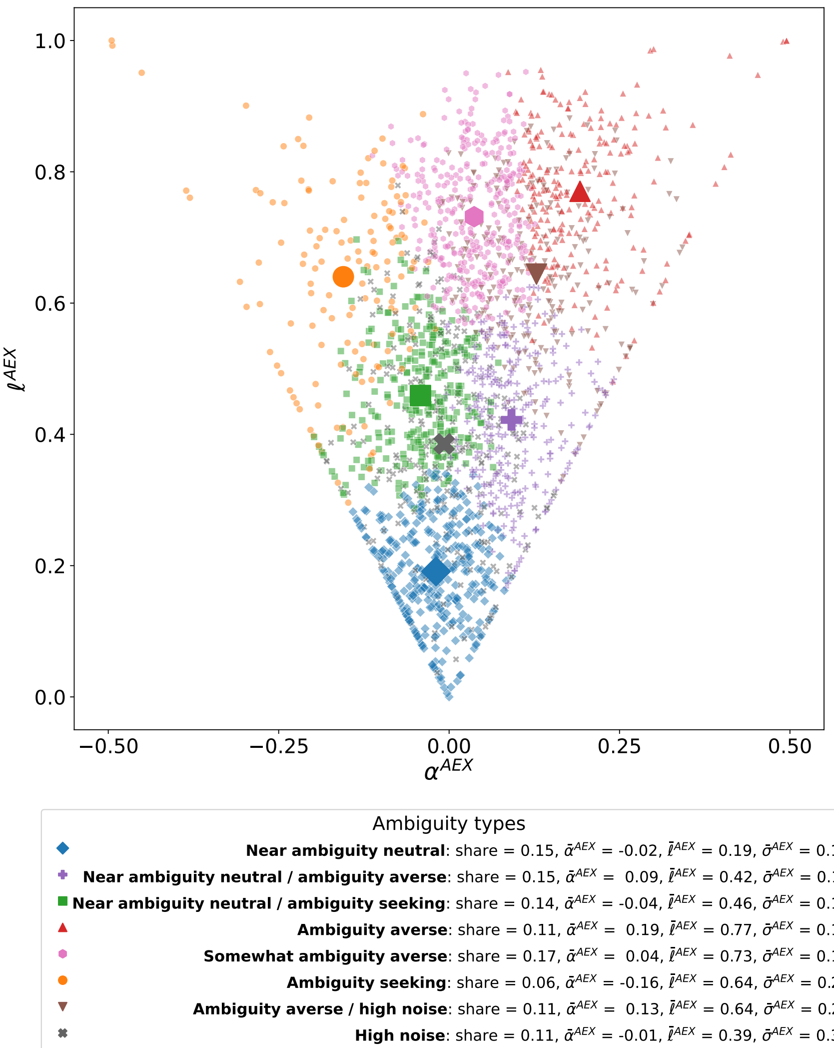


Figure E.7. Summarizing heterogeneity in ambiguity profiles with $k = 8$ discrete groups

Notes: This figure replicates Figure 3 when we classify individuals into eight ambiguity groups instead of four.

Table E.17. Deterministic matching probabilities and choice probabilities for ambiguity types (8 groups)

				$\Pr_{\text{subj}} = p = 0.25$		$\Pr_{\text{subj}} = p = 0.5$		$\Pr_{\text{subj}} = p = 0.75$	
Ambiguity type	α	ℓ	σ	$m^*(E) - p$	$\Pr(\text{choice} = AEX)$	$m^*(E) - p$	$\Pr(\text{choice} = AEX)$	$m^*(E) - p$	$\Pr(\text{choice} = AEX)$
Near ambiguity neutral	-0.019	0.19	0.13	0.067	0.69	0.019	0.56	−0.029	0.42
Near ambiguity neutral / ambiguity averse	0.091	0.42	0.17	0.014	0.53	−0.091	0.29	−0.2	0.12
Near ambiguity neutral / ambiguity seeking	-0.042	0.46	0.11	0.16	0.92	0.042	0.65	−0.073	0.26
Ambiguity averse	0.19	0.77	0.12	0.0006	0.5	−0.19	0.049	−0.38	0.0004
Somewhat ambiguity averse	0.037	0.73	0.14	0.15	0.86	−0.037	0.39	−0.22	0.055
Ambiguity seeking	-0.16	0.64	0.2	0.32	0.95	0.16	0.78	−0.0049	0.49
Ambiguity averse / high noise	0.13	0.64	0.27	0.033	0.55	−0.13	0.32	−0.29	0.14
High noise	-0.0073	0.39	0.3	0.1	0.63	0.0073	0.51	−0.089	0.38

Notes: This table replicates Table E.1 when we classify individuals into eight ambiguity groups instead of four.

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

	Ambiguity types							
	Near AN	Near AN / AA	Near AN / AS	AA	Somewhat AA	AS	AA / high noise	High noise
Share	0.15	0.15	0.14	0.11	0.17	0.06	0.11	0.11
α^{AEX}	−0.019	0.091	−0.042	0.19	0.037	−0.16	0.13	−0.0073
	(0.0027)	(0.0028)	(0.0031)	(0.0049)	(0.0025)	(0.0074)	(0.0049)	(0.0043)
ℓ^{AEX}	0.19	0.42	0.46	0.77	0.73	0.64	0.64	0.39
	(0.0042)	(0.0056)	(0.005)	(0.0066)	(0.0047)	(0.012)	(0.0076)	(0.0097)
σ^{AEX}	0.13	0.17	0.11	0.12	0.14	0.2	0.27	0.3
	(0.0026)	(0.002)	(0.002)	(0.003)	(0.0024)	(0.005)	(0.0032)	(0.0031)
Education: Lower secondary and below	0.11	0.2	0.14	0.3	0.27	0.35	0.45	0.42
	(0.017)	(0.022)	(0.02)	(0.03)	(0.023)	(0.041)	(0.033)	(0.031)
Education: Upper secondary	0.28	0.37	0.31	0.36	0.4	0.36	0.33	0.29
	(0.025)	(0.027)	(0.027)	(0.031)	(0.026)	(0.041)	(0.031)	(0.029)
Education: Tertiary	0.61	0.43	0.55	0.34	0.33	0.3	0.22	0.28
	(0.027)	(0.028)	(0.029)	(0.031)	(0.025)	(0.039)	(0.027)	(0.029)
Age	55	54	50	54	57	60	63	66
	(0.86)	(0.95)	(0.9)	(0.99)	(0.79)	(1.2)	(1)	(0.83)
Female	0.34	0.49	0.45	0.62	0.58	0.57	0.51	0.47
	(0.026)	(0.028)	(0.029)	(0.031)	(0.026)	(0.042)	(0.033)	(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)	(0.065)	(0.058)	(0.052)	(0.1)	(0.059)	(0.055)
Total hh financial assets (equiv., thousands)	64	35	49	18	34	35	26	34
	(10)	(5.1)	(11)	(2.9)	(6.4)	(6.4)	(5.5)	(5.6)
Risk aversion index	−0.094	−0.0053	−0.061	0.049	0.031	0.11	0.13	−0.075
	(0.048)	(0.053)	(0.054)	(0.063)	(0.055)	(0.1)	(0.071)	(0.072)
Numeracy index	0.73	0.29	0.56	−0.29	−0.079	−0.34	−0.7	−0.79
	(0.031)	(0.044)	(0.037)	(0.061)	(0.044)	(0.092)	(0.068)	(0.076)

Notes: This table replicates Table 6 when we classify individuals into eight ambiguity groups instead of four.

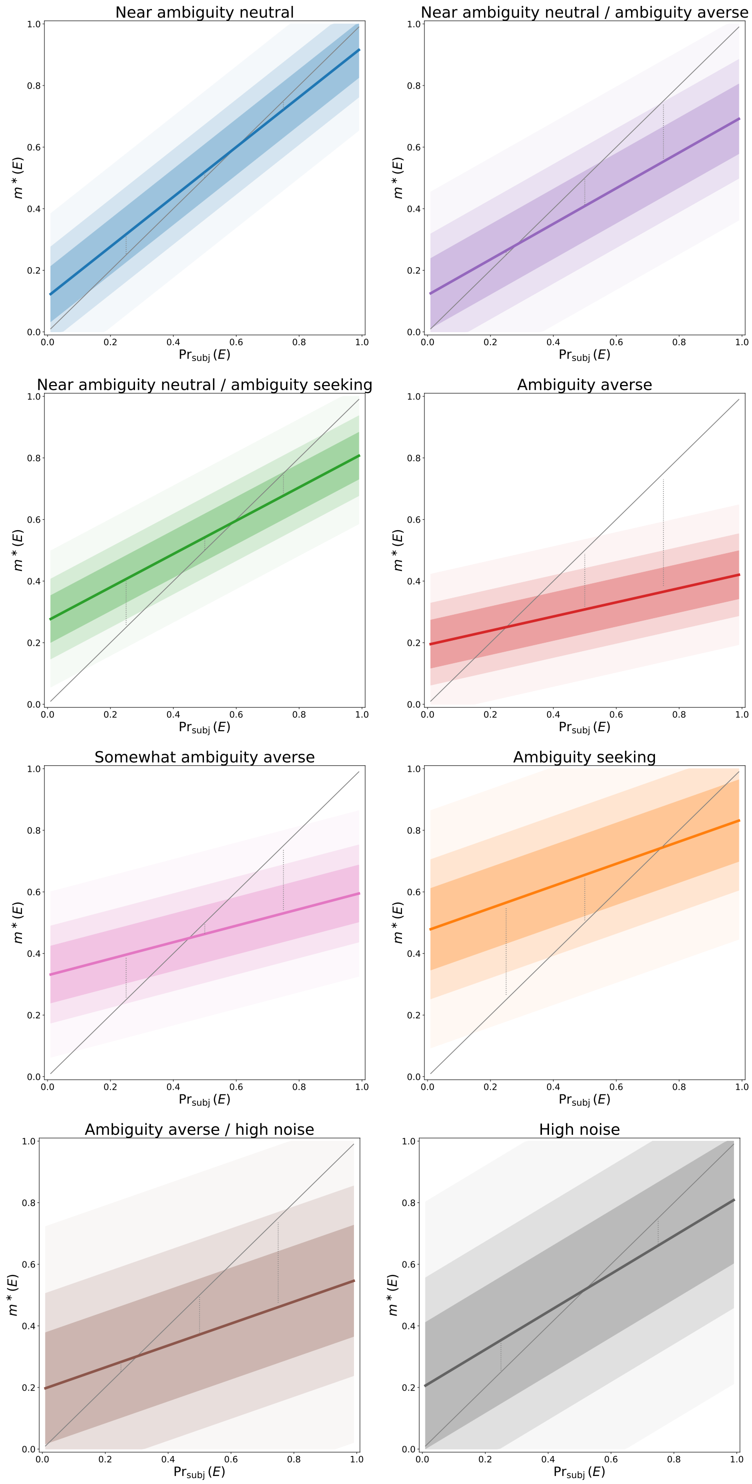


Figure E.8. Matching probabilities as a function of subjective probabilities, by group (8 groups)

Notes: This figure replicates Figure E.1 when we classify individuals into eight ambiguity groups instead of four.

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

	Ambiguity types							
	Near AN	Near AN / AA	Near AN / AS	AA	Somewhat AA	AS	AA / high noise	High noise
Age: $\in (35, 50]$	0.0083	-0.037	-0.02	-0.037	-0.0063	0.022	0.056	0.014
	(0.029)	(0.03)	(0.026)	(0.024)	(0.036)	(0.027)	(0.036)	(0.037)
Age: $\in (50, 65]$	0.011	-0.055^{*}	-0.05^{**}	-0.03	0.014	0.015	0.038	0.058^{*}
	(0.027)	(0.029)	(0.025)	(0.023)	(0.034)	(0.026)	(0.034)	(0.034)
Age: ≥ 65	0.0008	-0.06^{**}	-0.14^{***}	-0.056^{**}	0.023	0.027	0.087^{***}	0.11^{***}
	(0.027)	(0.029)	(0.028)	(0.024)	(0.033)	(0.025)	(0.033)	(0.033)
Female	-0.018	0.012	-0.0008	0.04^{***}	0.049^{**}	0.0052	-0.039^{**}	-0.047^{***}
	(0.019)	(0.018)	(0.019)	(0.015)	(0.02)	(0.012)	(0.015)	(0.015)
Education: Tertiary	0.06^{**}	-0.0027	-0.0023	-0.016	0.002	-0.014	-0.052^{**}	0.025
	(0.029)	(0.027)	(0.028)	(0.021)	(0.027)	(0.017)	(0.022)	(0.022)
Education: Upper secondary	0.024	0.015	-0.021	-0.0093	0.035	-0.018	-0.022	-0.0043
	(0.03)	(0.026)	(0.028)	(0.019)	(0.024)	(0.015)	(0.018)	(0.02)
Income: $\in (1.1, 1.6]$	-0.026	-0.035	0.011	-0.0048	0.052^{**}	-0.016	0.025	-0.0059
	(0.028)	(0.027)	(0.029)	(0.02)	(0.026)	(0.017)	(0.018)	(0.02)
Income: $\in (1.6, 2.2]$	0.0007	-0.016	-0.0051	0.015	0.038	-0.0025	-0.0086	-0.022
	(0.027)	(0.026)	(0.028)	(0.021)	(0.029)	(0.018)	(0.024)	(0.023)
Income: ≥ 2.2	-0.054^{*}	-0.051^{*}	0.039	0.0086	0.041	-0.0091	0.038	-0.013
	(0.029)	(0.028)	(0.028)	(0.025)	(0.031)	(0.02)	(0.024)	(0.026)
Financial assets: $\in (1.8, 11.2]$	0.0093	0.048^{*}	0.041	-0.048^{**}	0.0085	0.025	-0.037^{*}	-0.047^{**}
	(0.031)	(0.027)	(0.028)	(0.02)	(0.027)	(0.016)	(0.02)	(0.022)
Financial assets: $\in (11.2, 32]$	0.067^{**}	0.044	0.018	-0.034^{*}	-0.023	-0.022	-0.049^{**}	-0.002
	(0.029)	(0.028)	(0.03)	(0.021)	(0.03)	(0.022)	(0.021)	(0.022)
Financial assets: ≥ 32	0.054^{*}	-0.013	0.037	-0.066^{**}	-0.016	0.032^{*}	-0.045^{*}	0.016
	(0.03)	(0.031)	(0.029)	(0.026)	(0.032)	(0.018)	(0.023)	(0.024)
Risk aversion index	-0.0014	-0.0031	0.0036	0.0009	0.0004	-0.0013	0.015^{**}	-0.014^{**}
	(0.0098)	(0.0095)	(0.0098)	(0.0073)	(0.01)	(0.0062)	(0.007)	(0.0071)
Numeracy index	0.16^{***}	0.026^{*}	0.06^{***}	-0.028^{***}	-0.045^{***}	-0.028^{***}	-0.057^{***}	-0.086^{***}
	(0.019)	(0.013)	(0.016)	(0.0072)	(0.01)	(0.0069)	(0.0081)	(0.0086)
Observations	1624	1624	1624	1624	1624	1624	1624	1624
Pseudo R^2	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.12

Notes: This table replicates Table E.3 when we classify individuals into eight ambiguity groups instead of four.

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

	Owns risky assets (Probit)		Share risky assets (Tobit)	
	(1)	(2)	(3)	(4)
Near ambiguity neutral / ambiguity averse type	-0.19^{***}	-0.064^{**}	-0.28^{***}	-0.12^{**}
	(0.037)	(0.029)	(0.065)	(0.058)
Near ambiguity neutral / ambiguity seeking type	-0.076^{*}	-0.022	-0.14^{**}	-0.073
	(0.041)	(0.028)	(0.061)	(0.055)
Ambiguity averse type	-0.32^{***}	-0.15^{***}	-0.7^{***}	-0.34^{***}
	(0.033)	(0.035)	(0.1)	(0.094)
Somewhat ambiguity averse type	-0.22^{***}	-0.083^{***}	-0.35^{***}	-0.15^{**}
	(0.036)	(0.03)	(0.066)	(0.062)
Ambiguity seeking type	-0.18^{***}	-0.031	-0.25^{***}	-0.04
	(0.049)	(0.046)	(0.091)	(0.085)
Ambiguity averse / high noise type	-0.27^{***}	-0.08^{**}	-0.44^{***}	-0.14
	(0.036)	(0.039)	(0.086)	(0.083)
High noise type	-0.22^{***}	-0.06	-0.28^{***}	-0.085
	(0.039)	(0.037)	(0.076)	(0.073)
Controls	No	Yes	No	Yes
Observations	1727	1624	1584	1502
Pseudo R^2	0.066	0.31	0.053	0.29
p-values for differences between				
Near ambiguity neutral / ambiguity averse, Near ambiguity neutral / ambiguity seeking	0.0031	0.16	0.042	0.47
Near ambiguity neutral / ambiguity averse, Ambiguity averse	0	0.019	0.0001	0.02
Near ambiguity neutral / ambiguity seeking, Ambiguity averse	0	0.001	0	0.0049
Near ambiguity neutral / ambiguity averse, Somewhat ambiguity averse	0.22	0.52	0.34	0.63
Near ambiguity neutral / ambiguity seeking, Somewhat ambiguity averse	0	0.047	0.0029	0.23
Ambiguity averse, Somewhat ambiguity averse	0.0013	0.057	0.0009	0.046
Near ambiguity neutral / ambiguity averse, Ambiguity seeking	0.88	0.43	0.72	0.38
Near ambiguity neutral / ambiguity seeking, Ambiguity seeking	0.043	0.86	0.26	0.71
Ambiguity averse, Ambiguity seeking	0.0003	0.0089	0.0002	0.0075
Somewhat ambiguity averse, Ambiguity seeking	0.28	0.21	0.28	0.21
Near ambiguity neutral / ambiguity averse, Ambiguity averse / high noise	0.01	0.68	0.082	0.82
Near ambiguity neutral / ambiguity seeking, Ambiguity averse / high noise	0	0.15	0.0009	0.45
Ambiguity averse, Ambiguity averse / high noise	0.086	0.081	0.026	0.062
Somewhat ambiguity averse, Ambiguity averse / high noise	0.12	0.93	0.33	0.89
Ambiguity seeking, Ambiguity averse / high noise	0.026	0.3	0.083	0.34
Near ambiguity neutral / ambiguity averse, High noise	0.4	0.91	0.93	0.68
Near ambiguity neutral / ambiguity seeking, High noise	0.0005	0.31	0.093	0.87
Ambiguity averse, High noise	0.0012	0.023	0.0002	0.013
Somewhat ambiguity averse, High noise	0.8	0.5	0.36	0.4
Ambiguity seeking, High noise	0.42	0.52	0.78	0.63
Ambiguity averse / high noise, High noise	0.094	0.63	0.096	0.56

Notes: This table replicates the regressions shown in Table 7 when we classify individuals into eight ambiguity groups instead of four. The left-out type is 'Near ambiguity neutral'.

Appendix F Robustness within the model

F.1 Using all observations

This section reports on the changes in our results when we drop all restrictions that limit our sample size. In particular, we include waves regardless of whether there is variation across options, whether completion time falls among the fastest 15 % (see Section 2.2), or whether we have at least two waves per individual. Of course, the latter restriction may implicitly become binding—e.g., when considering stability over time—which was the original reason for its inclusion. The section is structured to reproduce all tables and figures from both the paper and this Online Appendix, providing the reader with a complete picture.

The number of individuals increases from 2177 to 2407. None of the descriptive statistics from Section 2 are affected in any meaningful way. Wave-by-wave parameter estimates remain very similar—if anything, average ambiguity aversion and a-insensitivity are slightly higher in Table F.6 than in Table D.4—and stability over time and across domains hardly change (cf. Table F.7 vs. Table 4 and Table F.8 vs. Table 5).

Perhaps more interestingly, the estimated types in Figure F.2 are very similar to those in Figure 3. This includes both the shares—none of which change by more than 2 percentage points—and the characteristics in terms of structural parameters. Looking at the joint distributions of types in both specifications (Table F.9), it becomes clear that 39% of additional observations are estimated to be of the "Ambiguity averse" type while 16 % are of the "High noise" type. The type classification adjusts very slightly so that the resulting shares are very similar to before. However, the diagonal elements remain dominant, with at least 93% of original observations being assigned to the same type in both specifications.

Despite the adjustments in the type means, the choice probabilities for our examples are often identical in Table F.10 and Table E.1; none of them differs by more than 5 percentage points. The ambiguity groups also exhibit similar observable characteristics (Table F.11). The coefficients for portfolio choice behavior attenuate slightly toward zero, and p-values for some comparisons increase (Table F.13). However, all comparisons highlighted in the main text—such as less risky investing among the ambiguity averse compared to near ambiguity neutral or ambiguity seeking types—remain significant.

Tables and figures corresponding to Section 2

Table F.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	0.28	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	0.75	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	
$E_2^{AEX}: Y_{t+6} \in (-\infty, 950)$	0.36	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	0.28	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: This table replicates Table 1 using all observations.

Table F.2. Average matching probabilities by wave

	2018-11	2019-05	2019-11	2020-05	2020-11	2021-05
$E_0^{AEX}: Y_{t+6} \in (1000, \infty)$	0.5	0.52	0.48	0.43	0.52	0.55
$E_1^{AEX}: Y_{t+6} \in (1100, \infty]$	0.35	0.37	0.36	0.33	0.36	0.42
$E_{1,C}^{AEX}: Y_{t+6} \in (-\infty, 1100]$	0.5	0.51	0.51	0.51	0.54	0.52
$E_2^{AEX}: Y_{t+6} \in (-\infty, 950)$	0.35	0.35	0.35	0.43	0.36	0.34
$E_{2,C}^{AEX}: Y_{t+6} \in [950, \infty)$	0.54	0.56	0.56	0.51	0.58	0.59
$E_3^{AEX}: Y_{t+6} \in [950, 1100]$	0.54	0.57	0.57	0.53	0.59	0.58
$E_{3,C}^{AEX}: Y_{t+6} \in (-\infty, 950) \cup (1100, \infty)$	0.41	0.41	0.4	0.44	0.41	0.43

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

Table F.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 B.3 using all observations.

Table F.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 F.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
Feels 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

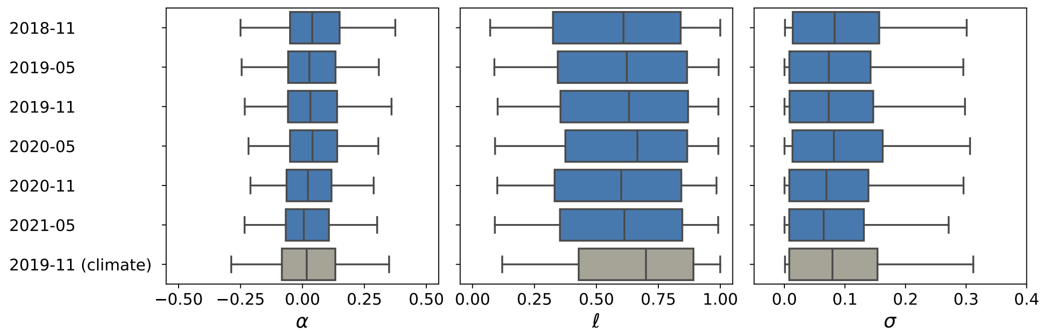


Figure F.1. Distributions of estimated parameters, wave by wave

Notes: This figure replicates Figure 2 using all observations.

Table F.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 D.4 using all observations.

Table F.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^{***}	0.94^{***}
		(0.01)	(0.03)	(0.05)
	Adj. R^2	0.14		
	1st st. F		563	320
$\sigma^{AEX}_{\text{last 3 waves}}$	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 F.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	437
$\sigma^{climate}_{2019-11}$	Intercept	0.055^{***}	0.022^{***}	
		(0.0029)	(0.0054)	
	$\sigma^{AEX}_{2019-11}$	0.49^{***}	0.84^{***}	0.87^{***}
		(0.03)	(0.06)	(0.08)
	Adj. R^2	0.21		
	1st st. F		233	205
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

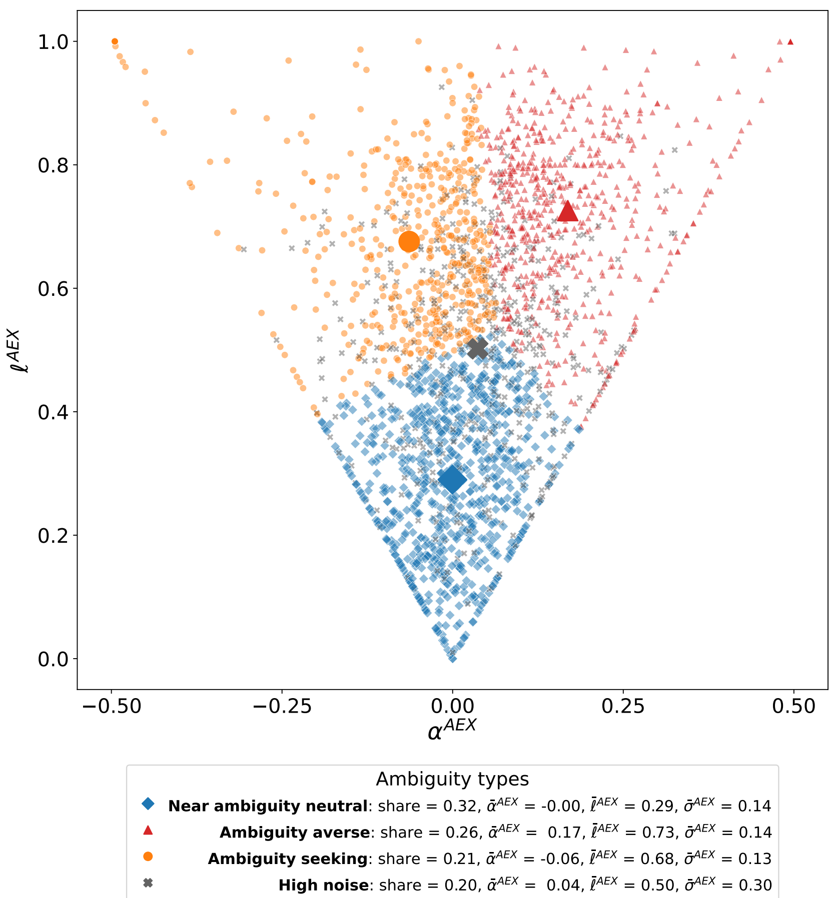


Figure F.2. Summarizing heterogeneity in ambiguity profiles with K=4 discrete groups

Notes: This figure replicates Figure 3 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 F.9. Cross-tabulation of group classification relative to main estimates

	Type using all observations				
	Near ambiguity neutral	Ambiguity averse	Ambiguity seeking	High noise	All
Baseline: Near ambiguity neutral	0.271	0.0004	0	0.001	0.272
Baseline: Ambiguity averse	0.006	0.225	0.010	0.007	0.247
Baseline: Ambiguity seeking	0.016	0.0004	0.179	0.011	0.206
Baseline: High noise	0.009	0.002	0.0004	0.169	0.180
Baseline: Missing	0.020	0.037	0.024	0.015	0.096
Baseline: All	0.322	0.265	0.212	0.201	1.000

Notes: 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 when using all observations. The row 'Baseline: Missing' refers to subjects who are part of the sample if all observations are used, but not part of our main sample.

Table F.10. Deterministic matching probabilities and choice probabilities for ambiguity types

				$\text{Pr}_{\text{subj}} = p = 0.25$		$\text{Pr}_{\text{subj}} = p = 0.5$		$\text{Pr}_{\text{subj}} = p = 0.75$	
Ambiguity type	α	ℓ	σ	$m^*(E) - p$	$\text{Pr}(\text{choice} = AEX)$	$m^*(E) - p$	$\text{Pr}(\text{choice} = AEX)$	$m^*(E) - p$	$\text{Pr}(\text{choice} = AEX)$
Near ambiguity neutral	-0.0003	0.29	0.14	0.073	0.7	0.0003	0.5	−0.072	0.3
Ambiguity averse	0.17	0.73	0.14	0.013	0.54	−0.17	0.11	−0.35	0.006
Ambiguity seeking	-0.064	0.68	0.13	0.23	0.96	0.064	0.68	−0.11	0.22
High noise	0.037	0.5	0.3	0.089	0.62	−0.037	0.45	−0.16	0.3

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

Table F.11. Average characteristics of group members

	Ambiguity types			
	Near ambiguity neutral	Ambiguity averse	Ambiguity seeking	High noise
Share	0.32	0.26	0.21	0.2
α^{AEX}	−0.0003	0.17	−0.064	0.037
	(0.0025)	(0.0037)	(0.0051)	(0.0045)
ℓ^{AEX}	0.29	0.73	0.68	0.5
	(0.0044)	(0.0052)	(0.0059)	(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	0.35	0.32
	(0.017)	(0.019)	(0.021)	(0.021)
Education: Tertiary	0.54	0.34	0.38	0.26
	(0.018)	(0.019)	(0.022)	(0.02)
Age	53	54	56	64
	(0.6)	(0.64)	(0.69)	(0.62)
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)	(0.039)
Total hh financial assets (equiv., thousands)	52	23	37	35
	(6.1)	(2.4)	(5.9)	(4.2)
Risk aversion index	−0.092	0.081	0.018	0.023
	(0.032)	(0.042)	(0.048)	(0.051)
Numeracy index	0.59	−0.23	0.063	−0.71
	(0.024)	(0.039)	(0.041)	(0.052)

Notes: This table replicates Table 6 using all observations.

Table F.12. Predictors of groups, marginal effects

	Ambiguity types			
	Near ambiguity neutral	Ambiguity averse	Ambiguity seeking	High noise
Age: $\in(35,50]$	-0.035	-0.017	-0.033	0.085^{**}
	(0.036)	(0.036)	(0.037)	(0.04)
Age: $\in(50,65]$	-0.059^{*}	-0.059^{*}	-0.015	0.13^{***}
	(0.035)	(0.035)	(0.035)	(0.038)
Age: ≥ 65	-0.095^{***}	-0.086^{**}	-0.034	0.21^{***}
	(0.035)	(0.035)	(0.035)	(0.037)
Female	-0.019	0.085^{***}	0.03	-0.097^{***}
	(0.022)	(0.021)	(0.021)	(0.019)
Education: Tertiary	0.079^{**}	-0.053^{*}	-0.031	0.0048
	(0.032)	(0.03)	(0.029)	(0.026)
Education: Upper secondary	0.071^{**}	-0.027	-0.033	-0.012
	(0.032)	(0.027)	(0.028)	(0.023)
Income: $\in(1.1,1.6]$	-0.057^{*}	0.038	0.019	-0.0009
	(0.032)	(0.029)	(0.03)	(0.024)
Income: $\in(1.6,2.2]$	-0.06^{*}	0.077^{**}	0.022	-0.04
	(0.032)	(0.031)	(0.031)	(0.027)
Income: ≥ 2.2	-0.088^{***}	0.068^{*}	0.015	0.0055
	(0.034)	(0.035)	(0.033)	(0.028)
Financial assets: $\in(1.8,11.2]$	0.071^{**}	-0.016	0.034	-0.088^{***}
	(0.034)	(0.029)	(0.03)	(0.026)
Financial assets: $\in(11.2,32]$	0.15^{***}	-0.074^{**}	-0.047	-0.028
	(0.033)	(0.031)	(0.033)	(0.026)
Financial assets: ≥ 32	0.086^{**}	-0.085^{**}	0.0034	-0.0047
	(0.034)	(0.035)	(0.034)	(0.028)
Risk aversion index	-0.016	0.016	-0.0025	0.002
	(0.011)	(0.011)	(0.011)	(0.0088)
Numeracy index	0.22^{***}	-0.066^{***}	-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 E.3 using all observations.

Table F.13. 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^{***}	-0.43^{***}	-0.16^{***}
	(0.023)	(0.023)	(0.059)	(0.055)
Ambiguity seeking type	-0.1^{***}	-0.0098	-0.15^{***}	-0.0094
	(0.027)	(0.023)	(0.05)	(0.046)
High noise type	-0.16^{***}	-0.045^{*}	-0.21^{***}	-0.077
	(0.026)	(0.026)	(0.057)	(0.057)
Age: $\in (35, 50]$		-0.028		-0.014
		(0.033)		(0.066)
Age: $\in (50, 65]$		-0.0027		0.031
		(0.031)		(0.062)
Age: ≥ 65		-0.022		0.025
		(0.032)		(0.063)
Education: Tertiary		0.038		0.12^{**}
		(0.026)		(0.058)
Education: Upper secondary		0.014		0.052
		(0.025)		(0.058)
Female		-0.027		-0.038
		(0.017)		(0.04)
Income: $\in (1.1, 1.6]$		0.0067		0.053
		(0.028)		(0.062)
Income: $\in (1.6, 2.2]$		-0.0068		0.02
		(0.027)		(0.061)
Income: ≥ 2.2		0.06^{**}		0.11^{*}
		(0.029)		(0.061)
Numeracy index		0.038^{**}		0.069^{**}
		(0.016)		(0.03)
Risk aversion index		-0.048^{***}		-0.12^{***}
		(0.0093)		(0.021)
Financial assets: $\in (1.8, 11.2]$		0.033^{*}		0.083
		(0.018)		(0.083)
Financial assets: $\in (11.2, 32]$		0.14^{***}		0.35^{***}
		(0.022)		(0.081)
Financial assets: ≥ 32		0.39^{***}		0.7^{***}
		(0.029)		(0.083)
Observations	1853	1692	1690	1561
Pseudo R^2	0.049	0.3	0.039	0.28
p-values for differences between				
Ambiguity averse, Ambiguity seeking	0	0.016	0	0.011
Ambiguity averse, High noise	0.025	0.32	0.0017	0.21
Ambiguity seeking, High noise	0.021	0.21	0.28	0.26

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

F.2 Restricting on a balanced panel

This section reports on changes to our results when we 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 2.2). 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 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 F.18 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 F.19 compared to Table D.4. Parameter estimates for stability over time / across domains are economically the same and statistically indistinguishable from each other (cf. Table F.20 vs. 4 and Table F.21 vs. 5).

Despite the large change in the number of individuals, the estimated types in Figure F.4 are almost identical to those in Figure 3. 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 F.26) 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 ambiguity neutral or ambiguity seeking types on the other hand continue to be significant with various p-values decreasing even more. The ambiguity seeking and near ambiguity neutral 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 F.14. 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
$E_0^{AEX} : Y_{t+6} \in (1000, \infty)$	0.51	0.27	0.15	0.45	0.93	0.63	0.52
$E_1^{AEX} : Y_{t+6} \in (1100, \infty]$	0.36	0.24	0.075	0.35	0.65	0.24	0.31
$E_{1,C}^{AEX} : Y_{t+6} \in (-\infty, 1100]$	0.53	0.28	0.15	0.45	0.93	0.76	
$E_2^{AEX} : Y_{t+6} \in (-\infty, 950)$	0.36	0.24	0.075	0.35	0.65	0.28	0.22
$E_{2,C}^{AEX} : Y_{t+6} \in [950, \infty)$	0.57	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 F.15. Average matching probabilities by wave

	2018-11	2019-05	2019-11	2020-05	2020-11	2021-05
$E_0^{AEX} : Y_{t+6} \in (1000, \infty)$	0.51	0.53	0.51	0.43	0.52	0.57
$E_1^{AEX} : Y_{t+6} \in (1100, \infty]$	0.36	0.36	0.36	0.33	0.35	0.43
$E_{1,C}^{AEX} : Y_{t+6} \in (-\infty, 1100]$	0.51	0.52	0.53	0.52	0.55	0.54
$E_2^{AEX} : Y_{t+6} \in (-\infty, 950)$	0.35	0.33	0.36	0.43	0.36	0.35
$E_{2,C}^{AEX} : Y_{t+6} \in [950, \infty)$	0.54	0.57	0.57	0.52	0.59	0.6
$E_3^{AEX} : Y_{t+6} \in [950, 1100]$	0.56	0.59	0.59	0.54	0.61	0.6
$E_{3,C}^{AEX} : Y_{t+6} \in (-\infty, 950) \cup (1100, \infty)$	0.42	0.4	0.4	0.45	0.41	0.44

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

Table F.16. 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 B.3 in a balanced panel.

Table F.17. 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 F.18. 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	0.34				
Education: Tertiary	1239	0.39				
Age	1239	59	15	50	63	70
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
Feels 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

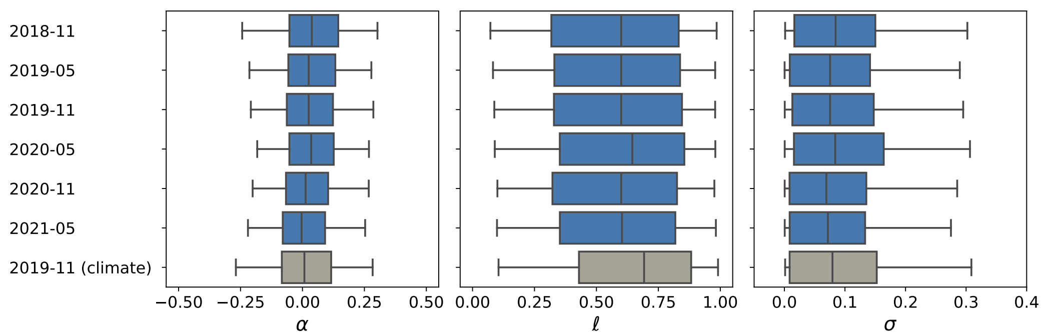


Figure F.3. Distributions of estimated parameters, wave by wave

Notes: This figure replicates Figure 2 in a balanced panel.

Table F.19. 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 D.4 in a balanced panel.

Table F.20. 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	244
$\sigma^{AEX}_{\text{last 3 waves}}$	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 F.21. 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	112
$\ell^{climate}_{2019-11}$	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

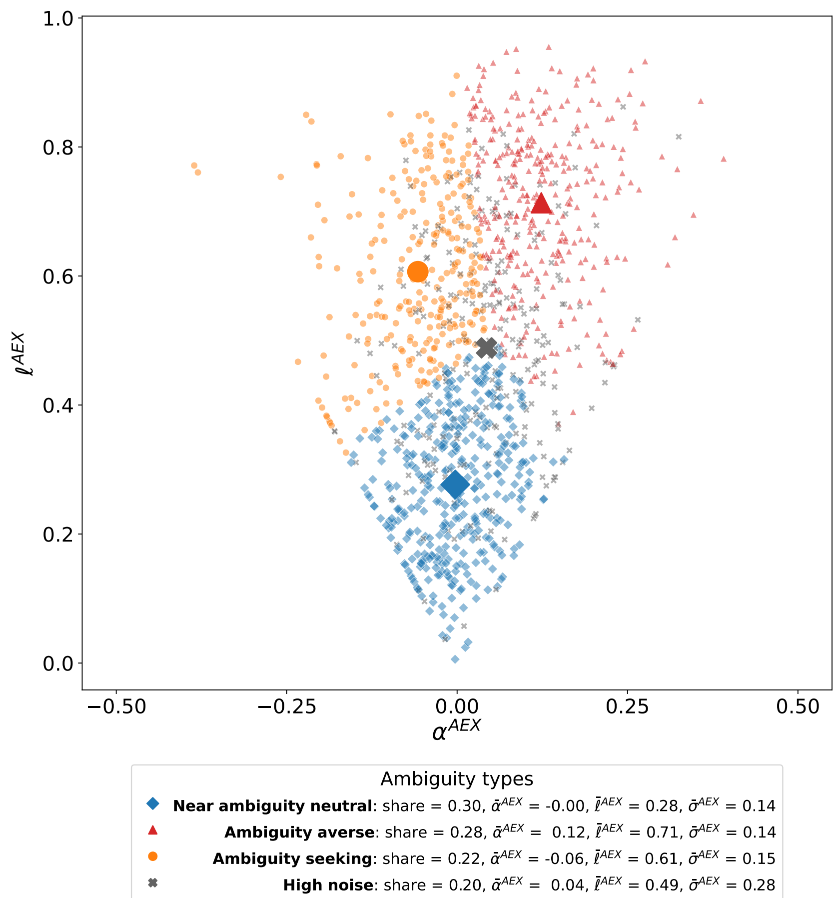


Figure F.4. Summarizing heterogeneity in ambiguity profiles with K=4 discrete groups

Notes: This figure replicates Figure 3 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 F.22. Cross-tabulation of group classification relative to main estimates

	Type in a balanced panel					
	Near ambiguity neutral	Ambiguity averse	Ambiguity seeking	High noise	Missing	All
Baseline: Near ambiguity neutral	0.171	0.002	0.007	0.0005	0.120	0.301
Baseline: Ambiguity averse	0	0.141	0	0.002	0.130	0.273
Baseline: Ambiguity seeking	0	0.015	0.119	0.003	0.090	0.227
Baseline: High noise	0.001	0	0.001	0.106	0.091	0.199
Baseline: All	0.172	0.158	0.127	0.112	0.431	1.000

Notes: 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 in a balanced panel. The column 'Missing' refers to subjects who are part of our main sample, but not the balanced panel.

Table F.23. Deterministic matching probabilities and choice probabilities for ambiguity types

				$\mathrm{Pr}_{\mathrm{subj}} = p = 0.25$		$\mathrm{Pr}_{\mathrm{subj}} = p = 0.5$		$\mathrm{Pr}_{\mathrm{subj}} = p = 0.75$	
Ambiguity type	α	ℓ	σ	$m^*(E)-p$	$\mathrm{Pr}(\mathrm{choice} = AEX)$	$m^*(E)-p$	$\mathrm{Pr}(\mathrm{choice} = AEX)$	$m^*(E)-p$	$\mathrm{Pr}(\mathrm{choice} = AEX)$
Near ambiguity neutral	-0.0026	0.28	0.14	0.072	0.7	0.0026	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	-0.058	0.61	0.15	0.21	0.92	0.058	0.65	−0.094	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 E.1 in a balanced panel.

Table F.24. Average characteristics of group members

	Ambiguity types			
	Near ambiguity neutral	Ambiguity averse	Ambiguity seeking	High noise
Share	0.3	0.28	0.22	0.2
α^{AEX}	−0.0026	0.12	−0.058	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	0.3	0.29	0.44
	(0.018)	(0.025)	(0.027)	(0.032)
Education: Upper secondary	0.32	0.38	0.33	0.31
	(0.024)	(0.026)	(0.028)	(0.03)
Education: Tertiary	0.54	0.31	0.38	0.25
	(0.026)	(0.025)	(0.029)	(0.028)
Age	57	57	59	66
	(0.8)	(0.82)	(0.84)	(0.79)
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	2.1	2.2	2
	(0.054)	(0.049)	(0.075)	(0.053)
Total hh financial assets (equiv., thousands)	61	32	51	34
	(8.8)	(4.2)	(9.8)	(5.4)
Risk aversion index	−0.085	0.11	−0.013	−0.0034
	(0.044)	(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 F.25. Predictors of groups, marginal effects

	Ambiguity types			
	Near ambiguity neutral	Ambiguity averse	Ambiguity seeking	High noise
Age: $\in (35, 50]$	0.029	−0.058	−0.047	0.076
	(0.054)	(0.056)	(0.056)	(0.06)
Age: $\in (50, 65]$	−0.037	−0.11**	0.034	0.11**
	(0.051)	(0.053)	(0.051)	(0.055)
Age: ≥ 65	−0.037	−0.12**	−0.066	0.22***
	(0.051)	(0.051)	(0.052)	(0.054)
Female	−0.022	0.07**	0.035	−0.083***
	(0.028)	(0.028)	(0.028)	(0.024)
Education: Tertiary	0.064	−0.062	0.014	−0.015
	(0.042)	(0.042)	(0.037)	(0.033)
Education: Upper secondary	0.056	0.0001	−0.037	−0.019
	(0.04)	(0.037)	(0.036)	(0.03)
Income: $\in (1.1, 1.6]$	−0.1**	0.1**	−0.0057	0.0085
	(0.042)	(0.04)	(0.039)	(0.031)
Income: $\in (1.6, 2.2]$	−0.074*	0.12***	−0.016	−0.035
	(0.041)	(0.044)	(0.041)	(0.036)
Income: ≥ 2.2	−0.12***	0.12***	−0.048	0.039
	(0.043)	(0.048)	(0.043)	(0.037)
Financial assets: $\in (1.8, 11.2]$	0.11**	−0.078**	0.09**	−0.12***
	(0.044)	(0.039)	(0.039)	(0.034)
Financial assets: $\in (11.2, 32]$	0.14***	−0.073*	−0.025	−0.038
	(0.043)	(0.041)	(0.044)	(0.033)
Financial assets: ≥ 32	0.11**	−0.09**	0.058	−0.073**
	(0.044)	(0.045)	(0.043)	(0.037)
Risk aversion index	−0.0082	0.027*	−0.016	−0.0029
	(0.014)	(0.014)	(0.014)	(0.011)
Numeracy index	0.25***	−0.087***	−0.037**	−0.13***
	(0.023)	(0.016)	(0.017)	(0.013)
Observations	995	995	995	995
Pseudo R^2	0.14	0.14	0.14	0.14

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

Table F.26. 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	0.076
	(0.04)	(0.031)	(0.057)	(0.051)
High noise type	-0.19^{***}	-0.056	-0.25^{***}	-0.078
	(0.035)	(0.039)	(0.071)	(0.068)
Age: $\in (35, 50]$		-0.018		0.042
		(0.052)		(0.088)
Age: $\in (50, 65]$		0.0071		0.065
		(0.049)		(0.081)
Age: ≥ 65		-0.015		0.067
		(0.05)		(0.082)
Education: Tertiary		0.079^{**}		0.21^{***}
		(0.037)		(0.069)
Education: Upper secondary		0.026		0.093
		(0.033)		(0.068)
Female		-0.024		-0.01
		(0.024)		(0.046)
Income: $\in (1.1, 1.6]$		0.016		0.052
		(0.04)		(0.069)
Income: $\in (1.6, 2.2]$		-0.062^{*}		-0.1
		(0.035)		(0.069)
Income: ≥ 2.2		0.042		0.035
		(0.037)		(0.066)
Numeracy index		0.036		0.069^{**}
		(0.026)		(0.034)
Risk aversion index		-0.052^{***}		-0.12^{***}
		(0.013)		(0.023)
Financial assets: $\in (1.8, 11.2]$		0.047^{*}		0.11
		(0.025)		(0.092)
Financial assets: $\in (11.2, 32]$		0.17^{***}		0.35^{***}
		(0.029)		(0.089)
Financial assets: ≥ 32		0.42^{***}		0.66^{***}
		(0.038)		(0.091)
Observations	1010	995	940	933
Pseudo R^2	0.054	0.33	0.047	0.33
p-values for differences between				
Ambiguity averse, Ambiguity seeking	0	0.0002	0	0.0004
Ambiguity averse, High noise	0.38	0.39	0.16	0.33
Ambiguity seeking, High noise	0.0001	0.017	0.0016	0.029

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

F.3 Ignoring the event E_0

This section reports on changes to our results when we re-estimate our model without using the event E_0. This assures that the set of the remaining six events form a 'belief hedge' which is necessary for the calculation of the indices by Baillon, Bleichrodt, et al. (2021). When we compare our results to the indices by Baillon, Bleichrodt, et al. (2021) in Section G, we use the results of this section such that both estimates are based on the same set of events.

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. As the sample compositions and matching probabilities are not affected, we only report tables and figures corresponding to Sections 3 and 4.

Overall, we find that our main results are hardly affected by including the additional event E_0. Comparing Table F.27 and Table D.4 reveals an increase in the mean of ℓ by 0.03 and an increase in the mean of α by 0.01. Although we decrease the number of events, θ decreases only by 0.03, indicating that the event E_0 in many cases does not influence our main estimates. Furthermore, parameter estimates for stability over time / across domains are economically the same and statistically indistinguishable from each other (cf. Table F.29 vs. 4 and Table F.30 vs. 5). As 93 % of subjects are assigned to the same ambiguity type as with our main estimates (Table F.31), the ambiguity type classification (Figure F.6), group compositions (Table F.33), and patterns of portfolio choice behavior (Table F.35) remain almost unchanged.

Tables and figures corresponding to Section 3

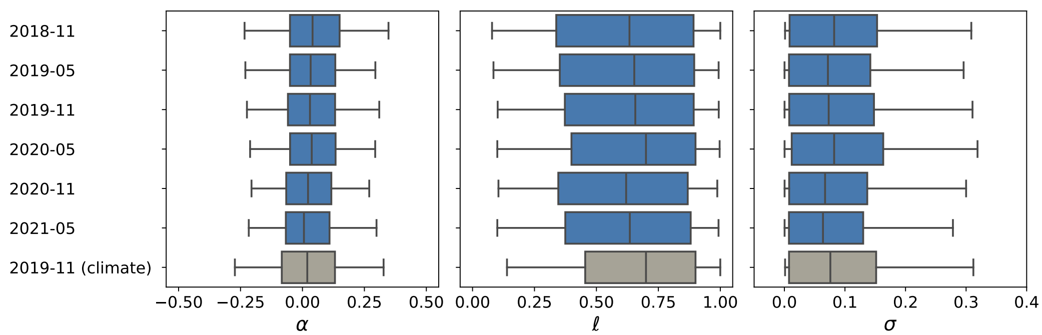


Figure F.5. Distributions of estimated parameters, wave by wave

Notes: This figure replicates Figure 2 without using the event E_0.

Table F.27. 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	0.048	0.18	−0.24	−0.05	0.041	0.15	0.35
	2019-05	0.036	0.16	−0.23	−0.05	0.033	0.13	0.29
	2019-11	0.035	0.16	−0.23	−0.059	0.03	0.13	0.31
	2020-05	0.04	0.16	−0.21	−0.05	0.037	0.13	0.29
	2020-11	0.027	0.15	−0.21	−0.066	0.023	0.12	0.27
	2021-05	0.021	0.16	−0.22	−0.067	0.006	0.11	0.3
	Observations from all AEX waves	0.035	0.16	−0.22	−0.057	0.03	0.13	0.3
	2019-11 (Climate Change)	0.024	0.18	−0.27	−0.083	0.019	0.13	0.33
ℓ	2018-11	0.6	0.3	0.078	0.34	0.63	0.89	1
	2019-05	0.61	0.3	0.084	0.35	0.65	0.89	0.99
	2019-11	0.61	0.29	0.1	0.37	0.66	0.89	0.99
	2020-05	0.62	0.29	0.1	0.4	0.7	0.9	1
	2020-11	0.6	0.29	0.1	0.35	0.62	0.87	0.99
	2021-05	0.61	0.29	0.1	0.37	0.63	0.88	0.99
	Observations from all AEX waves	0.61	0.3	0.099	0.36	0.65	0.89	0.99
	2019-11 (Climate Change)	0.66	0.28	0.14	0.45	0.7	0.9	1
σ	2018-11	0.1	0.1	0.0011	0.0085	0.082	0.15	0.31
	2019-05	0.094	0.097	0.0002	0.0076	0.072	0.14	0.3
	2019-11	0.098	0.099	0.0003	0.0079	0.073	0.15	0.31
	2020-05	0.11	0.1	0.0003	0.012	0.082	0.16	0.32
	2020-11	0.092	0.097	0.0003	0.0078	0.067	0.14	0.3
	2021-05	0.087	0.091	0.0003	0.0075	0.064	0.13	0.28
	Observations from all AEX waves	0.097	0.099	0.0004	0.0081	0.075	0.14	0.31
	2019-11 (Climate Change)	0.1	0.1	0.0011	0.0076	0.076	0.15	0.31

Notes: This table replicates Table D.4 without using the event E_0.

Table F.28. Cross-wave correlations of estimated parameters

		α	ℓ	σ
2018-11	2019-05	0.25	0.35	0.28
	2019-11	0.20	0.38	0.28
	2020-05	0.16	0.33	0.26
	2020-11	0.22	0.36	0.29
	2021-05	0.18	0.34	0.23
2019-05	2019-11	0.32	0.43	0.33
	2020-05	0.31	0.37	0.28
	2020-11	0.32	0.41	0.29
	2021-05	0.30	0.39	0.27
2019-11	2020-05	0.28	0.38	0.34
	2020-11	0.33	0.46	0.32
	2021-05	0.24	0.44	0.32
2020-05	2020-11	0.31	0.43	0.28
	2021-05	0.25	0.36	0.25
2020-11	2021-05	0.44	0.45	0.36
Average		0.27	0.39	0.29

Notes: This table replicates the correlations shown in Table F.28 without using the event E_0.

Table F.29. 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***	−0.01***	
		(0.0026)	(0.004)	
	$\alpha^{AEX}_{\text{first 3 waves}}$	0.24***	0.95***	0.98***
		(0.01)	(0.07)	(0.10)
	Adj. R^2	0.065		
	1st st. F		137	92
$\ell^{AEX}_{\text{last 3 waves}}$	Intercept	0.38***	0.017	
		(0.0091)	(0.023)	
	$\ell^{AEX}_{\text{first 3 waves}}$	0.38***	0.98***	0.96***
		(0.01)	(0.04)	(0.05)
	Adj. R^2	0.15		
	1st st. F		536	295
$\sigma^{AEX}_{\text{last 3 waves}}$	Intercept	0.067***	−0.0015	
		(0.0017)	(0.0062)	
	$\sigma^{AEX}_{\text{first 3 waves}}$	0.29***	0.99***	0.99***
		(0.01)	(0.07)	(0.09)
	Adj. R^2	0.083		
	1st st. F		184	103
Controls		No	No	Yes
N Subjects		1859	1859	1452

Notes: This table replicates the regressions shown in Table 4 without using the event E_0.

Table F.30. Predicting climate ambiguity parameters with AEX parameters

		OLS	2SLS	
		(1)	(2)	(3)
$\alpha^{climate}_{2019-11}$	Intercept	0.0008	-0.014^{***}	
		(0.0035)	(0.0041)	
	$\alpha^{AEX}_{2019-11}$	0.67^{***}	1.06^{***}	1.09^{***}
		(0.03)	(0.06)	(0.07)
	Adj. R^2	0.37		
	1st st. F		200	137
$\ell^{climate}_{2019-11}$	Intercept	0.45^{***}	0.3^{***}	
		(0.015)	(0.025)	
	$\ell^{AEX}_{2019-11}$	0.34^{***}	0.59^{***}	0.64^{***}
		(0.02)	(0.04)	(0.05)
	Adj. R^2	0.13		
	1st st. F		751	395
$\sigma^{climate}_{2019-11}$	Intercept	0.052^{***}	0.017^{***}	
		(0.0027)	(0.0052)	
	$\sigma^{AEX}_{2019-11}$	0.48^{***}	0.85^{***}	0.89^{***}
		(0.03)	(0.06)	(0.07)
	Adj. R^2	0.22		
	1st st. F		317	191
Controls		No	No	Yes
N Subjects		1843	1843	1411

Notes: This table replicates the regressions shown in Table 5 without using the event E_0.

Tables and figures corresponding to Section 4

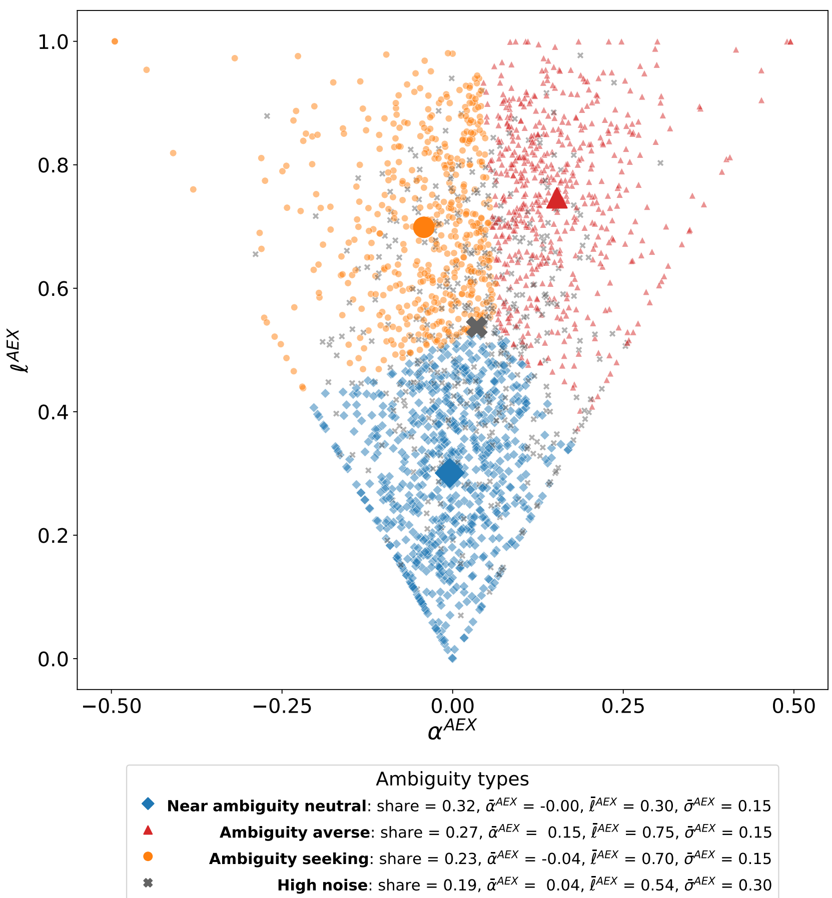


Figure F.6. Summarizing heterogeneity in ambiguity profiles with K=4 discrete groups

Notes: This figure replicates Figure 3 without using the event E_0.

	Mean	Std. dev.	$q_{0.05}$	$q_{0.25}$	$q_{0.5}$	$q_{0.75}$	$q_{0.95}$
α^{AEX}	0.036	0.11	−0.13	−0.03	0.033	0.1	0.22
ℓ^{AEX}	0.56	0.23	0.15	0.38	0.57	0.74	0.9
σ^{AEX}	0.18	0.081	0.069	0.12	0.16	0.22	0.33

Table F.31. Cross-tabulation of group classification relative to main estimates

	Type without using the event E_0				
	Near ambiguity neutral	Ambiguity averse	Ambiguity seeking	High noise	All
Baseline: Near ambiguity neutral	0.289	0.005	0.005	0.001	0.301
Baseline: Ambiguity averse	0.003	0.252	0.013	0.004	0.273
Baseline: Ambiguity seeking	0.017	0.001	0.205	0.003	0.227
Baseline: High noise	0.006	0.008	0.005	0.181	0.199
Baseline: All	0.316	0.266	0.228	0.189	1.000

Notes: 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 when not using the event E_0.

Table F.32. Deterministic matching probabilities and choice probabilities for ambiguity types

				$\text{Pr}_{\text{subj}} = p = 0.25$		$\text{Pr}_{\text{subj}} = p = 0.5$		$\text{Pr}_{\text{subj}} = p = 0.75$	
Ambiguity type	α	ℓ	σ	$m^*(E)-p$	Pr(choice $= AEX$)	$m^*(E)-p$	Pr(choice $= AEX$)	$m^*(E)-p$	Pr(choice $= AEX$)
Near ambiguity neutral	-0.0043	0.3	0.15	0.079	0.71	0.0043	0.51	−0.071	0.31
Ambiguity averse	0.15	0.75	0.15	0.034	0.59	−0.15	0.15	−0.34	0.011
Ambiguity seeking	-0.042	0.7	0.15	0.22	0.92	0.042	0.61	−0.13	0.19
High noise	0.035	0.54	0.3	0.099	0.63	−0.035	0.45	−0.17	0.29

Notes: This table replicates Table E.1 without using the event E_0.

Table F.33. Average characteristics of group members

	Ambiguity types			
	Near ambiguity neutral	Ambiguity averse	Ambiguity seeking	High noise
Share	0.32	0.27	0.23	0.19
α^{AEX}	−0.0043	0.15	−0.042	0.035
	(0.0026)	(0.0032)	(0.0039)	(0.0046)
ℓ^{AEX}	0.3	0.75	0.7	0.54
	(0.0047)	(0.0056)	(0.0059)	(0.0088)
σ^{AEX}	0.15	0.15	0.15	0.3
	(0.0018)	(0.0024)	(0.0024)	(0.0026)
Education: Lower secondary and below	0.12	0.29	0.27	0.43
	(0.013)	(0.019)	(0.02)	(0.024)
Education: Upper secondary	0.31	0.38	0.35	0.3
	(0.018)	(0.02)	(0.021)	(0.023)
Education: Tertiary	0.57	0.32	0.37	0.26
	(0.019)	(0.019)	(0.022)	(0.022)
Age	53	55	57	64
	(0.63)	(0.65)	(0.67)	(0.7)
Female	0.39	0.61	0.54	0.47
	(0.019)	(0.02)	(0.022)	(0.025)
Monthly hh net income (equiv., thousands)	2.5	2.1	2.2	2
	(0.041)	(0.039)	(0.048)	(0.041)
Total hh financial assets (equiv., thousands)	53	26	38	32
	(6.5)	(2.9)	(6)	(4.1)
Risk aversion index	−0.11	0.092	0.03	0.023
	(0.034)	(0.042)	(0.049)	(0.055)
Numeracy index	0.61	−0.21	−0.0073	−0.72
	(0.025)	(0.038)	(0.042)	(0.057)

Notes: This table replicates Table 6 without using the event E_0.

Table F.34. Predictors of groups, marginal effects

	Ambiguity types			
	Near ambiguity neutral	Ambiguity averse	Ambiguity seeking	High noise
Age: $\in (35, 50]$	-0.029	-0.0033	-0.015	0.047
	(0.037)	(0.037)	(0.039)	(0.039)
Age: $\in (50, 65]$	-0.048	-0.035	0.0069	0.076^{**}
	(0.035)	(0.035)	(0.037)	(0.036)
Age: ≥ 65	-0.082^{**}	-0.077^{**}	-0.0049	0.16^{***}
	(0.035)	(0.036)	(0.037)	(0.035)
Female	-0.01	0.075^{***}	0.026	-0.091^{***}
	(0.022)	(0.021)	(0.022)	(0.019)
Education: Tertiary	0.1^{***}	-0.05	-0.03	-0.02
	(0.033)	(0.031)	(0.03)	(0.026)
Education: Upper secondary	0.06^{*}	-0.0037	-0.029	-0.028
	(0.033)	(0.028)	(0.029)	(0.023)
Income: $\in (1.1, 1.6]$	-0.069^{**}	0.046	0.023	-0.0003
	(0.033)	(0.03)	(0.031)	(0.024)
Income: $\in (1.6, 2.2]$	-0.048	0.062^{*}	0.025	-0.04
	(0.032)	(0.032)	(0.032)	(0.028)
Income: ≥ 2.2	-0.091^{***}	0.062^{*}	0.032	-0.0038
	(0.034)	(0.036)	(0.034)	(0.03)
Financial assets: $\in (1.8, 11.2]$	0.099^{***}	-0.0007	0.017	-0.12^{***}
	(0.034)	(0.029)	(0.031)	(0.027)
Financial assets: $\in (11.2, 32]$	0.14^{***}	-0.063^{*}	-0.043	-0.03
	(0.034)	(0.032)	(0.034)	(0.026)
Financial assets: ≥ 32	0.099^{***}	-0.078^{**}	-0.012	-0.0087
	(0.034)	(0.036)	(0.035)	(0.029)
Risk aversion index	-0.022^{**}	0.021^{*}	-0.002	0.0034
	(0.011)	(0.011)	(0.012)	(0.0088)
Numeracy index	0.22^{***}	-0.069^{***}	-0.035^{***}	-0.12^{***}
	(0.017)	(0.012)	(0.013)	(0.01)
Observations	1624	1624	1624	1624
Pseudo R^2	0.13	0.13	0.13	0.13

Notes: This table replicates Table E.3 without using the event E_0.

Table F.35. Ambiguity attitudes and portfolio choice: Marginal effects

	Owns risky assets (Probit)		Share risky assets (Tobit)	
	(1)	(2)	(3)	(4)
Ambiguity averse type	-0.22^{***}	-0.088^{***}	-0.43^{***}	-0.19^{***}
	(0.024)	(0.024)	(0.059)	(0.055)
Ambiguity seeking type	-0.11^{***}	-0.018	-0.16^{***}	-0.029
	(0.028)	(0.024)	(0.05)	(0.046)
High noise type	-0.19^{***}	-0.069^{***}	-0.27^{***}	-0.12^{*}
	(0.026)	(0.026)	(0.061)	(0.06)
Age: $\in (35, 50]$		-0.023		-0.0084
		(0.033)		(0.066)
Age: $\in (50, 65]$		0.0048		0.05
		(0.032)		(0.062)
Age: ≥ 65		-0.013		0.047
		(0.034)		(0.063)
Education: Tertiary		0.041		0.14^{**}
		(0.027)		(0.059)
Education: Upper secondary		0.016		0.06
		(0.026)		(0.059)
Female		-0.028		-0.03
		(0.018)		(0.04)
Income: $\in (1.1, 1.6]$		0.021		0.082
		(0.029)		(0.063)
Income: $\in (1.6, 2.2]$		0.0033		0.041
		(0.027)		(0.062)
Income: ≥ 2.2		0.074^{**}		0.13^{**}
		(0.029)		(0.062)
Numeracy index		0.032^{**}		0.062^{**}
		(0.016)		(0.03)
Risk aversion index		-0.046^{***}		-0.12^{***}
		(0.0094)		(0.021)
Financial assets: $\in (1.8, 11.2]$		0.042^{**}		0.12
		(0.019)		(0.084)
Financial assets: $\in (11.2, 32]$		0.14^{***}		0.35^{***}
		(0.022)		(0.083)
Financial assets: ≥ 32		0.39^{***}		0.69^{***}
		(0.029)		(0.085)
Observations	1727	1624	1584	1502
Pseudo R^2	0.054	0.31	0.043	0.29
p-values for differences between				
Ambiguity averse, Ambiguity seeking	0	0.0058	0	0.0052
Ambiguity averse, High noise	0.18	0.48	0.028	0.26
Ambiguity seeking, High noise	0.0046	0.071	0.11	0.16

Notes: This table replicates the regressions shown in Table 7 without using the event E_0.

Table F.36. Individual ambiguity parameters and portfolio choice: Marginal effects

	Owns risky assets (Probit)		Share risky assets (Tobit)	
	(1)	(2)	(3)	(4)
α	-0.045^{***}	-0.028^{***}	-0.087^{***}	-0.056^{***}
	(0.0099)	(0.0095)	(0.023)	(0.021)
ℓ	-0.07^{***}	-0.022^{**}	-0.13^{***}	-0.041^{**}
	(0.0091)	(0.0089)	(0.021)	(0.02)
σ	-0.037^{***}	-0.01	-0.042^{**}	-0.011
	(0.0095)	(0.01)	(0.022)	(0.023)
Age: $\in (35, 50]$		-0.023		-0.0084
		(0.033)		(0.067)
Age: $\in (50, 65]$		0.0036		0.048
		(0.032)		(0.063)
Age: ≥ 65		-0.011		0.049
		(0.033)		(0.065)
Education: Tertiary		0.039		0.13^{**}
		(0.027)		(0.059)
Education: Upper secondary		0.016		0.059
		(0.026)		(0.059)
Female		-0.026		-0.027
		(0.018)		(0.04)
Income: $\in (1.1, 1.6]$		0.024		0.089
		(0.029)		(0.063)
Income: $\in (1.6, 2.2]$		0.0038		0.042
		(0.027)		(0.062)
Income: ≥ 2.2		0.074^{**}		0.14^{**}
		(0.029)		(0.062)
Numeracy index		0.031^{*}		0.064^{**}
		(0.016)		(0.031)
Risk aversion index		-0.047^{***}		-0.13^{***}
		(0.0094)		(0.021)
Financial assets: $\in (1.8, 11.2]$		0.043^{**}		0.12
		(0.019)		(0.084)
Financial assets: $\in (11.2, 32]$		0.14^{***}		0.35^{***}
		(0.023)		(0.083)
Financial assets: ≥ 32		0.39^{***}		0.69^{***}
		(0.029)		(0.085)
Observations	1727	1624	1584	1502
Pseudo R^2	0.066	0.31	0.051	0.29

Notes: This table replicates the regressions shown in Table E.8 without using the event E_0.

F.4 Not restricting a-insensitivity from below

This section reports on changes to our results when we re-estimate our model relaxing the restrictions we have made on the ambiguity parameters by not restricting ℓ from below. As in the previous 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. As the sample compositions and matching probabilities are not affected, 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 tractable class of α-maxmin multiple prior models, the ϵ-contamination model (Chateauneuf, Eichberger, and Grant, 2007). Dimmock, Kouwenberg, Mitchell, and Peijnenburg (2015) shows that ℓ corresponds to the size of the multiple prior set in this model and can, hence, be interpreted as a measure of percieved ambiguity. Therefore, we require $0 \leq \tau_1^S$, $0 \leq \tau_0^S \leq 1 - \tau_1^S$. While $\tau_1^S > 0$ leads to a negative slope of the source function and cannot be accommodated by any sensible choice model, the restriction $0 \leq \tau_0^S \leq 1 - \tau_1^S$ can be dropped if we interpret the parameters without a connection to multiple prior models.

We re-estimate our model without bounding τ_1^S from above or, respectively, ℓ from below. A large majority of subjects, 82% of the sample, are unaffected as their estimated parameters still fulfill $0 \leq \tau_0^S \leq 1 - \tau_1^S$.

Comparing Table F.37 and Table D.4 shows that the mean of ℓ drops by 0.04 driven. At the same time, the distributions of α and σ hardly change. Similarly, parameter estimates for stability over time / across domains for α and σ are economically the same and statistically indistinguishable from each other (cf. Table F.38 vs. 4 and Table F.39 vs. 5). For ℓ, OLS regressions indicate a slightly weaker stability across time and domains while IV estimates do hardly change.

When imposing stability across time, only 8% of subjects would have been affected by the no longer imposed parameter restrictions leading to a drop in average ℓ by 0.01. The most salient feature in Figure F.8 compared to Figure 3 is that these individuals' estimates now fall below the triangle that bounds the parameter space in our main estimation. Most of these are classified as either ambiguity averse or as near ambiguity neutral 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. The classification into types does barely change compared to our main results (Table F.40). Thus, it does not come as a surprise that group compositions (Table F.42) and patterns of portfolio choice behavior (Table F.44) remain unchanged.

Tables and figures corresponding to Section 3

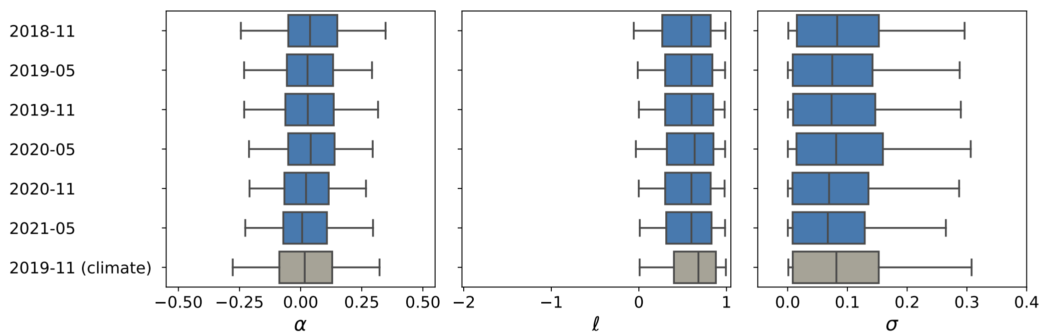


Figure F.7. Distributions of estimated parameters, wave by wave

Notes: This figure replicates Figure 2 without restricting ℓ from below.

Table F.37. 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	0.18	−0.25	−0.051	0.039	0.15	0.35
	2019-05	0.035	0.16	−0.23	−0.056	0.028	0.13	0.29
	2019-11	0.035	0.16	−0.23	−0.062	0.029	0.14	0.32
	2020-05	0.04	0.16	−0.21	−0.051	0.041	0.14	0.3
	2020-11	0.025	0.15	−0.21	−0.066	0.022	0.11	0.27
	2021-05	0.019	0.16	−0.23	−0.071	0.0062	0.11	0.3
	Observations from all AEX waves	0.034	0.16	−0.23	−0.06	0.028	0.13	0.3
	2019-11 (Climate Change)	0.02	0.18	−0.28	−0.087	0.017	0.13	0.32
ℓ	2018-11	0.53	0.37	−0.059	0.27	0.6	0.82	0.99
	2019-05	0.55	0.35	−0.015	0.3	0.6	0.84	0.98
	2019-11	0.55	0.35	0	0.3	0.6	0.85	0.98
	2020-05	0.56	0.36	−0.035	0.32	0.64	0.85	0.98
	2020-11	0.54	0.34	−0.0018	0.3	0.6	0.82	0.98
	2021-05	0.55	0.34	0.01	0.31	0.6	0.83	0.98
	Observations from all AEX waves	0.54	0.35	−0.01	0.3	0.6	0.84	0.98
	2019-11 (Climate Change)	0.59	0.35	0.0084	0.4	0.68	0.88	0.99
σ	2018-11	0.1	0.097	0.0011	0.015	0.083	0.15	0.3
	2019-05	0.095	0.094	0.0004	0.0086	0.075	0.14	0.29
	2019-11	0.097	0.095	0.0004	0.0091	0.074	0.15	0.29
	2020-05	0.11	0.1	0.0003	0.015	0.081	0.16	0.31
	2020-11	0.092	0.093	0.0004	0.0082	0.069	0.14	0.29
	2021-05	0.087	0.088	0.0003	0.0084	0.067	0.13	0.27
	Observations from all AEX waves	0.097	0.095	0.0005	0.009	0.075	0.14	0.29
	2019-11 (Climate Change)	0.1	0.1	0.0012	0.0086	0.082	0.15	0.31

Notes: This table replicates Table D.4 without restricting ℓ from below.

Table F.38. 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^{***}	-0.011^{***}	
		(0.0026)	(0.0039)	
	$\alpha^{AEX}_{\text{first 3 waves}}$	0.24^{***}	0.95^{***}	0.99^{***}
		(0.01)	(0.07)	(0.09)
	Adj. R^2	0.068		
	1st st. F		146	100
$\ell^{AEX}_{\text{last 3 waves}}$	Intercept	0.39^{***}	0.031	
		(0.0093)	(0.03)	
	$\ell^{AEX}_{\text{first 3 waves}}$	0.29^{***}	0.96^{***}	0.93^{***}
		(0.01)	(0.05)	(0.07)
	Adj. R^2	0.089		
	1st st. F		274	171
$\sigma^{AEX}_{\text{last 3 waves}}$	Intercept	0.064^{***}	-0.0019	
		(0.0017)	(0.0054)	
	$\sigma^{AEX}_{\text{first 3 waves}}$	0.31^{***}	0.98^{***}	0.98^{***}
		(0.01)	(0.06)	(0.08)
	Adj. R^2	0.098		
	1st st. F		241	121
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 F.39. Predicting climate ambiguity parameters with AEX parameters

		OLS	2SLS	
		(1)	(2)	(3)
$\alpha^{climate}_{2019-11}$	Intercept	-0.0029	-0.016^{***}	
		(0.0034)	(0.004)	
	$\alpha^{AEX}_{2019-11}$	0.68^{***}	1.04^{***}	1.07^{***}
		(0.03)	(0.05)	(0.07)
	Adj. R^2	0.39		
	1st st. F		214	148
$\ell^{climate}_{2019-11}$	Intercept	0.43^{***}	0.24^{***}	
		(0.018)	(0.031)	
	$\ell^{AEX}_{2019-11}$	0.30^{***}	0.64^{***}	0.69^{***}
		(0.03)	(0.05)	(0.07)
	Adj. R^2	0.089		
	1st st. F		406	239
$\sigma^{climate}_{2019-11}$	Intercept	0.054^{***}	0.02^{***}	
		(0.0027)	(0.005)	
	$\sigma^{AEX}_{2019-11}$	0.49^{***}	0.85^{***}	0.92^{***}
		(0.03)	(0.05)	(0.08)
	Adj. R^2	0.22		
	1st st. F		360	197
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

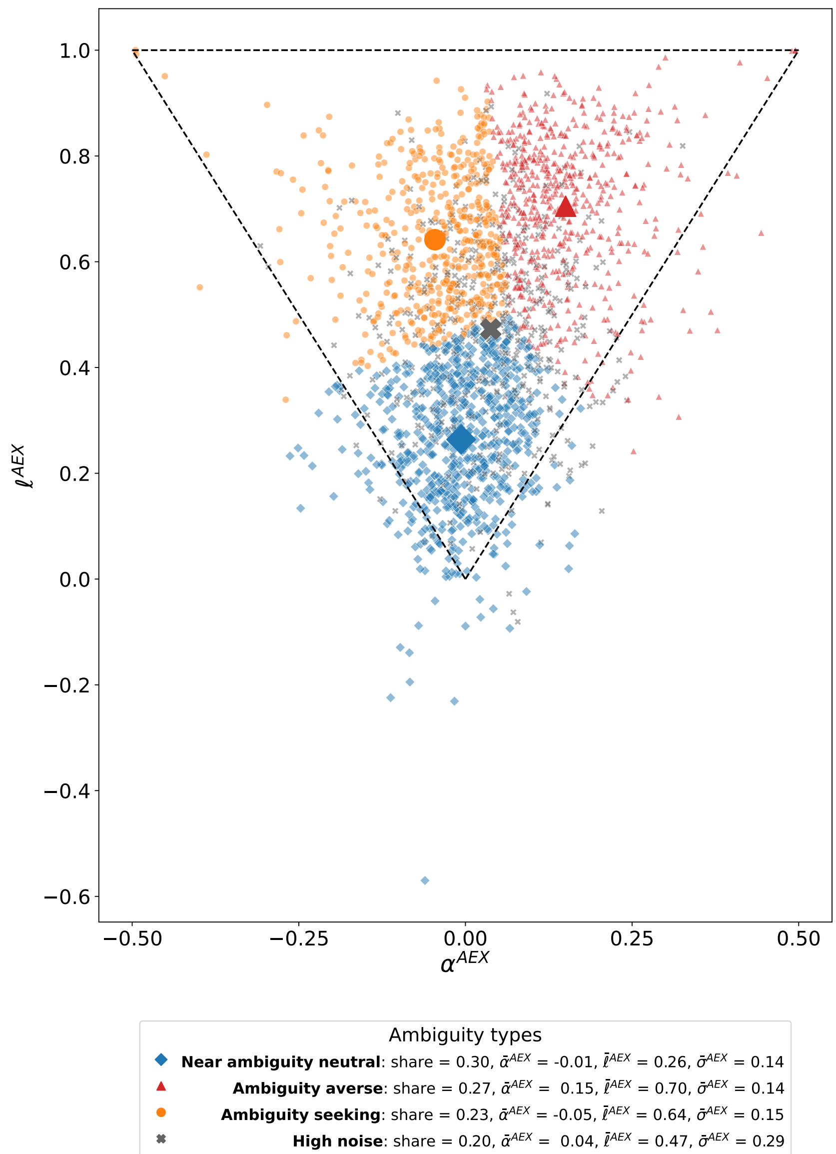


Figure F.8. Summarizing heterogeneity in ambiguity profiles with K=4 discrete groups

Notes: This figure replicates Figure 3 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	−0.032	0.032	0.1	0.22
ℓ^{AEX}	0.51	0.23	0.13	0.34	0.52	0.69	0.85
σ^{AEX}	0.17	0.08	0.066	0.12	0.16	0.22	0.33

Table F.40. Cross-tabulation of group classification relative to main estimates

	Type without restricting ℓ from below				
	Near ambiguity neutral	Ambiguity averse	Ambiguity seeking	High noise	All
Baseline: Near ambiguity neutral	0.290	0.002	0.005	0.003	0.301
Baseline: Ambiguity averse	0	0.264	0.007	0.002	0.273
Baseline: Ambiguity seeking	0.007	0.0005	0.216	0.004	0.227
Baseline: High noise	0.003	0	0.0005	0.196	0.199
Baseline: All	0.300	0.267	0.229	0.204	1.000

Notes: 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 when not restricting ℓ from below.

Table F.41. Deterministic matching probabilities and choice probabilities for ambiguity types

				$\Pr_{\text{subj}} = p = 0.25$		$\Pr_{\text{subj}} = p = 0.5$		$\Pr_{\text{subj}} = p = 0.75$	
Ambiguity type	α	ℓ	σ	$m^*(E)-p$	$\Pr(\text{choice} = AEX)$	$m^*(E)-p$	$\Pr(\text{choice} = AEX)$	$m^*(E)-p$	$\Pr(\text{choice} = AEX)$
Near ambiguity neutral	-0.0064	0.26	0.14	0.072	0.7	0.0064	0.52	−0.06	0.33
Ambiguity averse	0.15	0.7	0.14	0.026	0.57	−0.15	0.15	−0.33	0.012
Ambiguity seeking	-0.046	0.64	0.15	0.21	0.92	0.046	0.62	−0.11	0.22
High noise	0.038	0.47	0.29	0.08	0.61	−0.038	0.45	−0.16	0.3

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

Table F.42. 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}	−0.0064	0.15	−0.046	0.038
	(0.0027)	(0.0032)	(0.0038)	(0.0043)
ℓ^{AEX}	0.26	0.7	0.64	0.47
	(0.0052)	(0.0058)	(0.0056)	(0.0084)
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	0.25	0.42
	(0.013)	(0.019)	(0.019)	(0.023)
Education: Upper secondary	0.31	0.38	0.36	0.3
	(0.018)	(0.02)	(0.022)	(0.022)
Education: Tertiary	0.56	0.33	0.39	0.27
	(0.019)	(0.019)	(0.022)	(0.021)
Age	54	55	56	64
	(0.64)	(0.65)	(0.69)	(0.65)
Female	0.39	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
	(0.042)	(0.039)	(0.048)	(0.041)
Total hh financial assets (equiv., thousands)	55	22	40	34
	(6.9)	(2.4)	(5.9)	(4.4)
Risk aversion index	−0.11	0.088	0.018	0.023
	(0.035)	(0.042)	(0.048)	(0.052)
Numeracy index	0.63	−0.2	0.061	−0.72
	(0.024)	(0.038)	(0.041)	(0.056)

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

Table F.43. Predictors of groups, marginal effects

	Ambiguity types			
	Near ambiguity neutral	Ambiguity averse	Ambiguity seeking	High noise
Age: $\in (35, 50]$	-0.024	-0.017	-0.027	0.067^{*}
	(0.036)	(0.037)	(0.038)	(0.04)
Age: $\in (50, 65]$	-0.026	-0.046	-0.021	0.092^{**}
	(0.035)	(0.036)	(0.036)	(0.038)
Age: ≥ 65	-0.061^{*}	-0.086^{**}	-0.033	0.18^{***}
	(0.035)	(0.036)	(0.036)	(0.037)
Female	-0.0041	0.076^{***}	0.025	-0.097^{***}
	(0.022)	(0.022)	(0.022)	(0.019)
Education: Tertiary	0.073^{**}	-0.052^{*}	-0.02	-0.0013
	(0.033)	(0.031)	(0.031)	(0.027)
Education: Upper secondary	0.052	-0.0073	-0.018	-0.026
	(0.032)	(0.028)	(0.03)	(0.024)
Income: $\in (1.1, 1.6]$	-0.058^{*}	0.035	0.021	0.0024
	(0.032)	(0.03)	(0.032)	(0.025)
Income: $\in (1.6, 2.2]$	-0.049	0.067^{**}	0.024	-0.042
	(0.032)	(0.032)	(0.033)	(0.028)
Income: ≥ 2.2	-0.087^{***}	0.055	0.038	-0.0056
	(0.034)	(0.036)	(0.034)	(0.03)
Financial assets: $\in (1.8, 11.2]$	0.082^{**}	-0.032	0.029	-0.079^{***}
	(0.035)	(0.029)	(0.032)	(0.026)
Financial assets: $\in (11.2, 32]$	0.14^{***}	-0.081^{**}	-0.027	-0.035
	(0.034)	(0.032)	(0.035)	(0.027)
Financial assets: ≥ 32	0.11^{***}	-0.11^{***}	0.013	-0.012
	(0.035)	(0.036)	(0.035)	(0.029)
Risk aversion index	-0.023^{**}	0.018^{*}	-0.0021	0.0061
	(0.011)	(0.011)	(0.012)	(0.0088)
Numeracy index	0.23^{***}	-0.067^{***}	-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 replicates Table E.3 without restricting ℓ from below.

Table F.44. Ambiguity attitudes and portfolio choice: Marginal effects

	Owns risky assets (Probit)		Share risky assets (Tobit)	
	(1)	(2)	(3)	(4)
Ambiguity averse type	-0.23^{***}	-0.08^{***}	-0.45^{***}	-0.17^{***}
	(0.024)	(0.023)	(0.06)	(0.056)
Ambiguity seeking type	-0.098^{***}	-0.0084	-0.13^{***}	-0.0008
	(0.029)	(0.023)	(0.05)	(0.045)
High noise type	-0.18^{***}	-0.046^{*}	-0.24^{***}	-0.062
	(0.027)	(0.028)	(0.059)	(0.058)
Age: $\in (35, 50]$		-0.024		-0.01
		(0.034)		(0.067)
Age: $\in (50, 65]$		0.0035		0.048
		(0.032)		(0.063)
Age: ≥ 65		-0.016		0.041
		(0.033)		(0.063)
Education: Tertiary		0.043		0.14^{**}
		(0.027)		(0.059)
Education: Upper secondary		0.017		0.063
		(0.026)		(0.059)
Female		-0.027		-0.028
		(0.018)		(0.04)
Income: $\in (1.1, 1.6]$		0.022		0.083
		(0.029)		(0.063)
Income: $\in (1.6, 2.2]$		0.0053		0.045
		(0.027)		(0.062)
Income: ≥ 2.2		0.074^{**}		0.13^{**}
		(0.029)		(0.062)
Numeracy index		0.035^{**}		0.071^{**}
		(0.017)		(0.031)
Risk aversion index		-0.046^{***}		-0.12^{***}
		(0.0095)		(0.021)
Financial assets: $\in (1.8, 11.2]$		0.043^{**}		0.12
		(0.019)		(0.084)
Financial assets: $\in (11.2, 32]$		0.14^{***}		0.35^{***}
		(0.022)		(0.083)
Financial assets: ≥ 32		0.39^{***}		0.69^{***}
		(0.029)		(0.085)
Observations	1727	1624	1584	1502
Pseudo R^2	0.056	0.3	0.043	0.28
p-values for differences between				
Ambiguity averse, Ambiguity seeking	0	0.0043	0	0.0041
Ambiguity averse, High noise	0.036	0.21	0.0039	0.11
Ambiguity seeking, High noise	0.0025	0.18	0.078	0.31

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

Appendix G Analysis with BBLW-indices

In this section, we provide further details on the estimation of ambiguity attitudes using a least squares approach directly based on the indices proposed by Baillon, Bleichrodt, et al. (2021). Before turning to empirical results, we describe how we calculate a measure of decision noise for the indices.

G.1 Obtaining a measure of decision noise

The index-based ambiguity parameters $\hat{\alpha}_{\text{BBLW}}$ and $\hat{\ell}_{\text{BBLW}}$ can be directly calculated using the formulas (1) and (2). While this is sufficient for the analysis of marginal distributions and stability of the parameters, for the classification of subjects into ambiguity types, a measure of individual decision noise is desirable. As the indices naturally do not include a stochastic component of choice, we run a least squares estimation. As shown in Proposition 24 of Baillon, Bleichrodt, et al. (2021), estimating the respective ambiguity parameters and subjective probabilities by minimizing least squares leads to the same ambiguity parameters as using the formulas (1) and (2).

We operationalise this approach by choosing the parameters of the source function τ_0^S, τ_1^S and subjective probabilities $\Pr_{\text{subj}}(E_1^S), \Pr_{\text{subj}}(E_2^S), \Pr_{\text{subj}}(E_3^S)$ that minimize

$$D^S = \sum_{E \in \{E_1^S, \ldots, E_{3,C}^S\}} \left(m^{\dagger}(E) - \tau_0^S + \tau_1^S \cdot \Pr_{\text{subj}}(E) \right)^2 \tag{G.1}$$

where the $m^{\dagger}(\cdot)$ are the midpoints of observed matching probability intervals. Note that using the midpoints of the matching probability intervals leads to more subset-violations. Comparing Tables B.4 and B.5 reveals that the fraction of subjects with at least one set monotonicity violation in a given wave rises from 55 % to 77 %.

Note that in (G.1) we impose additivity of subjective probabilities with respect to the complementary events, but do not employ any restrictions on ambiguity parameters or the single-event subjective probabilities. The deviation D^S measures how well our model fits individual data. We scale it by the number of measured matching probabilities and calculate the standard error of individual decision noise as $\hat{\sigma}^S_{\text{BBLW}} = \sqrt{D^S/6}$. Because of the weaker parameter restrictions, the interpretation is somewhat different from σ^S. In particular, set-monotonicity errors do not necessarily lead to a larger $\hat{\sigma}_{\text{BBLW}}$ – they could be accommodated by $\ell > 1$ and/or subjective probabilities that are not in the unit interval. To pick a stylised example from the data, take the following midpoints of the matching probabilities: $m(E_1) = 0.15$, $m(E_2) = 0.55$, $m(E_3) = 0.45$, $m(E_{1,C}) = 0.65$, $m(E_{2,C}) = 0.25$, $m(E_{3,C}) = 0.35$. These data violate the set-monotonicity conditions $m(E_2) \leq m(E_{3,C})$ and $m(E_3) \leq m(E_{2,C})$. It is easy to verify that Equation (4) can fit these data perfectly when ignoring the parameter restrictions and setting $m^* = m$ and $\tau_0 = 0.35$, $\tau_1 = 0.1$, $\text{Pr}_{\text{subj}}(E_1) = -2$, $\text{Pr}_{\text{subj}}(E_2) = 2$. This clearly is not sensible. When imposing the restrictions on $\tau_0, \tau_1, \text{Pr}_{\text{subj}}(E_1), \text{Pr}_{\text{subj}}(E_2)$, the best-fitting estimates involve a fairly high error parameter $\sigma = 0.08$.

G.2 Results

Looking at wave-by-wave estimates, the parameter restrictions we enforce in our main estimation are fulfilled for about a third of our sample. For these subjects, the BBLW-indices are very similar to our main estimates. For the remaining two thirds, the restrictions for ambiguity parameters or subjective probabilities are binding and the BBLW-indices can be quite different from our main estimates. The strongest differences are found in the estimated ℓ. Its average rises from 0.6 (Table D.4) to 0.8 (Table G.1). In the latter case, about a quarter of person × wave observations have an estimated ℓ above one, indicating strong violations of set monotonicity. See Table G.1. The 95$^{\text{th}}$ percentile of ℓ^{AEX} is 1.6, more than one standard deviation above its bound. For 43 % of person × wave observations, at least one of the subjective probabilities falls out of the unit interval. This can only happen if set-monotonicity violations occur. 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, Kouwenberg, Mitchell, and Peijnenburg, 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).

All this has only minor consequences for the marginal distribution of α which is always very close to its index-based counterpart in Table D.4.

Not enforcing parameter restrictions implies that the stability of estimated a-insensitivity is substantially lower. The coefficients in the OLS regressions over time drop from 0.36 in Table 4 to 0.17 in Table G.3. Across domains, the change is from 0.35 (Table 5) to 0.14 (Table G.4). The respective instrumental variables regressions are not affected much, so the indices do not introduce any systematic differences over time. Correlations of α^{AEX} are again not affected by the choice of estimation strategy while correlations of σ^{AEX} are slightly lower when we do not enforce parameter restrictions (0.24 vs 0.29).

We furthermore show, that our main empirical approach leads to more precise out-of-sample choice predictions. We make use of the choices that subjects make at the end of each questionnaire if they have not answered the question selected for pay-out before. In Table G.5, we report mean squared differences between predicted choice probabilities and realized choices. We do not make use of the event E_0 and only use the choices from the respective wave for the prediction. In the first column, we predict the choice based on the matching probability of the respective event in the given wave without using data from other events and without a stochastic choice model. That is, the predicted choice probability of the AEX option is 1 if the matching probability exceeds the probability of the respective lottery and 0 otherwise. For the second and third column we calculate choice probabilities based on our main estimation approach and the BBLW-indices approach outlined in this section. In the last column, we consider the difference between the squared loss of our main estimates and index-based estimates indicating significance levels for t-tests.

We first note, that all three estimation approaches perform substantially better than a naive prediction. Assigning a choice probability of 50 % to each choice would result in a mean squared deviation of 0.25. Our main estimates (second column) deviate less from observed choices than the matching probability approach and the unrestricted, index-based choice model (third column) for which the mean squared error is 7% larger. The difference is statistically significant (fourth column). In the lower part of the table, we further show that the difference is primarily driven by subjects for whom ℓ_{BBLW} exceeds 1 and, hence, our parameter restrictions are binding.

We find further evidence that the improved stability of our estimates for ℓ arises from a more effective separation of decision error and ambiguity attitudes. In our main specification, ℓ is uncorrelated with σ. However, ℓ_{BBLW} exhibits a correlation of 0.30 with σ_{BBLW} (the correlation with σ, i.e., the estimates from our main specification, is even stronger). These differences have implications for predicting ambiguity attitudes based on individual characteristics (see Table G.6). For instance, our model estimates suggest that women have a higher ℓ^{AEX} but a lower stochastic component. In contrast, the indices-based approach finds no association between a-insensitivity and gender, as these effects effectively cancel out. Similarly, we find a stronger positive relation between ℓ^{AEX}_{BBLW} and the oldest age group, which seems to be partly driven by the relation with decision error.

For an analysis in the style of Section 4 of the paper, i.e., making use of multiple measurements per individual, we again employ a least squares estimation holding ambiguity parameters constant across waves, but allowing subjective probabilities to vary. This is equivalent to calculating the ambiguity indices based on data from all waves or taking the mean of indices over all waves.[3] 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.

When looking at the joint distribution of ambiguity attitudes and the associated type classification in Figure G.1, the most notable difference to Figure 3 is that a substantial share of observations is located outside of the triangular of parameters which we allow for in our main specification. As a-insensitivity ex-

3. The estimated ambiguity parameters are unaffected if we hold subjective probabilities constant over waves, but it changes estimated decision noise. We, therefore, follow the setup of our main estimation.

ceeds one for most of these observations and in line with the observed changes to the marginal distribution of ambiguity attitudes, the centroids of all ambiguity groups move towards higher values of ℓ. This change is the strongest for the "High noise" group whose new center is at $\ell = 1$ indicating that a substantial share of associated subjects violate set monotonicity.[4] Table G.7 reveals that the classification of subjects into types is, however, quite stable. Altogether, 80% of subjects are assigned to the same type, independent of the estimation method. The separation between the 'High noise' and 'Near ambiguity neutral' types is very stable as the number of subjects switching between these groups in any direction is negligible. Conversely, a small share of subjects switch between the other ambiguity types (at most 5 % for each pair). This is expected as the centroids of groups are also changing slightly. Overall, it comes as no surprise that the distribution of demographic variables over ambiguity types is almost unchanged. When predicting portfolio choice using ambiguity types (Table G.10) or the parameters directly (Table G.11), the overall pattern is very similar with some coefficient for the "High noise" group and σ being estimated less precisely.

4. Interestingly, when we increase the number of ambiguity types to 5, this group is split up into a "High noise" and a "Monotonicity violators" group where subjects in the latter group are almost exclusively assigned a value of ℓ above one and an error parameter below the "High noise" group but above the other groups. In terms of observable characteristics and the relation to portfolio choice, there are no notable differences between subjects in these groups, confirming our approach to group them in the same type in our main estimation.

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

		Mean	Std. dev.	$q_{0.05}$	$q_{0.25}$	$q_{0.5}$	$q_{0.75}$	$q_{0.95}$
α	2018-11	0.048	0.18	−0.24	−0.053	0.042	0.15	0.35
	2019-05	0.036	0.16	−0.23	−0.05	0.033	0.13	0.3
	2019-11	0.035	0.17	−0.23	−0.062	0.033	0.13	0.32
	2020-05	0.04	0.16	−0.22	−0.05	0.042	0.14	0.3
	2020-11	0.027	0.15	−0.22	−0.067	0.029	0.12	0.27
	2021-05	0.02	0.16	−0.23	−0.07	0.01	0.12	0.3
	Observations from all AEX waves	0.035	0.16	−0.23	−0.062	0.033	0.13	0.31
	2019-11 (Climate Change)	0.024	0.18	−0.28	−0.083	0.02	0.13	0.33
ℓ	2018-11	0.79	0.51	0.005	0.48	0.82	1	1.6
	2019-05	0.8	0.48	0.01	0.5	0.88	1	1.5
	2019-11	0.81	0.48	0.05	0.52	0.82	1	1.6
	2020-05	0.82	0.5	0.01	0.5	0.9	1.1	1.6
	2020-11	0.78	0.45	0.027	0.5	0.8	1	1.5
	2021-05	0.79	0.46	0.06	0.5	0.8	1	1.5
	Observations from all AEX waves	0.8	0.48	0.025	0.5	0.82	1	1.6
	2019-11 (Climate Change)	0.86	0.49	0.055	0.6	0.9	1.1	1.7
σ	2018-11	0.089	0.081	0	0.024	0.065	0.12	0.24
	2019-05	0.081	0.075	0	0.024	0.062	0.11	0.23
	2019-11	0.084	0.078	0	0.024	0.062	0.12	0.24
	2020-05	0.093	0.086	0	0.029	0.067	0.13	0.26
	2020-11	0.081	0.079	0	0.024	0.062	0.11	0.24
	2021-05	0.076	0.071	0	0.024	0.057	0.1	0.22
	Observations from all AEX waves	0.084	0.079	0	0.024	0.062	0.12	0.23
	2019-11 (Climate Change)	0.086	0.081	0	0.024	0.062	0.12	0.24

Notes: This table replicates Table D.4 for parameter estimates based on the indices by Baillon, Bleichrodt, et al. (2021).

Tables and figures corresponding to Section 3.

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

		α	ℓ	σ
2018-11	2019-05	0.25	0.16	0.22
	2019-11	0.20	0.16	0.23
	2020-05	0.15	0.16	0.22
	2020-11	0.22	0.16	0.21
	2021-05	0.18	0.14	0.16
2019-05	2019-11	0.32	0.19	0.28
	2020-05	0.31	0.16	0.26
	2020-11	0.33	0.23	0.22
	2021-05	0.30	0.20	0.23
2019-11	2020-05	0.27	0.17	0.28
	2020-11	0.33	0.18	0.27
	2021-05	0.25	0.19	0.24
2020-05	2020-11	0.31	0.18	0.26
	2021-05	0.24	0.15	0.19
2020-11	2021-05	0.44	0.22	0.29
Average		0.27	0.18	0.24

Notes: This table replicates the correlations shown in Table F.28 for parameter estimates based on the indices by Baillon, Bleichrodt, et al. (2021).

Table G.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	93
$\ell^{AEX}_{\text{last 3 waves}}$	Intercept	0.66^{***}	0.052	
		(0.013)	(0.079)	
	$\ell^{AEX}_{\text{first 3 waves}}$	0.17^{***}	0.93^{***}	0.86^{***}
		(0.01)	(0.10)	(0.15)
	Adj. R^2	0.03		
	1st st. F		83	34
$\sigma^{AEX}_{\text{last 3 waves}}$	Intercept	0.064^{***}	-0.0025	
		(0.0014)	(0.0072)	
	$\sigma^{AEX}_{\text{first 3 waves}}$	0.24^{***}	1.02^{***}	1.01^{***}
		(0.01)	(0.09)	(0.12)
	Adj. R^2	0.055		
	1st st. F		111	61
Controls		No	No	Yes
N Subjects		1859	1859	1452

Notes: This table replicates the regressions shown in Table 4 for parameter estimates based on the indices by Baillon, Bleichrodt, et al. (2021).

Table G.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	0.74^{***}	0.4^{***}	
		(0.027)	(0.076)	
	$\ell^{AEX}_{2019-11}$	0.14^{***}	0.57^{***}	0.58^{***}
		(0.03)	(0.10)	(0.16)
	Adj. R^2	0.019		
	1st st. F		124	46
$\sigma^{climate}_{2019-11}$	Intercept	0.05^{***}	0.017^{***}	
		(0.0025)	(0.0056)	
	$\sigma^{AEX}_{2019-11}$	0.42^{***}	0.81^{***}	0.86^{***}
		(0.03)	(0.07)	(0.10)
	Adj. R^2	0.17		
	1st st. F		184	101
Controls		No	No	Yes
N Subjects		1843	1843	1411

Notes: This table replicates the regressions shown in Table 5 for parameter estimates based on the indices by Baillon, Bleichrodt, et al. (2021).

Table G.5. Mean squared deviation when predicting final choices

	Matching probabilities	Main estimates	BBLW-Index based estimates	Difference Main - BBLW-Index
Full sample	0.122	0.107	0.114	-0.0066^{***}
	(0.0047)	(0.004)	(0.0042)	(0.001)
$\ell_{BBLW} > 1$	0.184	0.145	0.168	-0.0228^{***}
	(0.0104)	(0.0078)	(0.0092)	(0.0036)
$\ell_{BBLW} \leq 1$	0.102	0.0951	0.0965	-0.0014^{**}
	(0.0049)	(0.0044)	(0.0045)	(0.0007)

Notes: For this table, we predict the choices that subjects make at the end of the questionnaire if they have not answered the question selected for pay-out (see Section A for details of the questionnaire). We report mean squared differences between predicted choice probabilities and realized choices. Standard errors are clustered on the individual level and reported in parentheses. In the first column, we predict the choice based on the matching probability of the respective event in the given wave. That is, the predicted choice probability of the AEX option is 1 if the matching probability exceeds the probability of the respective lottery and 0 otherwise. For the second and third column, we calculate choice probabilities based on our main estimation approach and the BBLW-indices approach outlined in this section. For both, we do not use the event E_0 (using the estimates described in Appendix F.3 in the column 'Main estimates') and only make use of the choices from the respective wave. In the last column, we consider differences between the squared loss of our main estimates and index-based estimates indicating significance levels for t-tests with stars. In the second part of the table, we split the sample into observations whose estimated index-based ℓ exceeds one (25 % of observations) and those for which this is not the case. Employing the restrictions as described in Section 2.2, we obtain a sample of 6070 choices.
$* - p < 0.1, ** - p < 0.05, *** - p < 0.01$.

Table G.6. Predictors of marginal parameter estimates (BBLW-indices)

	α^{AEX}	ℓ^{AEX}	σ^{AEX}
Intercept	0.052^{***}	0.76^{***}	0.16^{***}
	(0.012)	(0.027)	(0.0069)
Age: $\in (35, 50]$	-0.0078	0.039^{*}	0.013^{***}
	(0.0088)	(0.021)	(0.0046)
Age: $\in (50, 65]$	-0.0098	0.068^{***}	0.019^{***}
	(0.0085)	(0.02)	(0.0047)
Age: ≥ 65	-0.0089	0.11^{***}	0.046^{***}
	(0.0083)	(0.021)	(0.005)
Female	0.0062	0.0054	-0.012^{***}
	(0.0056)	(0.013)	(0.0035)
Education: Tertiary	-0.016^{*}	-0.067^{***}	-0.0088
	(0.0086)	(0.02)	(0.0054)
Education: Upper secondary	-0.0055	0.0028	-0.009^{*}
	(0.008)	(0.019)	(0.005)
Income: $\in (1.1, 1.6]$	0.014^{*}	0.045^{**}	-0.0062
	(0.0081)	(0.019)	(0.0053)
Income: $\in (1.6, 2.2]$	0.008	0.026	-0.012^{**}
	(0.0086)	(0.019)	(0.0052)
Income: ≥ 2.2	0.0073	0.043^{**}	-0.0088
	(0.0089)	(0.021)	(0.0054)
Financial assets: $\in (1.8, 11.2]$	-0.015^{*}	-0.036^{*}	-0.0078
	(0.0084)	(0.019)	(0.005)
Financial assets: $\in (11.2, 32]$	-0.009	-0.052^{**}	-0.0002
	(0.008)	(0.021)	(0.0052)
Financial assets: ≥ 32	-0.024^{***}	-0.05^{**}	0.0003
	(0.0087)	(0.022)	(0.0056)
Risk aversion index	0.001	0.0083	-0.002
	(0.0031)	(0.007)	(0.0019)
Numeracy index	-0.0084^{**}	-0.091^{***}	-0.031^{***}
	(0.0036)	(0.0087)	(0.0022)
Observations	1624	1624	1624
Adj. R^2	0.022	0.18	0.26

Notes: This table replicates Table E.4 for parameter estimates based on the indices by Baillon, Bleichrodt, et al. (2021).

Tables and figures corresponding to Section 4.

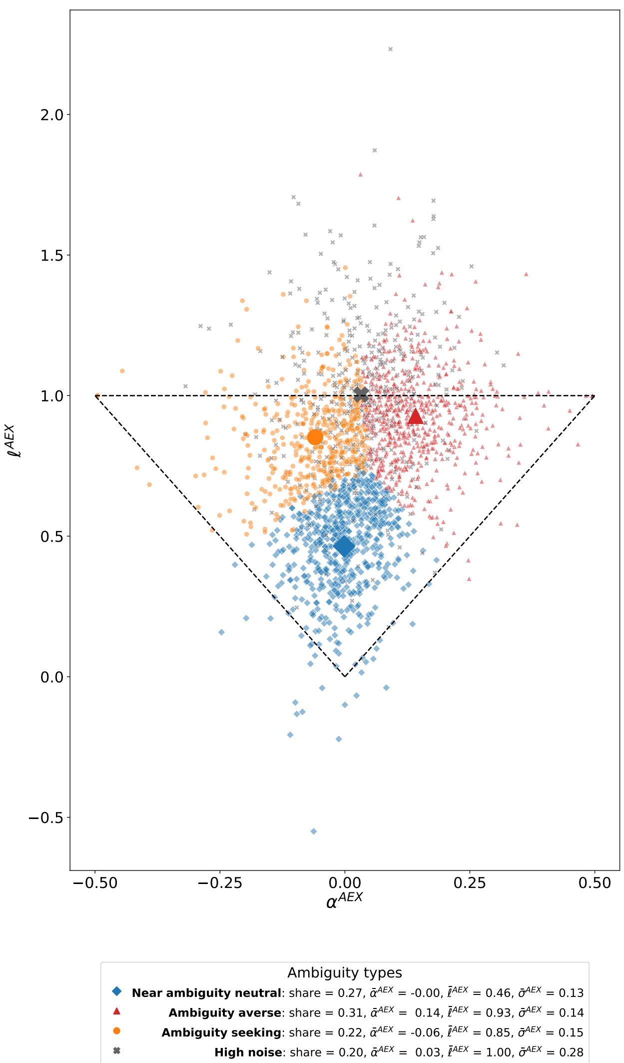


Figure G.1. Summarizing heterogeneity in ambiguity profiles with $k = 4$ discrete groups (BBLW-indices)

Notes: This figure replicates Figure 3 for parameter estimates based on the indices by Baillon, Bleichrodt, et al. (2021).

	Mean	Std. dev.	$q_{0.05}$	$q_{0.25}$	$q_{0.5}$	$q_{0.75}$	$q_{0.95}$
α^{AEX}	0.036	0.11	−0.13	−0.031	0.033	0.1	0.22
ℓ^{AEX}	0.8	0.29	0.32	0.61	0.82	0.98	1.2
σ^{AEX}	0.17	0.075	0.067	0.11	0.15	0.21	0.31

Table G.7. Cross-tabulation of group classification, main estimates vs. BBLW-indices

	Type using BBLW-indices				
	Near ambiguity neutral	Ambiguity averse	Ambiguity seeking	High noise	All
Baseline: Near ambiguity neutral	0.226	0.028	0.045	0.001	0.301
Baseline: Ambiguity averse	0.010	0.244	0.002	0.017	0.273
Baseline: Ambiguity seeking	0.029	0.014	0.167	0.017	0.227
Baseline: High noise	0.009	0.021	0.008	0.161	0.199
Baseline: All	0.275	0.307	0.222	0.196	1.000

Notes: 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.

Table G.8. Average characteristics of group members (BBLW-indices)

	Ambiguity types			
	Near ambiguity neutral	Ambiguity averse	Ambiguity seeking	High noise
Share	0.27	0.31	0.22	0.2
α^{AEX}	−0.0014	0.14	−0.06	0.032
	(0.0026)	(0.003)	(0.0038)	(0.0045)
ℓ^{AEX}	0.46	0.93	0.85	1
	(0.007)	(0.0067)	(0.0071)	(0.013)
σ^{AEX}	0.13	0.14	0.15	0.28
	(0.002)	(0.0019)	(0.0021)	(0.0026)
Education: Lower secondary and below	0.12	0.28	0.26	0.43
	(0.013)	(0.017)	(0.02)	(0.024)
Education: Upper secondary	0.3	0.37	0.36	0.31
	(0.019)	(0.019)	(0.022)	(0.023)
Education: Tertiary	0.59	0.35	0.38	0.25
	(0.02)	(0.018)	(0.022)	(0.021)
Age	52	55	58	64
	(0.69)	(0.6)	(0.65)	(0.7)
Female	0.38	0.59	0.52	0.49
	(0.02)	(0.019)	(0.023)	(0.024)
Monthly hh net income (equiv., thousands)	2.5	2.2	2.2	2
	(0.043)	(0.035)	(0.052)	(0.04)
Total hh financial assets (equiv., thousands)	56	28	40	30
	(7.5)	(2.9)	(6)	(3.8)
Risk aversion index	−0.094	0.086	0.026	−0.031
	(0.037)	(0.038)	(0.047)	(0.055)
Numeracy index	0.62	−0.12	0.071	−0.77
	(0.027)	(0.035)	(0.042)	(0.055)

Notes: This table replicates Table 6 for parameter estimates based on the indices by Baillon, Bleichrodt, et al. (2021).

Table G.9. Predictors of groups, marginal effects (BBLW-indices)

	Ambiguity types			
	Near ambiguity neutral	Ambiguity averse	Ambiguity seeking	High noise
Age: $\in (35, 50]$	-0.053	-0.031	-0.008	0.093^{**}
	(0.034)	(0.04)	(0.041)	(0.038)
Age: $\in (50, 65]$	-0.091^{***}	-0.051	0.055	0.087^{**}
	(0.033)	(0.038)	(0.038)	(0.037)
Age: ≥ 65	-0.14^{***}	-0.083^{**}	0.042	0.18^{***}
	(0.033)	(0.038)	(0.037)	(0.036)
Female	-0.036	0.083^{***}	0.034	-0.082^{***}
	(0.022)	(0.023)	(0.022)	(0.018)
Education: Tertiary	0.1^{***}	-0.063^{*}	-0.03	-0.009
	(0.033)	(0.033)	(0.031)	(0.026)
Education: Upper secondary	0.043	-0.016	-0.0096	-0.017
	(0.033)	(0.031)	(0.029)	(0.023)
Income: $\in (1.1, 1.6]$	-0.044	0.031	0.0014	0.012
	(0.034)	(0.033)	(0.031)	(0.024)
Income: $\in (1.6, 2.2]$	-0.0083	0.05	-0.018	-0.024
	(0.032)	(0.035)	(0.032)	(0.028)
Income: ≥ 2.2	-0.047	0.06	-0.0072	-0.0059
	(0.034)	(0.038)	(0.035)	(0.03)
Financial assets: $\in (1.8, 11.2]$	0.075^{**}	-0.025	0.018	-0.069^{***}
	(0.035)	(0.032)	(0.031)	(0.026)
Financial assets: $\in (11.2, 32]$	0.095^{***}	-0.027	-0.04	-0.028
	(0.036)	(0.034)	(0.034)	(0.027)
Financial assets: ≥ 32	0.093^{***}	-0.11^{***}	0.0055	0.0092
	(0.035)	(0.038)	(0.035)	(0.029)
Risk aversion index	-0.012	0.022^{*}	-0.0039	-0.0058
	(0.012)	(0.012)	(0.012)	(0.0088)
Numeracy index	0.18^{***}	-0.055^{***}	-0.0001	-0.13^{***}
	(0.019)	(0.014)	(0.014)	(0.01)
Observations	1624	1624	1624	1624
Pseudo R^2	0.13	0.13	0.13	0.13

Notes: This table replicates the regressions shown in Table E.3 for parameter estimates based on the indices by Baillon, Bleichrodt, et al. (2021).

Table G.10. Ambiguity attitudes and portfolio choice: Marginal effects (BBLW-indices)

	Owns risky assets (Probit)		Share risky assets (Tobit)	
	(1)	(2)	(3)	(4)
Ambiguity averse type	-0.23^{***}	-0.11^{***}	-0.44^{***}	-0.25^{***}
	(0.024)	(0.023)	(0.056)	(0.052)
Ambiguity seeking type	-0.098^{***}	-0.011	-0.12^{**}	0.0048
	(0.03)	(0.025)	(0.05)	(0.046)
High noise type	-0.19^{***}	-0.052^{*}	-0.25^{***}	-0.054
	(0.028)	(0.029)	(0.06)	(0.059)
Age: $\in (35, 50]$		-0.021		-0.0039
		(0.033)		(0.066)
Age: $\in (50, 65]$		0.0069		0.053
		(0.032)		(0.062)
Age: ≥ 65		-0.012		0.046
		(0.033)		(0.063)
Education: Tertiary		0.042		0.14^{**}
		(0.027)		(0.058)
Education: Upper secondary		0.02		0.068
		(0.026)		(0.058)
Female		-0.025		-0.023
		(0.018)		(0.04)
Income: $\in (1.1, 1.6]$		0.021		0.08
		(0.028)		(0.062)
Income: $\in (1.6, 2.2]$		0.005		0.046
		(0.027)		(0.061)
Income: ≥ 2.2		0.076^{***}		0.14^{**}
		(0.029)		(0.061)
Numeracy index		0.035^{**}		0.071^{**}
		(0.015)		(0.03)
Risk aversion index		-0.046^{***}		-0.12^{***}
		(0.0094)		(0.02)
Financial assets: $\in (1.8, 11.2]$		0.043^{**}		0.12
		(0.019)		(0.084)
Financial assets: $\in (11.2, 32]$		0.15^{***}		0.36^{***}
		(0.022)		(0.082)
Financial assets: ≥ 32		0.38^{***}		0.68^{***}
		(0.029)		(0.084)
Observations	1727	1624	1584	1502
Pseudo R^2	0.057	0.31	0.047	0.3
p-values for differences between				
Ambiguity averse, Ambiguity seeking	0	0	0	0
Ambiguity averse, High noise	0.095	0.025	0.0054	0.0023
Ambiguity seeking, High noise	0.0011	0.16	0.036	0.33

Notes: This table replicates the regressions shown in Table 7 for parameter estimates based on the indices by Baillon, Bleichrodt, et al. (2021).

Table G.11. Individual ambiguity parameters and portfolio choice: Marginal effects (BBLW-indices)

	Owns risky assets (Probit)		Share risky assets (Tobit)	
	(1)	(2)	(3)	(4)
α	-0.049^{***}	-0.028^{***}	-0.093^{***}	-0.055^{**}
	(0.0096)	(0.0096)	(0.023)	(0.022)
ℓ	-0.056^{***}	-0.021^{**}	-0.11^{***}	-0.042^{**}
	(0.01)	(0.0097)	(0.022)	(0.021)
σ	-0.023^{**}	-0.0012	-0.016	0.0084
	(0.0097)	(0.0098)	(0.023)	(0.023)
Age: $\in (35, 50]$		-0.023		-0.0074
		(0.033)		(0.066)
Age: $\in (50, 65]$		0.0039		0.049
		(0.032)		(0.063)
Age: ≥ 65		-0.013		0.047
		(0.034)		(0.065)
Education: Tertiary		0.04		0.14^{**}
		(0.027)		(0.059)
Education: Upper secondary		0.017		0.061
		(0.026)		(0.059)
Female		-0.027		-0.028
		(0.018)		(0.04)
Income: $\in (1.1, 1.6]$		0.025		0.093
		(0.029)		(0.063)
Income: $\in (1.6, 2.2]$		0.0048		0.045
		(0.027)		(0.062)
Income: ≥ 2.2		0.075^{***}		0.14^{**}
		(0.029)		(0.062)
Numeracy index		0.035^{**}		0.071^{**}
		(0.016)		(0.031)
Risk aversion index		-0.047^{***}		-0.12^{***}
		(0.0094)		(0.021)
Financial assets: $\in (1.8, 11.2]$		0.042^{**}		0.11
		(0.019)		(0.084)
Financial assets: $\in (11.2, 32]$		0.14^{***}		0.35^{***}
		(0.023)		(0.083)
Financial assets: ≥ 32		0.39^{***}		0.68^{***}
		(0.029)		(0.085)
Observations	1727	1624	1584	1502
Pseudo R^2	0.053	0.31	0.04	0.29

Notes: This table replicates the regressions shown in Table E.8 for parameter estimates based on the indices by Baillon, Bleichrodt, et al. (2021).

Appendix H 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, et al. (2021), which have been employed by most of the recent literature, as documented in Appendix G.

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.[5] Trautmann and van de Kuilen (2015) compare various studies using the "ambiguity premium relative to 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.[6] 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. (2024) estimate a median $\alpha^{AEX} = 0.05$ in a sample of Dutch

5. To some extent, we enforce it in our main specification with the exception of the special case of ambiguity neutrality. However, when we allow for the reversed pattern in Online Appendix F.4, we find it to be relevant for only 18 % of person × wave observations or 8 % of individuals when imposing parameter stability over time.

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

investors along with a standard deviation of 0.24, both of which are slightly above our estimates.

In order to ease the comparison with prior studies, we regress α^{AEX} on a set of correlates (see Tables E.4 for our model, G.6 for BBLW-indices). 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, 2022 find a negative relation; Dimmock, Kouwenberg, Mitchell, et al., 2015, and Anantanasuwong et al., 2024, 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 6 and Table E.3. In terms of 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, 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.

While Dimmock, Kouwenberg, Mitchell, et al. (2015), Dimmock, Kouwenberg, and Wakker (2016), and Anantanasuwong et al. (2024) do not find financial numeracy to be a significant predictor of α^{AEX}, we find a negative relation, 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 E.4).

For a-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) 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 this holds true regardless of whether we use our model or the indices-based approach, the latter masks some interesting patterns. For example, there does not seem to be a correlation between gender and a-insensitivity in the indices-based approach. Estimates from our model (Table E.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. (2024) also do not find a relation between gender and a-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 (2023) 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 E.4 reports that older, less educated, and low numeracy subjects are associated with a higher σ^{AEX}. While we do not find a consistent relation to financial assets in Table E.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. (2024) 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 of owning any stocks or funds, but with all controls the relation is only significant at the 0.1-level. For both the indices (Table G.11) and our model estimates (Table E.8), we find a similar effect size

(2.2 percentage points), 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 −0.028 and −0.029, respectively. To the best of our knowledge, we are the first to look at shares invested in risky assets in this context. 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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