

Ambiguity Attitudes for Real-World Sources: Field Evidence from a Large Sample of Investors

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Abstract

Empirical studies of ambiguity aversion mostly use artificial events such as Ellsberg urns to control for unknown probability beliefs. The present study measures ambiguity attitudes using real-world events in a large sample of investors. We elicit *ambiguity aversion* and *perceived ambiguity* for a familiar company stock, a local stock index, a foreign stock index, and Bitcoin. Measurement reliability is higher than for artificial sources in previous studies. Ambiguity aversion is highly correlated for different assets, while perceived ambiguity varies more between assets. We show that ambiguity aversion and perceived ambiguity are related to actual investment choices, validating the measures.

JEL Codes: D81; C93; D14

Keywords: Ambiguity, decision-making under uncertainty, investments, preferences, financial literacy

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1. Introduction

Real-life decisions made under uncertainty nearly always involve ambiguity, as the probability distribution of future outcomes is not precisely known (Keynes 1921; Knight 1921). Most people are ambiguity averse, meaning that they prefer to make decisions with known probabilities (risk) rather than with unknown probabilities (ambiguity), a fact that the subjective expected utility model cannot explain (Ellsberg 1961). Models that accommodate ambiguity aversion were first developed in the late 1980s by Gilboa and Schmeidler (1989), and extensive empirical studies on ambiguity have since been conducted (Trautmann & van de Kuilen 2015). These show that people's choices not only reveal ambiguity aversion, common for likely gains, but also ambiguity *seeking* for unlikely gains and for losses, similar to the four-fold pattern of risk attitudes proposed by Tversky and Kahneman (1992).

One limitation of the available evidence on ambiguity attitudes is that these have mostly been measured with artificial events such as Ellsberg urns, rather than sources of ambiguity that decision makers face in real life. Artificial events are convenient because they can be designed to minimize the influence of people's subjective beliefs.¹ Yet, as suggested by l'Haridon et al. (2018), the use of such artificial events may also make the experimental tasks less relevant for subjects and more difficult to understand. Recently, Baillon et al. (2018b) developed a novel method to measure ambiguity for naturally occurring sources that controls for unknown probability beliefs and risk preferences. So far, this new method has been applied in laboratory settings with student samples.

Our paper's contribution is to measure ambiguity attitudes for relevant real-world sources in a large set of real-world investors. In particular, households often confront financial decision problems such as saving, investment, and insurance, where the probability distribution of future outcomes is not precisely known. Our objective is to measure ambiguity attitudes toward return distributions that people typically face when making investment choices. We field a purpose-built survey module to elicit ambiguity attitudes in a representative sample of about 300 Dutch investors in the De Nederlandse Bank (DNB) Household Survey (DHS), using the method of Baillon et al. (2018b). At the individual level, we estimate both *preferences toward ambiguity* and *perceived levels of ambiguity* about four investments: a familiar individual stock, the local stock market index,

¹ For example, consider a person who prefers to win \$15 with a known chance of 50%, rather than receiving \$15 when the Dow Jones index goes up next month. This choice could be the result of ambiguity aversion, but it might also be due to pessimistic beliefs about the chance of the Dow Jones index having a positive return.

a foreign stock market index, and the crypto-currency Bitcoin. We focus on investments, as there is a large theoretical literature in finance on the implications of ambiguity.

To assess the reliability of the ambiguity attitude measures for natural sources in the field, we first conduct an econometric analysis with panel models. Correlations between repeated measures of ambiguity aversion prove to be moderate to high, in the 0.6 to 0.8 range. Individual characteristics also display significant and plausible correlations with ambiguity attitudes, and these explain 28% of the variation in ambiguity aversion. This is an improvement over previous studies that used artificial urn experiments to measure ambiguity, where individual characteristics explained only up to 3% (see Dimmock et al. 2015; l’Haridon et al. 2018). Second, our research using real-world sources confirms that ambiguity aversion is not universal.² We show that about 60% of the investors, on average, are ambiguity averse toward the four investments, but a sizeable fraction (40%) is ambiguity seeking or neutral.

Previous studies have shown that ambiguity attitudes have an important second component called a-insensitivity, which refers to the tendency to treat all ambiguous events as if they are 50/50% (Tversky and Fox 1995; Fox et al. 1996; Abdellaoui et al. 2011). For unlikely events, such as new ventures that offer a large payoff with a small unknown probability, a-insensitivity implies ambiguity seeking behavior. Our results confirm that the large majority of investors displays a-insensitivity toward real-world investments, at relatively high levels on average. In the multiple prior model of Chateauneuf et al. (2007), a-insensitivity can also be interpreted as a measure of the level of *perceived ambiguity*. Seen this way, our results suggest that most retail investors perceive relatively high ambiguity about the probabilities of future investment returns, most likely due to limited financial sophistication as documented in the household finance literature (Gomes et al. 2021). Nonetheless, a-insensitivity (perceived ambiguity) is lower for the familiar stock, and lower among investors with higher financial literacy and better education.

Our data also allow us to test whether ambiguity aversion and perceived ambiguity vary with the decision maker and the source of ambiguity. Popular theoretical formulations of ambiguity such as the smooth model (Klibanoff et al. 2005) and the alpha-MaxMin model (Ghirardato et al. 2004) assume that ambiguity aversion is subject-dependent but constant between sources, while

² In previous studies with Ellsberg urns, ambiguity aversion is typically the modal finding, but with strong heterogeneity between subjects and a sizeable fraction of ambiguity seeking responses. See van de Kuilen and Wakker (2011), Trautmann and van de Kuilen (2015), Dimmock et al. (2015), Dimmock, Kouwenberg & Wakker (2016), Cubitt et al. (2018), and Kocher et al. (2018).

perceived ambiguity is both source- and subject-dependent. These key assumptions in theoretical models have, thus far, not been based on empirical evidence. We show that ambiguity aversion toward the four investments we examine is strongly related and mostly driven by one underlying variable. This implies that, if an investor has relatively high ambiguity aversion toward one specific financial asset (e.g., a stock market index), he also tends to display high ambiguity aversion toward other investments. In contrast, we find that investors' perceived levels of ambiguity differ substantially between assets and cannot be summarized by a single measure. Accordingly, the same investor may perceive low ambiguity about a familiar stock and high ambiguity about Bitcoin.

Finally, we validate the ambiguity attitude measures by showing how they relate to the investors' actual investment choices. We find that investors who perceive less ambiguity about a particular financial asset are more likely to invest in it, as expected based on theory. Further, investors with higher ambiguity aversion are less likely to invest in Bitcoin. Previous studies have measured ambiguity attitudes with Ellsberg urns to avoid issues with subjective beliefs and then related these measures to portfolio choices (Dimmock, Kouwenberg, & Wakker 2016; Dimmock, Kouwenberg, Mitchell, & Peijnenburg 2016; Bianchi and Tallon 2019; and Kostopoulos et al. 2019). Our paper is the first to confirm such a link using measures of non-artificial ambiguity directly relevant for the investments.

We contribute to the empirical literature on ambiguity by measuring ambiguity attitudes toward economically relevant sources in a large sample of investors.³ We analyze the reliability of the new elicitation method of Baillon et al. (2018b) when it is used in a survey of the general population, and we externally validate the measures by testing the link with actual household investments. We add to recent papers that have used the new method with students in laboratory experiments (Baillon et al. 2018b; Li et al. 2019) and in a classroom setting (Li 2017).⁴ Compared to earlier large-sample ambiguity studies using artificial events (Dimmock et al. 2015; l'Haridon et al. 2018), we find that, when using real-world sources, measurement reliability is higher and individual characteristics explain a larger proportion of the heterogeneity in ambiguity aversion.

³ Potamites and Zhang (2012) study ambiguity attitudes of Chinese investors, using artificial Ellsberg-type events.

⁴ Baillon et al. (2018b) measure ambiguity attitudes about a stock market index in a laboratory setting with students. Li (2017) measures ambiguity attitudes toward phrases in foreign languages among Chinese high school students. Li et al. (2019) measure ambiguity aversion about the actions of other subjects in a trust game.

In addition, we add to the literature on natural sources of ambiguity⁵. Fox et al. (1996) already found that even professional option traders displayed high a-insensitivity toward familiar stock return distributions. Kilka and Weber (2001) showed that German students were more ambiguity averse and insensitive about a foreign stock compared to a domestic stock, displaying home bias. We can now confirm these results in a large field study of retail investors, using the latest methodology that controls for both unknown beliefs and risk preferences. In addition, our research adds to the literature on portfolio choice under ambiguity (e.g., Uppal & Wang 2003; Boyle et al. 2012; and Peijnenburg 2018), providing empirical evidence on how to model the ambiguity attitudes of households investing in financial markets.

2. Data and elicitation methods

2.1. DNB Household Panel

We fielded a purpose-built module to measure ambiguity and risk attitudes in the DNB Household Survey (DHS), a representative household survey of about 2,000 respondents conducted by CentERdata at Tilburg University in the Netherlands.⁶ The survey is computer-based and subjects can participate from their homes. To limit selection bias, households lacking internet access at the recruiting stage were provided with a set-top box for their television sets (and with a TV if they had none). Each year, the DHS fields modules to obtain information about the panel members' income, assets, and liabilities. We merged those data with results from our module on ambiguity and risk attitudes. The DHS is representative of the Dutch population and has previously been used to provide insight into household financial decisions (e.g., Guiso et al. 2008; van Rooij et al. 2011; and von Gaudecker 2015).

As the DHS is nationally representative, it includes a large number of people who do not invest in financial markets: about 85% of the panel members as of December 2016. Ambiguity about all investments is likely to be high in this group, without much meaningful variation between sources. To better utilize resources, our questionnaire was targeted at the 15% of DHS panel members who invested in financial assets, defined to include mutual funds (about 68% of the investors), individual company stocks (45%), bonds (11%), or options (2.5%).⁷ Our survey module

⁵ See Heath and Tversky (1991), Tversky and Fox (1995), Fox et al. (1996), Kilka and Weber (2001), Abdellaoui et al. (2011), Baillon and Bleichrodt (2015), and Li et al. (2017) for natural sources of ambiguity, amongst others.

⁶ Additional information on the DHS is available at <https://www.centerdata.nl/en/databank/dhs-data-access>.

⁷ Asset ownership figures as of 31 December 2016 based on the October 2017 DHS survey of wealth and assets.

was fielded from 27 April-14 May 2018, yielding 295 complete and valid responses.⁸ Our survey was also given to a random sample of non-investors from the general population, with 230 complete responses. The non-investor sample allows us to compare the ambiguity attitudes of investors and non-investors, which we do in Section 5.4. For our main results, we focus only on investors, as our goal is to assess ambiguity attitudes of investors in financial markets and to validate our measures by confirming that ambiguity attitudes are associated with investment decisions.

Summary statistics on the DHS investor sample appear in Appendix Table A1. *Education* is an ordinal variable ranging from 1 to 6, where 1 indicates primary education and 6 indicates a university degree. *Household Income* averages €3,193 per month. *Household Financial Wealth* consists of the sum of all current accounts, savings accounts, term deposits, cash value of insurance policies, bonds, mutual funds, stocks, options, and other financial assets such as loans to friends or family, all reported as of 31 December 2017. Mean (median) wealth was €142,357 (€84,489). We also have measures for *Age*, *Female*, *Single*, *Number of Children* living at home, *Employed*, and *Retired*. Table A1 shows that the average Dutch investor in financial markets is relatively old, male, and well educated. We note that this is the profile of a typical Dutch individual investor, as the DHS data is representative, and it is also in line with other studies of investors in the Netherlands (e.g., von Gaudecker 2015; Cox et al. 2020).

2.2 Elicitation of ambiguity attitudes

We elicit ambiguity attitudes toward real-world investments following the method of Baillon et al. (2018b). The first source of ambiguity we evaluate is the return on the Amsterdam Exchange Index (AEX) over a 1-month period.⁹ The method divides the possible outcomes of the AEX into three mutually exclusive and exhaustive events, denoted as E_1 , E_2 , and E_3 :

$$\begin{aligned}
 E_1 &= (-\infty, -4\%] && : \text{the AEX index decreases by 4\% or more} \\
 E_2 &= (-4\%, +4\%) && : \text{the AEX index decreases or increases by less than 4\%} \\
 E_3 &= [+4\%, \infty) && : \text{the AEX index increases by 4\% or more.}
 \end{aligned}$$

For each event E_i separately, we elicit the respondent's matching probability with a choice list, shown in Figure 1 for event E_1 as an example. The *matching probability* m_i is the known probability of winning $p = m_i$ at which the respondent is indifferent between Option A (winning

⁸ Out of 391 DHS panel members who indicated that they invested in financial assets as of December 2016 or December 2015, 308 completed the survey questions, for a response rate of 79%. Then we excluded 13 respondents who gave invalid responses when asked to name a familiar stock, leaving 295 valid responses.

⁹ The AEX is a stock market index composed of the shares of 25 companies traded on the Amsterdam stock market.

€15 if Event E_1 happens) and Option B (winning €15 with known chance p).¹⁰ We approximate the matching probability by taking the average of the probabilities p in the two rows that define the respondent's switching point from Option A to B. For example, in Figure 1 the matching probability is: $m_1 = \frac{20\% + 30\%}{2} = 25\%$.

We also elicit a matching probability for the complement of each event:

$$\begin{aligned}
 E_{23} &= (-4\%, \infty) && : \text{the AEX index does not decrease by 4\% or more} \\
 E_{13} &= (-\infty, -4\%] \cup [+4\%, \infty) && : \text{the AEX index decreases or increases by 4\% or more} \\
 E_{12} &= (-\infty, +4\%) && : \text{the AEX index does not increase by 4\% or more.}
 \end{aligned}$$

The matching probability for the composite event $E_{ij} = E_i \cup E_j$ is denoted by m_{ij} , with $i \neq j$. For example, Figure 2 shows the choice list for the composite event E_{23} , with $m_{23} = 55\%$.

A key insight of the method is that, for an ambiguity neutral decision-maker, the matching probabilities of an event and its complement add up to 1 ($m_1 + m_{23} = 1$), but under ambiguity aversion, the sum is less than 1 ($m_1 + m_{23} < 1$). For example, the choices in Figures 1 and 2 imply that $1 - m_1 - m_{23} = 1 - 0.25 - 0.55 = 0.2$, indicating ambiguity aversion. Baillon et al. (2018b) define their *ambiguity aversion index* b , averaging over the three events, as follows:

$$(1) \quad b = 1 - \bar{m}_c - \bar{m}_s,$$

with $-1 \leq b \leq 1$. Here $\bar{m}_s = (m_1 + m_2 + m_3)/3$ denotes the average single-event matching probability, and $\bar{m}_c = (m_{12} + m_{13} + m_{23})/3$ is the average composite-event matching probability. The decision-maker is ambiguity averse for $b > 0$, ambiguity seeking for $b < 0$, and ambiguity neutrality implies $b = 0$.

In practice, ambiguity attitudes have a second component apart from ambiguity aversion, namely a tendency to treat all uncertain events as though they had a 50-50% chance, which is called ambiguity-generated insensitivity or *a-insensitivity* (Tversky and Fox, 1995; Abdellaoui et al. 2011). For unlikely events, a-insensitivity leads to overweighting and more ambiguity-seeking choices. Empirical studies have shown that a-insensitivity is a typical feature of decision-making

¹⁰ If the respondent clicks on B in a particular row, all answers in previous rows are set to A, and answers in all subsequent rows to B (i.e., multiple switching between A and B was not allowed). Assuming the event E_i has some positive probability between 0 and 1, choosing B in the first row of the list is a dominated choice, as is preferring Option A in the last row. Both choices (all A, or all B) were allowed, to check for respondent errors.

under ambiguity (Trautmann and van de Kuilen 2015; Dimmock, Kouwenberg, & Wakker 2016). Baillon et al. (2018b) define the following index to measure *a-insensitivity*:

$$(2) \quad a = 3 \times (1/3 - (\bar{m}_c - \bar{m}_s)),$$

with $-2 \leq a \leq 4$. For ambiguity neutral decision-makers, $a = 0$, while $a > 0$ denotes *a-insensitivity*. Negative values, $a < 0$, indicate that the decision-maker is overly sensitive to changes in likelihood, implying underweighting of unlikely events and overweighting of likely events. Monotonicity requires $a \leq 1$, as the average matching probability of the composite events should exceed the average for the single events ($\bar{m}_c \geq \bar{m}_s$). However, in practice, respondents can make errors and violate monotonicity, leading to $a > 1$.

The measurement method has two major advantages: first, risk preferences (both the utility and probability weighting function) cancel out in the comparison between Options A and B, so risk preferences do not need to be estimated to identify ambiguity attitudes (Dimmock, Kouwenberg, & Wakker 2016). Second, using events and their complements in the calculation of index *b* and *a* ensures that the unknown subjective probabilities drop out of the equation (Baillon et al. 2018b; Baillon et al. 2021). Accordingly, we can measure ambiguity aversion without knowing respondents' subjective beliefs. This solves the important issue that, when observing a dislike of ambiguity, it is difficult to disentangle whether this is due to ambiguity aversion or pessimistic beliefs.

2.2.1 A model for ambiguity aversion and perceived ambiguity

To explain the measures, we now show that index *b* and *a* can be interpreted, respectively, as *ambiguity aversion* and the *perceived level of ambiguity* in the neo-additive ambiguity model of Chateauneuf et al. (2007).¹¹ Ambiguity occurs when the decision-maker does not know the exact probability of the event *E*, but for instance considers an interval I_E of possible probabilities for event *E*. Let $x_E 0$ denote a two-outcome prospect that pays amount $x \geq 0$ if the ambiguous event *E* occurs, and 0 otherwise. In the model, the decision maker evaluates ambiguous prospect $x_E 0$ with the α -MaxMin criterion (Hurwicz, 1951; Ghirardato et al., 2004), as follows:

$$(3) \quad v = \alpha \min_{p \in I_E} \{pU(x)\} + (1 - \alpha) \max_{p \in I_E} \{pU(x)\}, \text{ with } \alpha \in [0,1],$$

¹¹ See Dimmock et al. (2015) and Baillon et al. (2018a) for more details.

$$(4) \quad I_{E,\delta} = \{p: (1 - \delta)\pi(E) \leq p \leq (1 - \delta)\pi(E) + \delta\}, \text{ with } \delta \in [0,1].$$

where $U(x)$ is a utility function, normalized such that $U(0) = 0$. In this model, α captures *ambiguity preferences*, while the probability interval I_E reflects *perceived ambiguity*. The value $\alpha = 1$ indicates maximum ambiguity aversion (MaxMin) and maximum ambiguity seeking occurs at $\alpha = 0$, while ambiguity neutrality implies $\alpha = 1/2$.

The reference probability, $\pi(E)$, represents the decision-maker's assessment of the unknown probability based on his subjective beliefs. However, the decision maker does not fully trust his prior and has a degree of confidence of only $(1 - \delta)$ in $\pi(E)$, with $\delta \in [0,1]$. He then considers all probabilities of *at least* $(1 - \delta)\pi(E)$ for event E . Applying the same rule to the complement of E , gives the interval of prior probabilities $I_{E,\delta}$ in (4). A higher value of δ means that the decision maker perceives more ambiguity as the probability interval becomes wider. In the special case $\delta = 0$, the model reduces to subjective expected utility.

We now apply this model to the choices between Options A and B in Figure 1, where event E_1 is a decrease of the AEX index by 4% or more. The ambiguity model evaluates Option A as: $v = ((1 - \delta)\pi_1 + (1 - \alpha)\delta)U(15)$, where $\pi_1 = \pi(E_1)$ is the reference probability. Option B is evaluated as: $v = pU(15)$. The matching probability m_1 is the known probability p that makes the respondent indifferent between Option A and Option B: $m_1 = (1 - \delta)\pi_1 + (1 - \alpha)\delta$.

Similarly, the matching probability for the complement event E_{23} , shown in Figure 2, is: $m_{23} = (1 - \delta)\pi_{23} + (1 - \alpha)\delta$. We can now define a simplified ambiguity aversion index b by measuring how much the sum of m_1 and m_{23} deviates from 1:

$$(5) \quad b = 1 - (m_1 + m_{23}) = 1 - (1 - \delta)(\pi_1 + \pi_{23}) - 2(1 - \alpha)\delta = 2\left(\alpha - \frac{1}{2}\right)\delta.$$

Note that π_1 and π_{23} have dropped out in (5), as $\pi_1 + \pi_{23} = 1$. Hence, we can measure ambiguity aversion index b without having to know the decision-maker's subjective probabilities. This result also applies to the definition of index b in (1), which averages over three events. Further, Equation (5) also shows that index b is a rescaled version of α , ranging from $-\delta$ to δ (Baillon et al. 2018b).¹²

Similarly, for a-insensitivity index a , we can derive the following expression in the model:

¹² Alternatively, $2\left(\alpha - \frac{1}{2}\right) = b/a$ is a standardized measure of ambiguity aversion, ranging from -1 to 1 . Estimating α from index b and a in practice entails numerical difficulties, as b/a is not defined for $a = 0$.

$$(6) \quad a = 3 \times \left(\frac{1}{3} - (\bar{m}_c - \bar{m}_s) \right) = (1 - (1 - \delta)(\pi_{23} + \pi_{13} + \pi_{12} - (\pi_1 + \pi_2 + \pi_3))) \\ = (1 - (1 - \delta)((1 - \pi_1) + (1 - \pi_2) + (1 - \pi_3) - 1)) = (1 - (1 - \delta)) = \delta.$$

Hence, index a measures the perceived level of ambiguity (δ). Interpreting index a as perceived ambiguity requires $0 \leq a \leq 1$. Because mistakes and measurement errors in the field may give rise to different values, below we analyze how often index a falls within these boundaries.

We note that the interpretation of index b as a measure of ambiguity aversion is independent of the model above, as it is consistent with the “ambiguity premium” defined in Schmeidler (1989). Nevertheless, the interpretation of index a as perceived ambiguity does rely on it.¹³ Tversky and Fox (1995) provide another interpretation of a-insensitivity, namely as an indicator of “hope and fear” driven by affective responses to positive and negative outcomes. Seen this way, people overweight events that turn the impossible into a possibility as they provide hope (e.g., a long shot bet), and overweight events that change a likely outcome into certainty (e.g., insurance) due to fear.

2.2.2 Implementation of the elicitation method in the DHS

Our DHS module for eliciting ambiguity attitudes started with one practice question in the same choice list format as Figure 1, where the uncertain event for Option A was whether the temperature in Amsterdam at 3 p.m. one month from now would be more than 20 degrees Celsius. After the practice question, a set of questions followed for each investment asset: the AEX index, a familiar individual company stock, a foreign stock index (MSCI World), and a crypto-currency (Bitcoin). Six matching probabilities were measured for each investment separately, so that index b and a can be estimated. The order of the four sets of questions was randomized, as was the order of the six events. Our final ambiguity aversion measures are labelled b_{aex} , b_{stock} , b_{msci} , and $b_{bitcoin}$ and our measures for a-insensitivity are labelled a_{aex} , a_{stock} , a_{msci} , and $a_{bitcoin}$. Furthermore, we define b_{avg} (a_{avg}) as the average of the four b -indexes (a -indexes).

Before beginning the questions about the individual stock, each respondent was first asked to name a familiar company stock; subsequently, that stock name was used in the six choice lists shown to the respondent. For those who indicated they did not know any familiar company stock, we used Philips, a well-known Dutch consumer electronics brand. For the well-diversified AEX

¹³ Insensitivity can also be seen as insufficiently discriminating the likelihood of different events (Gonzales and Wu, 1999), with $a = 0$ meaning perfect discrimination and $a = 1$ no discrimination at all. In a sense, discriminating poorly between likelihoods of ambiguous events is similar to perceiving high ambiguity about what the probabilities are.

Index and the MSCI World Index, the event E_1 (E_3) represented a return of 4% (-4%) in one month. For the individual stock, the percentage change was set to 8% and for Bitcoin to 30%, to reflect the higher historical volatility of these investments.¹⁴

2.3. Elicitation of risk attitudes

The DHS module also included four separate choice lists to measure risk attitudes (a screenshot is provided in Online Appendix A). The first risk attitude choice list elicited a certainty equivalent for a known 50% chance of winning €15 or €0 otherwise, based on a fair coin toss. The other three choice lists elicited a certainty equivalent for winning chances of €15 of 33%, 17%, and 83%, respectively, using a die throw. Respondents could win real money for the risk questions, and the order was randomized of the risk and ambiguity question sets in the survey.

Following Abdellaoui et al. (2011), we use index b_r for risk as a measure of *Risk Aversion*, and index a_r for risk as a measure of *Likelihood Insensitivity*, which is the tendency to treat all known probabilities as 50-50% and thus overweight small-probability events. To estimate these measures, we assume a rank-dependent utility model with a neo-additive probability weighting function and a linear utility function. We do this for two reasons. First, these two risk attitude measures are conceptually related to index b for ambiguity aversion and index a for a-insensitivity (Abdellaoui et al. 2011). Second, utility curvature is often close to linear for small payoffs. We refer to Online Appendix B for more details about these measures, and for a robustness check using two non-parametric risk measures that do not rely on any model assumptions.

Appendix Table A1 shows that on average investors were risk averse (mean > 0) but with strong heterogeneity, and about one third of the investors were risk seeking. Further, the *Likelihood Insensitivity* measure is positive for 85% of the investors, indicating a tendency to overweight small probabilities, in line with the findings of previous studies (see, e.g., Fehr-Duda and Epper 2011 and Dimmock et al. 2021).

2.4. Real incentives

At the outset of the survey, each subject was told that one of his or her choices in the ambiguity and risk questions would be randomly selected and played for real money. Hence all respondents who completed the survey had a chance to win a prize based on their choices, and a total of €2,758 in real incentives was paid out. The incentives were determined and paid by the

¹⁴ The percentage change was set based on the approximate volatility of the asset (15% for the AEX index and the MSCI World index, 40% for a typical individual stock, and 100% for Bitcoin in February 2018), to ensure that the events E_1 , E_2 and E_3 had non-negligible probabilities of occurring.

DHS one month after the end of the survey, when the changes in the asset values were known. As subjects in the DHS regularly receive payments for their participation, the involvement of the DHS minimizes subjects' potential concerns about the credibility of the incentives.

2.5. Financial literacy and asset ownership

Our DHS survey module also collected data on financial literacy and asset ownership. Financial literacy is one of our key independent variables, as we aim to assess whether financial knowledge relates to ambiguity attitudes. To measure this, we use 12 questions from Lusardi and Mitchell (2007) and van Rooij et al. (2011), shown in Online Appendix B. *Financial Literacy* is the number of correct responses to the 12 questions (the average is 10.6; see Appendix Table A1).¹⁵

We validate our ambiguity measures by examining whether they relate to the financial assets owned by the investors. Our survey module asked the DHS panel members whether they currently invested in the familiar company stock they mentioned, in mutual funds tracking the MSCI World index, or any crypto-currencies such as Bitcoin. *Invests in Familiar Stock* is an indicator variable equal to one if the investor currently held the familiar company stock, which 30.2% did (see Appendix Table A1). *Invests in Crypto-Currencies* and *Invests in MSCI World* are equal to one if the investor held any crypto-currencies or funds tracking the MSCI World stock index, which was true for 2.4% and 1.4%, respectively. Finally, none of the investors in the sample owned funds tracking the domestic AEX stock index.

We note that even in the group of financial assets owners we label as “investors”, ownership of the four assets presented in our ambiguity survey is rather low, as most only own some mutual funds or bonds. Further, only half (55%) in the investor group could name a listed company stock with which they were familiar. All of this indicates that financial sophistication is not that high on average among Dutch retail investors, as is typically found in other household finance studies as well (see Gomes et al. 2021, for a review).

3. Results for ambiguity aversion

3.1. Descriptive statistics

Figure 3 shows the fraction of respondents who were ambiguity averse, neutral, and seeking, for the four sources of ambiguity: the familiar stock, the domestic stock market index

¹⁵ The average financial literacy score is relatively high because our sample consists of investors. In the subsample of 230 non-investors in the DHS panel, the average score is only 8.6 out of 12 (see Online Appendix F).

(AEX), a foreign stock market index (MSCI World), and Bitcoin. To account for possible measurement error, we classify small values of index b that are not significantly different from zero as ambiguity neutral.¹⁶ About 58% of the respondents were ambiguity averse, while 30% were ambiguity seeking, a pattern that is similar across the sources of financial ambiguity. Furthermore, ambiguity neutrality was less common (12%), implying that only few investors' choices were consistent with the expected utility model. Our results confirm for real-world sources of uncertainty that ambiguity aversion is common, but not universal. These findings are comparable to earlier large-scale studies that used artificial sources, such as Dimmock et al. (2015), Dimmock, Kouwenberg, & Wakker (2016), and Kocher et al. (2018), showing that ambiguity seeking choices are not limited to Ellsberg urns.

Table 1 shows descriptive statistics for the b -indexes. Investors on average to display higher ambiguity aversion toward the foreign stock index (0.21), compared to the domestic AEX index (0.17), the familiar individual stock (0.16), and Bitcoin (0.17), in line with the well-documented home bias (French and Poterba 1991). There was strong heterogeneity in ambiguity aversion between investors, as indicated by the high standard deviation of the b -indexes (about 0.5 on average). We use Hotelling's T -squared statistic¹⁷ to test the hypothesis that the mean b -index is equal for the four investments, which cannot be rejected at the 5% level ($T^2 = 7.56$; $p = 0.057$). This implies that the mean level of ambiguity aversion does not depend strongly on the source of financial uncertainty. Still, ambiguity aversion for the familiar stock (0.16) is 34% lower compared to the foreign stock index (0.21; $p = 0.008$ for the mean difference), so investors on aggregate do display some source preference.

Dimmock, Kouwenberg, & Wakker (2016) measured index b with Ellsberg urns in a large sample of the Dutch population (similar to the DHS panel, but there were no overlapping respondents with this study). As a comparison, the average of index b for the artificial urns they used is 0.14, similar to the average value of 0.18 that we find for investments.¹⁸ This suggests that

¹⁶ We label $b = 0$ as ambiguity neutral in our paper, following the standard terminology in the literature that typically only measures the ambiguity aversion/seeking component. While less conventional, in models with a -insensitivity it might be better to reserve the term ambiguity neutral for the special case $b = 0$ and $a = 0$, which includes the subjective expected utility model.

¹⁷ Hotelling's T -squared statistic (T^2) is a generalization of the paired samples t -test used in a multivariate setting with more than two related measurements.

¹⁸ We restricted their original sample of 666 subjects from the general Dutch population to 126 investors owning some financial assets, using the same criteria for defining investors as in our own DHS sample.

the mean level of ambiguity aversion is not that source-dependent, even between artificial and real-world sources.

Figure 4 illustrates the relation between the ambiguity aversion measures for the four different investment sources at the subject level, shown with scatter plots. The correlations are all relatively strong, ranging between 0.62 and 0.74. This implies that if an investor had relatively high ambiguity aversion toward one specific financial source (e.g., the AEX index), he also tended to display high ambiguity aversion toward the other three investments. A factor analysis shows that the first factor explains 77% of the cross-sectional variation in the four ambiguity aversion measures, indicating that a single underlying variable is driving most of the variation.

3.2. Econometric model

Previous empirical studies by Borghans et al. (2009), Stahl (2014), and l’Haridon et al. (2018) found high levels of unexplained heterogeneity and noise in ambiguity attitudes when measured with Ellsberg urns. An open question is: to what extent does using real-world investments help to improve measurement reliability? In this section, we analyze the heterogeneity in ambiguity attitudes using econometric models, following the approach of Dimmock et al. (2015) and l’Haridon et al. (2018). We estimate a panel regression model, where the cross-sectional unit i is the individual respondent, and the “time dimension” s (or repeated measurement) comes from the four investments:

$$(7) \quad b_{i,s} = \beta_1 + \sum_{s=2}^4 (\beta_s + v_{i,s}^b) d_s + \sum_{k=1}^K \gamma_k^b X_{i,k} + u_i^b + \varepsilon_{i,s}^b, \quad i=1, 2, \dots, I, \text{ and } s=1, 2, 3, 4,$$

where $b_{i,s}$ is index b (ambiguity aversion) of respondent i toward source s , for the AEX index ($s = 1$), the familiar stock ($s = 2$), the MSCI World index ($s = 3$), and Bitcoin ($s = 4$).

The dummy variable d_s is 1 for source s , and 0 otherwise. The constant β_1 represents ambiguity aversion for the AEX index, whereas the coefficients β_2, β_3 and β_4 for the familiar stock, MSCI World and Bitcoin represent differences in mean ambiguity aversion relative to the AEX index. A set of K observable individual characteristics $X_{i,k}$, such as age and gender, can also impact ambiguity aversion, with regression slope coefficients γ_k^b . The error term $\varepsilon_{i,s}^b$ is identically and independently distributed, with $Var[\varepsilon_{i,s}^b] = (\sigma_\varepsilon^b)^2$.

Random effect u_i^b represents unobserved heterogeneity in ambiguity aversion, which is independent of the error term and uncorrelated between individuals, with $Var[u_i^b] = (\sigma_u^b)^2$. Further, random effect $v_{i,s}^b$ is known as a “random slope” (with $Var[v_{i,s}^b] = (\sigma_{v,s}^b)^2$), as it changes

the beta of the source dummy d_s . For example, $v_{i,2}^b$ captures individual heterogeneity in ambiguity aversion toward the familiar stock ($s = 2$), in addition to the heterogeneity in ambiguity aversion that affects all sources captured by the “random constant” u_i^b . Correlations between random effects ($u_i^b, v_{i,s}^b$) are also estimated as part of the model.

The total variance of ambiguity attitudes can now be decomposed as follows:

$$(8) \quad Var[b_{i,s}] = Var[\beta'D + \gamma^{b'}X] + Var[u_i^b] + Var[\sum_{s=2}^4 \beta_s v_{i,s}^b d_s] + Var[\varepsilon_{i,s}^b],$$

with the four right-hand-side components representing variance explained by observed variables, unobserved individual heterogeneity in ambiguity attitudes that is common to all sources (u_i^b), unobserved source-specific individual heterogeneity ($v_{i,s}^b$), and random errors ($\varepsilon_{i,s}^b$).

Our estimation approach is as follows: first, we estimate a model with only a random constant, and then random slopes are added to the model one at a time, followed by a test for their significance (a likelihood-ratio test).¹⁹ Suppose $v_{i,2}^b$ (familiar stock) and $v_{i,4}^b$ (Bitcoin) are significant individually: then a model with both random slopes is estimated and tested as well. Finally, if an estimated random slope model turns out to have insignificant variance ($\sigma_{v,s}^b = 0$), or perfect correlation with the random constant ($Cor(u_i^b, v_{i,s}^b) = 1$ or -1), then it is considered invalid and not used.

3.3. Analysis of heterogeneity in ambiguity aversion

The estimation results for index b , ambiguity aversion, appear in Table 2. The sample consists of all 295 investors. All values of index $b_{i,s}$ are included, even if the respondent violated monotonicity or made other errors, to show the impact of noise in the data. Model 1 in Table 2 includes only a random effect capturing individual heterogeneity in ambiguity aversion that is common to the four investments, which explains 69% of the variation. The constant in the model is 0.177 ($p < 0.001$), implying that investors on average are ambiguity averse toward the investments. Table 2 also reports the interclass correlation coefficient (ICC), which in our dataset captures the correlation of ambiguity aversion toward the four sources.²⁰ The ICC is 0.69, indicating that the correlation in ambiguity aversion for the four investments is high.

¹⁹ A model with a full set of 3 random slopes plus a random constant is too complex to estimate, given that there are only 4 repeated measurements and such an approach would give infeasible coefficients. For this reason, we add random slopes one at a time, and then test for their significance.

²⁰ The interclass correlation coefficient is typically measured in a model without independent variables and defined as: $ICC = Var[u_i^a]/(Var[u_i^a] + Var[\varepsilon_{i,s}^a])$, or the proportion of variance explained by the individual-level random effect.

Model 2 adds dummies to allow for differences in the mean level of ambiguity aversion toward the four investments. The dummy for the MSCI World index is positive ($p = 0.042$), implying investors are more ambiguity averse toward foreign stocks. Random slopes for source-specific ambiguity aversion are added next, and a chi-square test (reported in Online Appendix C.1) shows that only adding a random slope for Bitcoin leads to an improvement of model fit ($p < 0.001$). Heterogeneity in ambiguity aversion toward Bitcoin (the random slope) explains 5% of the variation in Model 3, on top of the 70% captured by ambiguity aversion toward all four sources (random constant). Overall, the results imply that ambiguity aversion toward investments is driven mainly by one underlying factor, with high correlation between measurements for different sources.

3.4. Variation in ambiguity attitudes explained by individual characteristics

Model 4 in Table 2 adds observed individual socio-demographic variables such as age, gender, education, employment, income, and financial assets, which together account for about 6% of the variation in ambiguity aversion. Ambiguity aversion toward investments is lower for younger investors ($p = 0.008$) and singles ($p = 0.044$). In Model 5, proxies for financial literacy and risk attitudes are added, which account for an additional 17% of the variation. Specifically, ambiguity aversion toward investments and risk aversion have a positive relation ($p < 0.001$). Ambiguity aversion is not related to financial literacy and also not lower for the familiar stock, suggesting limited competence effects (Heath and Tversky 1991) in ambiguity aversion for investments.

In l'Haridon et al. (2018), observed individual characteristics like gender and age explain at most 3% of the variation in ambiguity attitudes measured for Ellsberg urns, and correlations between repeated measurements of ambiguity aversion are only 0.15-0.18. Relatedly, Dimmock et al. (2015) estimated ambiguity aversion with artificial urns in the U.S. population, where a large set of observed variables explained only 2.2% of the variation, and their ICC was 0.30. In the present study using real-world sources, the ICC is 0.69 and up to 23% of the variation in ambiguity aversion is explained. This suggests that ambiguity aversion for natural sources measured with the Baillon et al. (2018b) method has high reliability compared to traditional measures based on Ellsberg urns.²¹

²¹ Apart from using natural sources, another reason for reduced noise can be that the new methodology better separates the measurement of ambiguity aversion and perceived ambiguity.

3.5. Estimating index b with only two events

The higher measurement reliability, apart from using natural sources, can also stem from the fact that the index b measure is an average over three events, which reduces the impact of noise. To test this, in Online Appendix D we redo the analysis using three separate estimates for index b per source without averaging: $b_1 = 1 - (m_1 + m_{23})$, $b_2 = 1 - (m_2 + m_{13})$, and $b_3 = 1 - (m_3 + m_{12})$. The average within-source correlation between the three b -indexes is 0.74, and ICC for the 12 measurements is 0.60. The fraction of variation explained by individual characteristics is 5% for socio-demographic variables, and 19% when risk attitudes and financial literacy are included. Based on these results, we conclude that the higher measurement reliability is likely due to using real-world sources instead of artificial events, rather than due to averaging.

3.6. Monotonicity violations

Panel A in Table 3 shows the percentage of investors who violated the weak monotonicity condition, $\bar{m}_s > \bar{m}_c$, which implies $a > 1$. About 25% violated monotonicity when looking at each investment separately, and 20% after averaging over the four investments ($a_{avg} > 1$). In Online Appendix Table E3 we also report monotonicity violations at the event level ($m_s > m_c$) for each source, which is 22.7% on average. Similar rates are reported by Li et al. (2017), ranging from 14% to 28%, depending on the source. In the ambiguity dataset of Dimmock, Kouwenberg, & Wakker (2016) using Ellsberg urns, 25.4% of investors violated monotonicity. Overall, the rates of monotonicity violations are similar to those in previous ambiguity studies.²²

As a robustness check, in Online Appendix E we repeat the analysis in Table 2 after excluding values of $b_{i,s}$ when monotonicity is violated ($a_{i,s} > 1$). The ICC increases from 0.69 to 0.73 (in Model 2), while the percentage of variation explained by individual characteristics increases from 23% to 28%. In Online Appendix E we also report results after excluding b -index values with more than two violations of set-inclusion monotonicity (out of six possible). Overall, the coefficient estimates are similar and the original results for index b in Table 2 are robust to screening out violations of monotonicity.

²² An exception is the study by Baillon et al. (2018a), who report low monotonicity violations rates ranging from 4% to 10%. The choice lists design in Baillon et al. (2018a) was different, such that subjects who switch in the middle of the list get a matching probability 35% for single events, but 70% for composite events. Always switching near the middle of the list without thinking in that case gives an a -index close to 0 and no violations of monotonicity. Further, it may have also signaled that the composite event was more likely, possibly further reducing monotonicity violations.

4. Results for a-insensitivity and perceived ambiguity

4.1. Descriptive statistics

Panel B of Table 1 summarizes the a -index values. On average, a-insensitivity is high (0.79), implying that investors do not much discriminate between single and composite events, suggesting they perceive high ambiguity about their probabilities. Further tests show that the mean of index a is significantly lower for the familiar stock (0.69). Overall, about two thirds of the investors are insensitive to the likelihood of ambiguous events ($a > 0$) for the four investment sources, as shown in Panel A of Table 3. Hence, a-insensitivity is common, in line with earlier results for stocks in Fox et al. (1996) and Kilka and Weber (2001), but we can now confirm this in a large field study of investors, using measurements that control for beliefs and risk preferences. These findings are also in line with results for Ellsberg urns in Dimmock et al. (2015) and Dimmock, Kouwenberg, & Wakker (2016).

As we aim to interpret index a as a proxy for perceived ambiguity, from now on we exclude monotonicity violations ($a > 1$) and negative values of a , using pairwise deletion.²³ Panel B of Table 3 shows descriptive statistics for perceived ambiguity. On average, investors perceived less ambiguity about the familiar individual stock (0.64) than toward the foreign index (0.72), the domestic stock index (0.74), and Bitcoin (0.75).²⁴ For comparison, in Dimmock, Kouwenberg, & Wakker (2016), perceived ambiguity toward Ellsberg urns on average was 0.35, considerably lower. Hence, perceived ambiguity is source-dependent, also between artificial and real-world sources. Further, perceived ambiguity about investments is relatively high.

There are several reasons why perceived ambiguity about investment can be expected to be high in our field study. First, the household finance literature shows that typical retail investors are not sophisticated, lack financial knowledge, and suffer from a host of biases (see Gomes et al. 2021 for a review). In line with this, even in the group of financial asset owners that we labelled as investors, only 55% could mention a familiar stock name, and less than half owned individual stocks. Second, the probabilities of the one-month investment return events are hard to estimate, as both the mean and standard deviation are time-varying (Lettau and Ludvigson 2010), requiring quite a high level of financial sophistication. Finally, our choice lists do not reveal any information

²³ As a robustness check, later in Section 4.4 we also report model estimation using all values of index a .

²⁴ Hotelling's T -squared test rejects the null hypothesis of equal means ($p = 0.003$). A follow-up analysis shows that the mean level of perceived ambiguity for the familiar stock is significantly lower than for the other three investments.

about the event probabilities; a respondent who always selects the middle row due to lack of knowledge or attention will end up with an a -index equal to one (100%).²⁵

Figure 5 shows scatter plots of the relations between perceived ambiguity toward the four financial sources. The correlations between the a -indexes are positive, ranging from 0.35 to 0.55, but lower than correlations between the b -indexes. A factor analysis indicates that the first component accounts for about 60% of the cross-sectional variation in the four measures. This implies that, for a given respondent, the perceived ambiguity toward different investments is related, but not strongly. Hence, the same investor may perceive relatively low ambiguity about a familiar stock, while concurrently perceiving high ambiguity about another investment.²⁶

4.2. Analysis of heterogeneity in perceived ambiguity

We now analyze the variance in perceived ambiguity, using a similar panel model as above:

$$(9) \quad a_{i,s} = \lambda_1 + \sum_{s=2}^4 (\lambda_s + v_{i,s}^a) d_s + \sum_{k=1}^K \gamma_k^a X_{i,k} + u_i^a + \varepsilon_{i,s}^a, \quad i = 1, 2, \dots, I, s = 1, 2, 3, 4,$$

where $a_{i,s}$ is index a (perceived ambiguity) of respondent i toward source s , with $0 \leq a_{i,s} \leq 1$. The constant λ_1 represents perceived ambiguity for the AEX index, whereas the coefficients λ_2, λ_3 and λ_4 for the familiar stock, MSCI World and Bitcoin represent differences in the mean relative to the AEX. The random effect and the error term are denoted by u_i^a and $\varepsilon_{i,s}^a$, respectively, whereas $v_{i,s}^a$ represents random slopes (added if significant based on a likelihood ratio test).

Table 4 shows the estimation results. Model 1 includes only a random effect, capturing individual heterogeneity in perceived ambiguity that is common to the four sources, which explains 44% of the variation. Model 2 shows that investors perceive less ambiguity about the familiar stock, $\lambda_2 = -0.091$ ($p < 0.001$), relative to $\lambda_1 = 0.718$ for the other investments on average. The ICC is 0.45, implying that levels of perceived ambiguity toward the four different investments have a moderate positive correlation.

Next, including random slopes for the familiar stock and Bitcoin in Model 3 leads to a significant improvement of model fit (see Online Appendix C.2). Individual variation in perceived

²⁵ By contrast, Baillon et al. (2018a) used different choice lists such that switching on the middle row gave a matching probability of 35% for single events but 70% for composite events, resulting in an a -index of 0. The choice list design may also have provided some information about the objective event probabilities, reducing ambiguity.

²⁶ Further, the correlations between index b and a are low, ranging from 0.11 to 0.32, indicating that ambiguity aversion and perceived ambiguity are two separate aspects of ambiguity attitudes (in line with evidence in Abdellaoui et al. 2011; Dimmock et al. 2015; Dimmock, Kouwenberg, Mitchell & Peijnenberg 2016; and Baillon et al. 2018b). The neo-additive model in Section 2.2.1 implies that the *absolute value* of b increases linearly as a function of index a . In the data, the average correlation between $\text{abs}(b)$ and a is 0.47 (when $0 \leq a \leq 1$).

ambiguity toward the familiar stock explains 6% of the total variation, versus 4% for Bitcoin, on top of the 43% captured by general perceived ambiguity about all investments (random constant). Hence, whereas ambiguity aversion is mostly driven by one underlying preference variable, perceived levels of ambiguity tend to differ more depending on the specific source considered.

4.3. Variation in perceived ambiguity explained by individual characteristics

Model 4 adds observed individual socio-demographic variables to the model, which now accounts for 8% of the variation (= 10% - 2%) in perceived ambiguity. Older investors perceive more ambiguity about investments ($p = 0.005$), whereas investors with higher education ($p < 0.001$) and more income ($p = 0.026$) perceive less ambiguity. Model 5 adds proxies for financial literacy and risk attitudes, which explain an additional 4%. Specifically, investors with better financial literacy perceive less ambiguity ($p = 0.011$). Further, perceived ambiguity is positively related to index a_r for risk ($p = 0.005$), a proxy for likelihood insensitivity. All variables together explain 14% of the variation, whereas 39% is driven by unobserved heterogeneity, and 47% is error. Together, the results indicate that measurement reliability for perceived ambiguity is reasonable, although clearly lower than for ambiguity aversion. A possible reason is that index a is measured from small differences in matching probabilities, as discussed below.

4.4. Results for a-insensitivity

In Appendix B we repeat the analyses above using all values of index a , without screening out monotonicity violations and negative values. A-insensitivity is not much correlated across the four investments: the correlations range from 0.10 to 0.24, and the first component in a factor analysis account for only 37% of the variation. When estimating the econometric model (9), the ICC is just 0.16 and measurement error is high (75%).²⁷

These analyses provide two insights. First, in contrast to ambiguity aversion (index b), the a-insensitivity measure is strongly influenced by violations of monotonicity. Second, screening out such violations leads to substantially higher reliability for index a . A plausible explanation is that index a is measured using differences in matching probabilities between composite events and single events (see Equation (2)), making the measure more sensitive to errors and violations of monotonicity than index b . A possible remedy that can be considered in the future studies is to

²⁷ Socio-demographic variables explain 4% of the variation in a-insensitivity, which increases to 7% when risk attitudes and financial literacy are included.

measure index a for a single source more than once (for example using slightly different partitions of the outcome space), and then to average the multiple estimates of index a .

5. Validity of the measures

5.1. Relation with risk preferences, education and financial literacy

We assess the validity of the ambiguity measures by testing whether they relate to other variables in expected ways. For example, a priori we expect that ambiguity aversion is positively related to risk aversion, as that is the most common finding in previous studies summarized by Trautmann and van de Kuilen (2015) and Baillon, Schlesinger, & van de Kuilen (2018). Similarly, we expect that likelihood insensitivity (overweighting of small probabilities) is positively related to a-insensitivity (overweighting of unlikely events), and thus to perceived ambiguity. The results in Table 2 and Table 4 confirm these relations ($p < 0.01$).²⁸

A priori, we also expect that investors with better financial knowledge and higher education perceive less ambiguity about the distribution of investment returns. Table 4 confirms both of these relations ($p < 0.05$), suggesting that more knowledge reduces the level of perceived ambiguity.²⁹ As an additional test, we also included a dummy for investors who named a specific stock they are familiar with (see Online Appendix G). As expected, investors naming a familiar stock perceive lower ambiguity about it (-0.087 ; $p = 0.027$), compared to those answering questions about Philips.

The competence hypothesis of Heath and Tversky (1991) predicts that ambiguity aversion is stronger when the decision maker feels less competent or less knowledgeable about the source, suggesting a negative relation between financial literacy and ambiguity aversion. The coefficient in Table 2 is negative as expected, but the effect is too small to be statistically significant.³⁰ Further, investors who named a specific familiar stock also did not display significantly lower ambiguity aversion to it (see Online Appendix G). Still, investors were significantly more ambiguity averse toward the foreign MSCI stock index in Table 2 compared to the domestic AEX index, displaying home bias (French and Poterba 1991). In addition, the difference in ambiguity aversion for the

²⁸ The correlations between risk preferences and ambiguity attitudes are moderate ($r = 0.49$ for b_{avg} and b_r ; $r = 0.32$ for a_{avg} and a_r), confirming that risk and ambiguity attitudes are separate concepts, as suggested by Abdellaoui et al. (2011) and Dimmock, Kouwenberg, Mitchell, & Peijnenburg (2015, 2016).

²⁹ Unfortunately, no direct measurement of cognitive ability is available in the DHS panel.

³⁰ Conversely, Soo Hong, Ratchford, & Sagi (2018) report that only high comprehension subjects display ambiguity aversion when the elicitation method presents ambiguity in a relatively complex way, whereas low comprehension subjects choose randomly and are close to ambiguity neutral. In Table 2, education does not have a significant relation with ambiguity aversion, suggesting that our choice lists are not too complex for the subjects.

familiar stock ($b = 0.156$) and the MSCI index ($b = 0.210$) is 34% in relative terms, a sizeable difference ($p = 0.008$). All in all, we find that there are strong competence effects in perceived ambiguity (a-insensitivity), but less so in ambiguity aversion.

5.2. External validation: The relation to investments

Next, we evaluate how ambiguity attitudes correlate with actual investment choices. Based on theory, we expect a negative relation between ambiguity aversion and asset ownership, and also a negative relation between perceived ambiguity and owning the asset (Uppal and Wang 2003; and Boyle et al. 2012).³¹ As the direction of these effects could run either way, our goal is to validate our ambiguity attitude measures, rather than making a claim about causality.

We estimate a pooled probit model for asset ownership, $DI_{i,s}$, a dummy variable indicating ownership of the familiar stock ($s = 2$), the MSCI World index ($s = 3$), and Bitcoin ($s = 4$):

$$(10) \quad P[DI_{i,s} = 1] = \mu_s d_s + \theta_1 b_{i,s} + \theta_2 a_{i,s} + \sum_{k=1}^K \theta_{k+2} X_{i,k} + \epsilon_{i,s}, \quad i = 1, 2, \dots, I, s = 2, 3, 4,$$

where indexes $b_{i,s}$ and $a_{i,s}$ have slope coefficients θ_1 and θ_2 . The constant μ_2 represents average ownership of the familiar stock, whereas μ_3 and μ_4 indicate differences in ownership rates for MSCI World and Bitcoin. Investment in the AEX index ($s = 1$) is excluded, as none in our sample invested in a fund tracking the AEX. The model includes K observable individual characteristics $X_{i,k}$ as control variables, with slope coefficients θ_{k+2} , for $k = 1, 2, \dots, K$.

The results in Model 1 of Table 5 show that index a has a negative relation with investing in an asset ($p = 0.005$). The coefficient of index b is also negative, as expected, but only marginally significant ($p = 0.060$). As more controls are added in Models 2 and 3, we note that the effect of index a becomes smaller, probably because it is related to financial literacy and education.

To reduce the impact of measurement error, Models 4 to 6 of Table 5 use as independent variables the predicted values $\hat{b}_{i,s}$ and $\hat{a}_{i,s}$ of ambiguity aversion and perceived ambiguity from the estimated panel models in Tables 2 and 4 (Model 3).³² Using the predicted values, we effectively remove the error terms $\hat{\epsilon}_{i,s}^b$ and $\hat{\epsilon}_{i,s}^a$ from index b and a . The sample size in Models 4 to 6 is smaller, as it includes only observations with $0 \leq a_{i,s} \leq 1$, similar to Table 4. The results in Model 4

³¹ One caveat is that these relations also depend on how much ambiguity the investor perceives about all other available investment opportunities considered, for which we lack complete information.

³² Predicted values are based on fitted values of the random effects (\hat{u}_i^b, \hat{u}_i^a) and random slopes ($\hat{v}_{4,s}^b, \hat{v}_{2,s}^a, \hat{v}_{4,s}^a$) for each investor, as well as differences in means of index b and a between sources ($\hat{\beta}_s, \lambda_s$), from Model 3 in Tables 2 and 4.

confirm that investors who perceive more ambiguity about an asset are less likely to invest in it, while ambiguity aversion is not significant.

Online Appendix C.3 shows results for several model specification tests. First, adding a random effect to the panel probit model (10) does not add value, because ownership of different investments is not very correlated. Second, allowing ambiguity aversion and perceived ambiguity to have a different effect on each investment does not improve the model fit either. In Table E6 of Online Appendix E we also estimate a probit model for each investment separately, as a robustness check. The results show that higher perceived ambiguity is negatively related to investing in MSCI World and Bitcoin, but not significant for the familiar stock. Further, investors with higher ambiguity aversion (index b) are less likely to invest in Bitcoin. Overall, these results support the validity of the ambiguity measures.

5.3. Robustness tests

We performed several additional robustness checks for our main results, reported in Online Appendix E. First, we repeated the main analysis after screening out investors who make mistakes on the ambiguity choice lists, by preferring Option A or B on every row. The main effect is that the mean level of index b drops, as the most common error is selecting the unambiguous Option B on every row of the choice list; this results in high values of index b .³³ Apart from that, the measurement reliability (ICC), the percentage of variance explained by observable variables, and the correlates of ambiguity attitudes are similar to the full-sample results.

Second, we repeated the main analysis after excluding values of b and a from subjects with many violations of set-inclusion monotonicity. Third, we excluded 30 respondents who spent less than ten minutes on the ambiguity survey module, to screen out subjects who devoted insufficient attention to the questions. The results in Online Appendix E are similar to the main findings in Table 2, 4 and 5, supporting the expected relations formulated in sub-section 5.1. Overall, the three robustness checks show that the main results are not driven by respondents who made many mistakes, or who spent little time on the ambiguity questions.

5.4. Comparison with the sample of non-investors

Online Appendix F presents results for the group of 230 non-investors who owned no financial assets. Non-investors display significantly higher a -insensitivity and perceived ambiguity to the four investments overall compared to investors, as expected. Ambiguity aversion on average

³³ Always selecting option B may also reflect extreme ambiguity aversion (MaxMin) and an extreme prior ($[0,1]$).

is not different from investors, in line with our earlier conclusion that competence effects are most pronounced in perceived ambiguity, the cognitive component of ambiguity attitudes.

In the non-investor group, heterogeneity in ambiguity aversion is driven by a single underlying factor, while random slopes for Bitcoin and other sources are not significant. Further, perceived ambiguity toward different investment is also largely driven by one underlying factor, explaining 48% of the variation. The means of ambiguity aversion and perceived ambiguity are also not different between sources. Hence, non-investors make less distinction in ambiguity between investments, most likely due to high unfamiliarity with all types of investments.

6. Conclusion

This paper measures ambiguity attitudes for relevant real-world sources of ambiguity in a large representative sample of investors, while controlling for unknown probability beliefs and risk preferences. One concern raised in the literature is that ambiguity measurements for artificial events such as Ellsberg urns are often noisy, and not related to individual characteristics and economic outcomes (see, e.g., Sutter et al. 2013; Stahl 2014; and l’Haridon et al. 2018). Focusing on investments, our results show that the reliability of ambiguity aversion for natural sources is high, measured using the new method of Baillon et al. (2018b), as correlations between repeated measures of ambiguity aversion are in the 0.6 to 0.8 range. Individual characteristics also are significantly correlated with ambiguity attitudes: thus, demographics, income, wealth, financial literacy, and risk aversion explain 23% of the variation in ambiguity aversion and 14% of perceived ambiguity. Perceived ambiguity is lower among investors with better financial literacy and higher education, while ambiguity aversion is positively related to risk aversion. We also confirm that investors who perceive higher ambiguity about a particular asset are less likely to invest in it, and investors with higher ambiguity aversion are less likely to invest in Bitcoin, supporting the external validity of the new measures.

Our results further indicate that ambiguity aversion toward different investments is largely driven by one underlying subject-dependent preference variable, while perceived ambiguity tends to differ more depending on the specific source considered. Our results support theoretical models that treat ambiguity aversion as subject-dependent, and perceived ambiguity as both subject- and source-dependent (Klibanoff et al. 2005; Hurwicz 1951; Ghirardato et al. 2004). Furthermore, we confirm for relevant real-world sources that ambiguity aversion is common but not universal

(Kocher et al. 2018). A sizeable fraction of investors is ambiguity neutral or seeking, while for unlikely events, ambiguity seeking prevails.

Our evidence also confirms insensitivity to the likelihood of ambiguous events as a second component of ambiguity attitudes, displayed by the large majority of investors. Early studies on natural ambiguity by Fox et al. (1996) and Kilka and Weber (2001) already reported a-insensitivity for stocks that was source-dependent; we can now confirm this in a large field study, using the latest methodology that controls for both unknown beliefs and risk preferences.

In addition, our research contributes to the literature on portfolio choice under ambiguity, by providing insight on how to model ambiguity attitudes.³⁴ Our findings support theoretical work that has modelled ambiguity attitudes with a single ambiguity preference parameter, but with different levels of perceived ambiguity depending on the investment source (e.g., Uppal and Wang 2003; Boyle et al. 2012; and Peijnenburg 2018). Further, the result on heterogeneity in ambiguity aversion for investments can have asset pricing implications, as demonstrated by Bossaerts et al. (2010), and Dimmock, Kowenberg, Mitchell & Peijnenburg (2016). In asset pricing models, ambiguity averse investors may drop out of the markets for highly ambiguous investments, leaving only ambiguity seeking and neutral investors to drive prices.

Our results suggest that ambiguity aversion is a source-independent trait, like a preference, not dependent much on financial knowledge or education. As ambiguity aversion or seeking leads to sub-optimal decision making (people would be better off being ambiguity neutral), a relevant question is how the negative influence of this trait can be reduced? A possible avenue is to provide decision makers more information to reduce the amount of uncertainty that they *perceive* about a source. The reason is that the impact of ambiguity aversion (or seeking) on decisions is *lower* when people perceive less ambiguity about a source. For example, in the best case, when people perceive no ambiguity ($\delta = 0$), they maximize utility without being influenced by ambiguity aversion.³⁵ As expected, we find that perceived ambiguity is lower among investors with higher financial literacy and better education, and perceived ambiguity is also lower for the familiar stock.

³⁴ See for instance Dow and Werlang (1992); Mukerji and Tallon (2001); Cao et al. (2005); Easley and O'Hara (2009); Garlappi et al. (2007); Bossaerts et al. (2010); Epstein and Schneider (2010); Gollier (2011); and Boyle et al. (2012).

³⁵ Unfortunately, we find that index a is rather high among investors (and even higher among non-investors), implying that people perceive high uncertainty about the probabilities of investment returns. Having a wide range of priors in turn will exacerbate the negative effects of ambiguity aversion (or seeking) on financial decision making.

In sum, our results tentatively suggest that policies aimed at reducing perceived ambiguity appear to be more promising for stimulating equity market participation than are policies targeting ambiguity aversion (as find we competence effects for perceived ambiguity, but not for aversion). To confirm these conjectures, an interesting avenue for future research would be to reduce perceived ambiguity through an experimental intervention such as financial literacy training (see Nieddu and Pandolfi 2021), and then to measure the subsequent impact on actual investments

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Table 1: Descriptive Statistics for Ambiguity Attitudes

Panel A shows summary statistics for ambiguity aversion regarding the local stock market index (*b_aex*), a familiar company stock (*b_stock*), the MSCI World stock index (*b_msci*) and Bitcoin (*b_bitcoin*), as well as the average of the four *b*-indexes (*b_avg*). Positive values of the *b*-index denote ambiguity aversion, and negative values indicate ambiguity seeking. Panel B shows summary statistics of index *a* (a-insensitivity) for the local stock market index (*a_aex*), a familiar company stock (*a_stock*), the MSCI World stock index (*a_msci*) and Bitcoin (*a_bitcoin*), as well as the average of the four *a*-indexes (*a_avg*). The sample consists of $n = 295$ investors.

Panel A: Ambiguity Aversion

	Mean	Median	St dev	Min	Max	<i>n</i> (obs.)
<i>b_aex</i>	0.17	0.10	0.48	-1.00	1.00	295
<i>b_stock</i>	0.16	0.10	0.48	-1.00	1.00	295
<i>b_msci</i>	0.21	0.16	0.48	-1.00	1.00	295
<i>b_bitcoin</i>	0.17	0.13	0.52	-1.00	1.00	295
<i>b_avg</i>	0.18	0.15	0.43	-1.00	1.00	295

Panel B: A-Insensitivity

	Mean	Median	St dev	Min	Max	<i>n</i> (obs.)
<i>a_aex</i>	0.83	1.00	0.53	-0.70	2.99	295
<i>a_stock</i>	0.69	0.85	0.64	-1.81	2.90	295
<i>a_msci</i>	0.78	0.90	0.52	-1.51	2.80	295
<i>a_bitcoin</i>	0.84	1.00	0.50	-1.02	2.61	295
<i>a_avg</i>	0.79	0.88	0.33	-0.29	1.73	295

Table 2: Analysis of Heterogeneity in Ambiguity Aversion

The table shows estimation results for the panel regression model in Equation (7), with index b (ambiguity aversion) toward the four investments as the dependent variable. Model 1 includes a constant and a random effect for individual-level heterogeneity in ambiguity aversion common to all sources. Model 2 adds dummies for differences in mean b between the four investments. Model 3 includes a random slope to capture heterogeneity in ambiguity aversion toward Bitcoin, shown to be significant by a likelihood ratio test (see Online App. C.1). Model 4 includes education, age, gender, single, employment, log number of children, family income, and household financial wealth, plus a missing wealth dummy. Model 5 adds financial literacy, risk aversion and likelihood insensitivity. Sample: $n = 1180$ observations of index b , for 295 investors. Standard errors clustered by investor shown in parentheses.

	Dependent variable: Ambiguity aversion (Index b)				
	Model 1	Model 2	Model 3	Model 4	Model 5
Constant	0.177*** (0.025)	0.168*** (0.028)	0.168*** (0.028)	0.153 (0.219)	0.213 (0.240)
Dummy Familiar Stock		-0.012 (0.020)	-0.012 (0.020)	-0.012 (0.020)	-0.012 (0.020)
Dummy MSCI World		0.042** (0.021)	0.042** (0.021)	0.042** (0.021)	0.042** (0.021)
Dummy Bitcoin		0.007 (0.024)	0.007 (0.024)	0.007 (0.024)	0.007 (0.024)
Education				-0.010 (0.017)	-0.018 (0.016)
Age				0.006*** (0.002)	0.003* (0.002)
Female				0.072 (0.062)	0.059 (0.053)
Single				-0.116** (0.058)	-0.090* (0.049)
Employed				-0.040 (0.070)	-0.042 (0.058)
Number of Children (log)				0.059 (0.062)	0.048 (0.057)
Family Income (log)				-0.011 (0.014)	0.016 (0.016)
HH Fin. Wealth (log)				-0.016* (0.009)	-0.011* (0.007)
HH Wealth Imputed				-0.130 (0.115)	-0.050 (0.092)
Financial Literacy					-0.015 (0.017)
Risk Aversion					0.466*** (0.065)
Likelihood Insensitivity					-0.084* (0.048)
Random Slope: Bitcoin	No	No	Yes	Yes	Yes
Observations n	1180	1180	1180	1180	1180
ICC of Random Effect u_i^b	0.69	0.69	0.74	0.72	0.65
$Var[\varepsilon_{i,s}^b]$, Error	0.075 (31%)	0.075 (31%)	0.061 (25%)	0.061 (25%)	0.061 (25%)
$Var[u_i^b]$, Random Constant	0.165 (69%)	0.165 (69%)	0.167 (70%)	0.152 (64%)	0.112 (47%)
$Var[v_{i,4}^b]$, Slope Bitcoin	-	-	0.011 (5%)	0.012 (5%)	0.012 (5%)
$Var[\beta'D + \gamma'X]$, Observed	-	0.0004 (0%)	0.0004 (0%)	0.015 (6%)	0.056 (23%)

Table 3: Descriptive Statistics for Perceived Ambiguity

The table shows summary statistics for index a , for the local stock market index (a_{aex}), a familiar company stock (a_{stock}), the MSCI World stock index (a_{msci}) and Bitcoin ($a_{bitcoin}$), as well as the average of the four a -indexes (a_{avg}). Panel A of the table shows the percentage of a -index values that are negative (over-sensitive to likelihoods), between 0 and 1 (in line with the interpretation of index a as perceived ambiguity), and larger than 1 (violations of monotonicity). The sample consists of $n = 295$ investors. In Panel B, the sample has been restricted to only those observations of index a that are between 0 and 1, after pairwise deletion, so that the a -indexes can be interpreted as measures of perceived ambiguity. For this reason, in Panel B the sample size varies, as indicated in the last column.

Panel A: Negative Values of Index a and Violations of Monotonicity

	<i>Within limits for perceived ambiguity</i> % with $0 \leq a \leq 1$	<i>Over-sensitive to likelihoods</i> % with $a < 0$	<i>Violation of monotonicity</i> % with $a > 1$
a_{aex}	65.1	8.8	26.1
a_{stock}	65.1	12.5	22.4
a_{msci}	69.5	7.8	22.7
$a_{bitcoin}$	69.5	5.4	25.1
a_{avg}	77.6	2.0	20.3

Panel B: Summary Statistics of Perceived Ambiguity

	Mean	Median	St dev	Min	Max	n (obs.)
a_{aex}	0.74	0.89	0.30	0.00	1.00	192
a_{stock}	0.64	0.74	0.35	0.01	1.00	192
a_{msci}	0.72	0.80	0.30	0.00	1.00	205
$a_{bitcoin}$	0.75	0.91	0.30	0.01	1.00	205
a_{avg}	0.71	0.76	0.26	0.02	1.00	229

Table 4: Analysis of Heterogeneity in Perceived Ambiguity

The table shows estimation results for the panel regression model in Equation (9), with index a toward the four investments as dependent variable. Only values of index a between 0 and 1 are included, so index a can be interpreted as perceived ambiguity. Model 1 includes a constant and a random effect for individual-level heterogeneity in perceived ambiguity common to all sources. Model 2 adds dummies for differences in the mean of perceived ambiguity between investments. Model 3 includes a random slope to capture heterogeneity in perceived ambiguity toward the familiar stock and Bitcoin (see Online App. C.2). Model 4 includes observed socio-demographic variables. Model 5 adds financial literacy, risk aversion and likelihood insensitivity. Sample: $n = 794$ observations of perceived ambiguity (a -index values between 0 and 1), for 295 investors. Standard errors clustered by investor in parentheses.

	Dependent variable: Perceived ambiguity (Index a , between 0 and 1)				
	Model 1	Model 2	Model 3	Model 4	Model 5
Constant	0.696*** (0.015)	0.718*** (0.021)	0.721*** (0.021)	0.796*** (0.117)	0.915*** (0.143)
Dummy Familiar Stock		-0.091*** (0.026)	-0.099*** (0.025)	-0.102*** (0.025)	-0.103*** (0.025)
Dummy MSCI World		-0.011 (0.023)	-0.013 (0.023)	-0.014 (0.023)	-0.016 (0.023)
Dummy Bitcoin		0.013 (0.025)	0.014 (0.025)	0.013 (0.025)	0.011 (0.025)
Education				-0.041*** (0.010)	-0.034*** (0.009)
Age				0.003*** (0.001)	0.002* (0.001)
Female				0.019 (0.030)	0.005 (0.030)
Single				-0.059* (0.032)	-0.045 (0.030)
Employed				0.027 (0.036)	0.028 (0.034)
Number of Children (log)				-0.029 (0.038)	-0.032 (0.037)
Family Income (log)				-0.019** (0.008)	-0.010 (0.010)
HH Fin. Wealth (log)				0.005 (0.006)	0.007 (0.006)
HH Wealth Imputed				0.068 (0.049)	0.069 (0.055)
Financial Literacy					-0.022** (0.009)
Risk Aversion					0.041 (0.030)
Likelihood Insensitivity					0.087*** (0.031)
Random Slope: Stock/Bitcoin	No	No	Yes	Yes	Yes
Observations n	794	794	794	794	794
ICC of Random Effect u_i^b	0.44	0.45	0.49	0.44	0.41
$Var[\varepsilon_{i,s}^a]$, Error	0.057 (56%)	0.055 (54%)	0.046 (45%)	0.046 (46%)	0.047 (47%)
$Var[u_i^a]$, Random Constant	0.044 (44%)	0.044 (44%)	0.044 (43%)	0.035 (34%)	0.031 (30%)
$Var[v_{i,4}^a]$, Slope Bitcoin	-	-	0.004 (4%)	0.005 (5%)	0.004 (4%)
$Var[v_{i,2}^a]$, Slope Stock	-	-	0.006 (6%)	0.006 (6%)	0.004 (4%)
$Var[\alpha'D + \gamma'X]$, Observed	-	0.002 (2%)	0.002 (2%)	0.010 (10%)	0.014 (14%)

Table 5: Investment in the Familiar Stock, MSCI World and Crypto-Currencies

This table reports estimation results for a panel probit model explaining asset ownership with index a and b , see Equation (10). The dependent variable is 1 if the respondent invests in the asset (familiar individual stock, MSCI World or Bitcoin), and 0 otherwise. Investment in the AEX index is excluded, as no respondents hold an AEX fund. The data for ownership of the three assets is treated as a panel dataset similar to Table 2 and 4, see model Equation (10) in the text for details. The coefficients displayed are estimated marginal effects. Standard errors clustered by investor shown in parentheses. In Model 4, 5, and 6 index a and b are replaced by fitted values from the panel regression models in Table 2 and Table 4, using specification Model 3 with source dummies and random slopes. Further, only observations with $0 \leq a \leq 1$ are included in Model 4-6, so that fitted a can be interpreted as perceived ambiguity. The set of control variables is the same as in Table 2 and 4.

	Dependent variable: Invests in the Asset (1 = yes, 0 = no)					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Perc. Ambiguity (index a)	-0.043*** (0.015)	-0.033** (0.015)	-0.029* (0.015)			
Amb. Aversion (index b)	-0.035* (0.019)	-0.020 (0.019)	-0.028 (0.022)			
Perc. Ambiguity (fitted \hat{a})				-0.135*** (0.047)	-0.097** (0.046)	-0.089* (0.052)
Amb. Aversion (fitted \hat{b})				-0.018 (0.025)	-0.004 (0.026)	-0.018 (0.033)
Dummy MSCI World	-0.242*** (0.028)	-0.242*** (0.027)	-0.242*** (0.027)	-0.214*** (0.034)	-0.219*** (0.032)	-0.220*** (0.032)
Dummy Bitcoin	-0.205*** (0.024)	-0.207*** (0.022)	-0.208*** (0.022)	-0.169*** (0.028)	-0.176*** (0.025)	-0.179*** (0.025)
Education		0.011 (0.007)	0.008 (0.007)		0.008 (0.008)	0.005 (0.008)
Age		0.000 (0.001)	0.000 (0.001)		0.000 (0.001)	0.000 (0.001)
Female		-0.058** (0.024)	-0.048** (0.024)		-0.063** (0.028)	-0.050* (0.028)
Single		0.008 (0.022)	0.002 (0.021)		-0.015 (0.025)	-0.020 (0.024)
Employed		0.051** (0.025)	0.053** (0.024)		0.059** (0.027)	0.059** (0.026)
Number of Children (log)		0.001 (0.025)	0.003 (0.025)		-0.025 (0.031)	-0.020 (0.031)
Family Income (log)		0.002 (0.009)	0.000 (0.009)		-0.003 (0.009)	-0.005 (0.009)
HH Fin. Wealth (log)		0.001 (0.004)	0.000 (0.003)		-0.001 (0.004)	-0.002 (0.004)
HH Wealth Imputed		-0.063 (0.047)	-0.060 (0.047)		-0.055 (0.052)	-0.042 (0.051)
Financial Literacy			0.016** (0.007)			0.015* (0.008)
Risk Aversion			0.018 (0.024)			0.019 (0.030)
Likelihood Insensitivity			-0.007 (0.018)			0.015 (0.022)
Observations n	885	885	885	602	602	602
Pseudo R-square	0.267	0.304	0.315	0.244	0.281	0.293

Figure 1: Example of a Choice List for Eliciting Ambiguity Attitudes

The following questions will be about the value of the AEX index: the Amsterdam Exchange index, a stock market index composed of the shares of 25 Dutch companies that trade on the stock market in Amsterdam.

For each of the 15 rows below, please choose whether you prefer Option A or Option B.

Option A: pays off €15 if the AEX *decreases by 4% or more* in one month time compared to what the index value is today.

Option B: pays off €15 with a given chance, with the chance increasing down the rows of the table. For example, in row 1 the chance is 0%, in row 2 the chance is 2.5%, etc., until in row 15 the chance is 100%.

Note: any amount you win will be paid after one month, both for Option A and Option B.

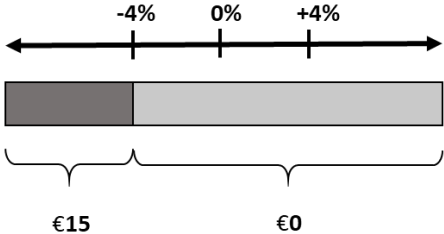
Option A You win €15 if the AEX <i>decreases by 4% or more</i> in one month time compared to what the index value is today (and nothing otherwise)	A	B	Option B You win €15 in one month time with the following chance (and nothing otherwise)
<p>A: Win €15 if the AEX <i>decreases by 4% or more</i> in 1 month time</p> 	X		B: Win €15 with chance of 0%
	X		B: Win €15 with chance of 2.5%
	X		B: Win €15 with chance of 5%
	X		B: Win €15 with chance of 10%
	X		B: Win €15 with chance of 20%
		X	B: Win €15 with chance of 30%
		X	B: Win €15 with chance of 40%
		X	B: Win €15 with chance of 50%
		X	B: Win €15 with chance of 60%
		X	B: Win €15 with chance of 70%
		X	B: Win €15 with chance of 80%
		X	B: Win €15 with chance of 90%
		X	B: Win €15 with chance of 97.5%
		X	B: Win €15 with chance of 100%

Figure 2: Second Choice List for Eliciting Ambiguity Attitudes about the AEX Index

For each of the 15 rows below, please choose whether you prefer Option A or Option B.

Option A: pays off €15 if the AEX does *not decrease by 4% or more* in one month time compared to what the index value is today.

Option B: pays off €15 with a given chance, with the chance increasing down the rows of the table. For example, in row 1 the chance is 0%, in row 2 the chance is 2.5%, etc., until in row 15 the chance is 100%.

Note: any amount you win will be paid after one month, both for Option A and Option B.

<u>Option A</u> You win €15 if the AEX does <i>not decrease by 4% or more</i> in one month time compared to what the index value is today (and nothing otherwise)			<u>Option B</u> You win €15 in one month time with the following chance (and nothing otherwise)
	A	B	
<p>A: Win €15 if the AEX does <i>not decrease by 4% or more</i> in 1 month time</p>	X		B: Win €15 with chance of 0%
	X		B: Win €15 with chance of 2.5%
	X		B: Win €15 with chance of 5%
	X		B: Win €15 with chance of 10%
	X		B: Win €15 with chance of 20%
	X		B: Win €15 with chance of 30%
	X		B: Win €15 with chance of 40%
	X		B: Win €15 with chance of 50%
		X	B: Win €15 with chance of 60%
		X	B: Win €15 with chance of 70%
		X	B: Win €15 with chance of 80%
		X	B: Win €15 with chance of 90%
		X	B: Win €15 with chance of 95%
		X	B: Win €15 with chance of 97.5%
		X	B: Win €15 with chance of 100%

Figure 3: Ambiguity Attitudes toward Financial Sources (Averse, Neutral and Seeking)

This Figure shows the percent of investors who are ambiguity averse ($b\text{-index} > 0$, significant at 5%), ambiguity neutral (cannot reject $b\text{-index} = 0$), and ambiguity seeking ($b\text{-index} < 0$, significant at 5%) for the local stock market index (b_{aex}), a familiar company stock (b_{stock}), the MSCI World stock index (b_{msci}), and Bitcoin ($b_{bitcoin}$). The sample consists of $n = 295$ investors.

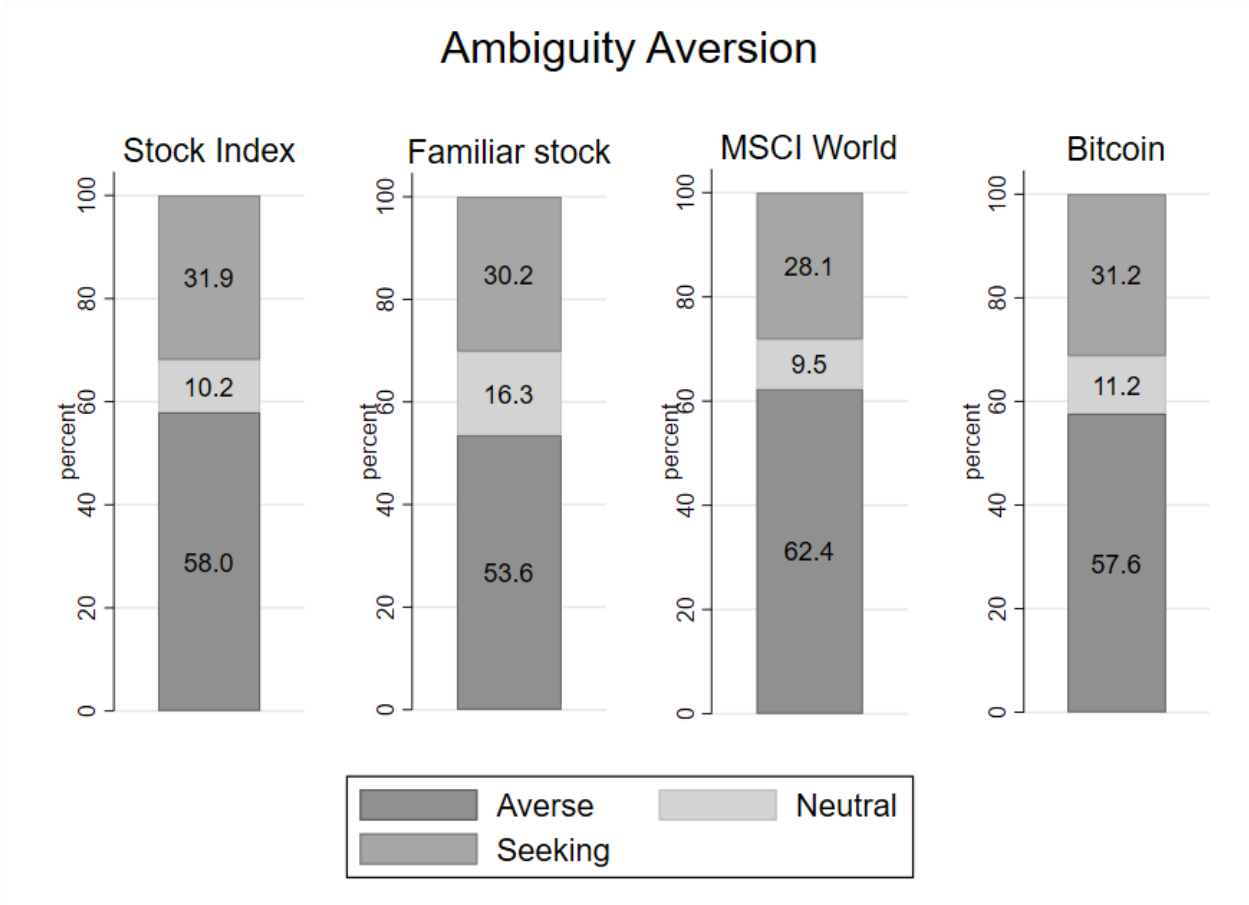


Figure 4: Scatter Plots of Ambiguity Attitudes toward Different Financial Sources

This Figure shows scatter plots of the relationships between ambiguity aversion (the b -indexes) for different investments: the local stock market index (b_{aex}), a familiar company stock (b_{stock}), the MSCI World stock index (b_{msci}), and Bitcoin ($b_{bitcoin}$). The correlation (r) is shown above each scatter plot, with *, **, *** denoting significance at the 10%, 5% and 1%, respectively. The sample consists of $n = 295$ investors.

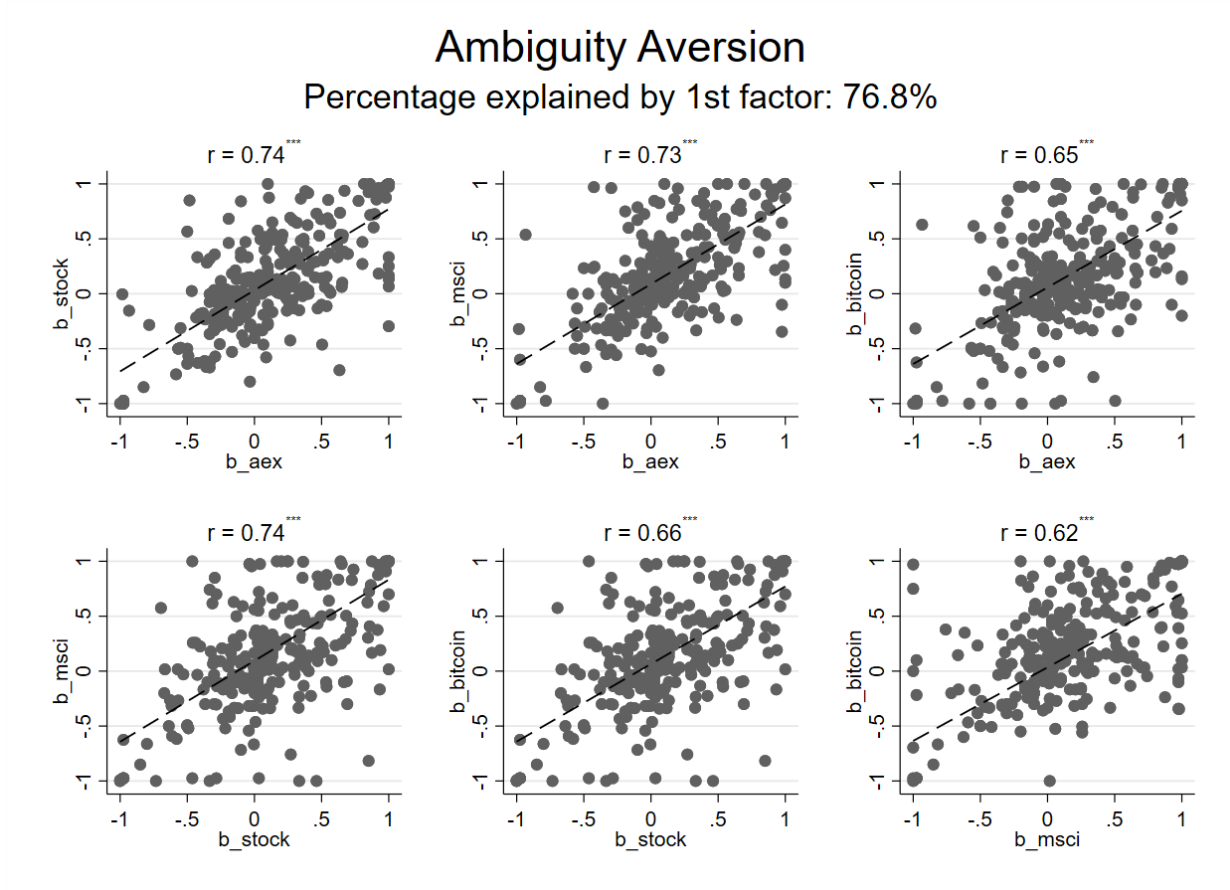
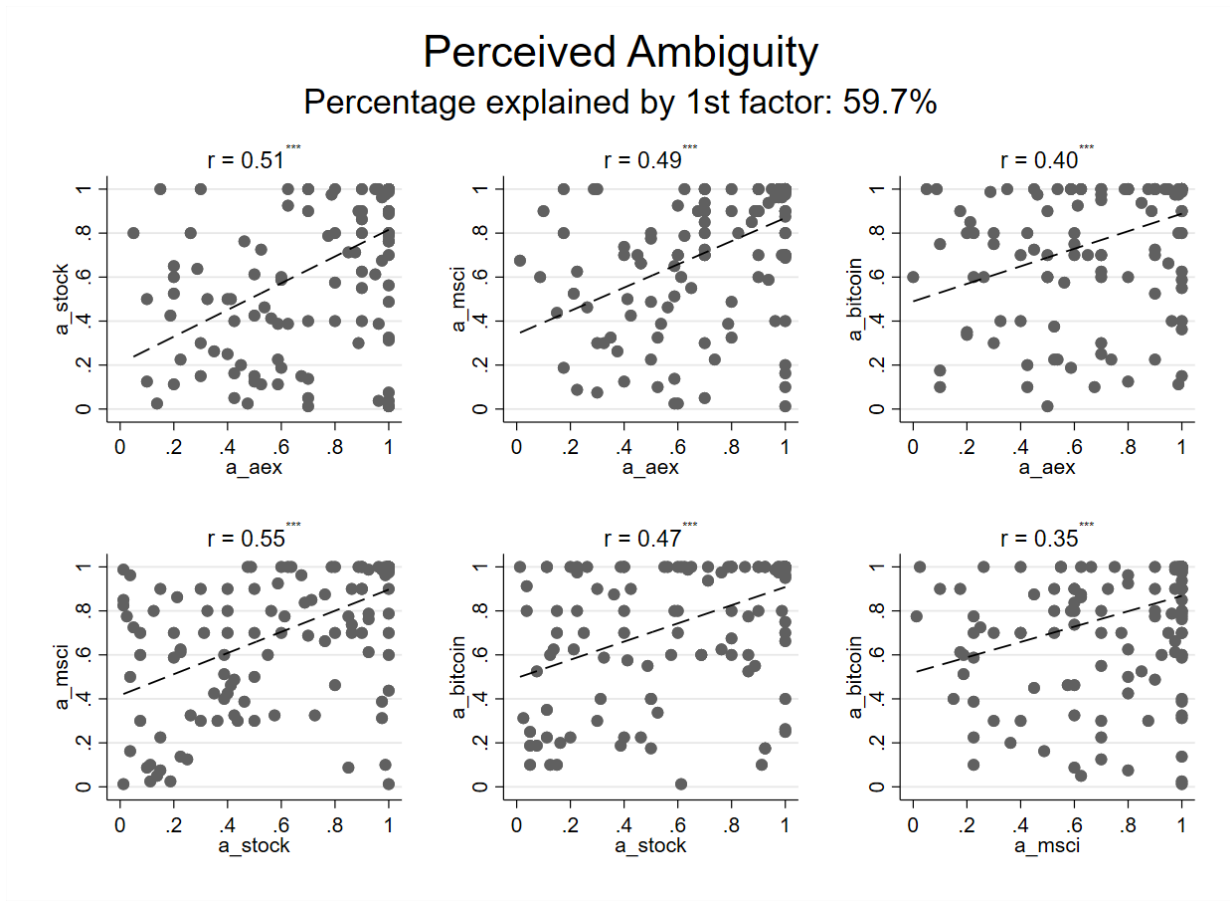


Figure 5: Scatter Plots of Perceived Ambiguity about Different Financial Sources

This Figure shows scatter plots of the relation between perceived ambiguity (the *a*-indexes) for different investments: the local AEX stock market index (*a_aex*), a familiar company stock (*a_stock*), the MSCI World stock index (*a_msci*), and Bitcoin (*a_bitcoin*). The correlation (*r*) is shown above each scatter plot, with *, **, *** denoting significance at the 10%, 5% and 1%, respectively. The original sample consists of $n = 295$ investors, but values of index *a* that are negative or larger than 1 are excluded pairwise.



Appendix A. Dataset

Table A1: Descriptive Statistics of the DHS Investor Dataset

This table reports summary statistics of the socio-demographics, risk preferences, financial literacy and asset ownership of investors in the DHS panel. Sample size is $n = 295$ investors who owned bonds, mutual funds, individual stocks, or stock options as of 31 December 2016. Family income (monthly, after tax) and household financial wealth are measured in euros. The reference category for employment status is either unemployed or not actively seeking work (13%). Risk attitudes and investment in the familiar stock, crypto-currencies and funds tracking the MSCI World index are measured in our ambiguity survey module (see text).

	Mean	Median	St dev	Min	Max
<i><u>Socio-demographics</u></i>					
Age	61.22	63	14.42	21	93
Female	0.25	0	0.43	0	1
Single	0.29	0	0.45	0	1
Number of Children	0.38	0	0.82	0	3
Education	4.30	5	1.42	1	6
Employed	0.45	0	0.50	0	1
Retired	0.42	0	0.49	0	1
Household Income	3,193	2,915	1,659	0	11,975
Household Financial Wealth	142,357	84,489	244,997	0	3,260,448
<i><u>Risk Preferences</u></i>					
Risk Aversion (b_r)	0.12	0.08	0.46	-1.00	1.00
Indicator for Risk Aversion > 0	0.64	1.00	0.48	0.00	1.00
Likelihood Insensitivity (a_r)	0.58	0.57	0.53	-0.73	1.83
Indicator for L. Insensitivity > 0	0.85	1.00	0.35	0.00	1.00
<i><u>Financial Literacy and Investments</u></i>					
Financial Literacy	10.56	11	1.70	3	12
Knows a Familiar Company Stock	0.549	1	0.50	0	1
Invests in Familiar Stock	0.302	0	0.46	0	1
Invests in Crypto-Currencies	0.024	0	0.15	0	1
Invests in MSCI World	0.014	0	0.12	0	1

Appendix B. Analysis of A-Insensitivity

Table B2: Analysis of Heterogeneity in A-Insensitivity

The table shows estimation results for Equation (9) with index a (a-insensitivity) as the dependent variable, similar to Table 4 of the main text, but including all values of index a (also when $a < 0$ or $a > 1$) for the 295 investors ($n = 1180$). Standard errors clustered by investor shown in parentheses.

	Dependent variable: a-Insensitivity (Index a)				
	Model 1	Model 2	Model 3	Model 4	Model 5
Constant	0.785*** (0.019)	0.826*** (0.031)	0.826*** (0.031)	1.077*** (0.171)	1.177*** (0.183)
Dummy Familiar Stock		-0.136*** (0.044)	-0.136*** (0.044)	-0.136*** (0.044)	-0.136*** (0.044)
Dummy MSCI World		-0.046 (0.040)	-0.046 (0.040)	-0.046 (0.040)	-0.046 (0.040)
Dummy Bitcoin		0.019 (0.040)	0.019 (0.040)	0.019 (0.040)	0.019 (0.040)
Education				-0.056*** (0.013)	-0.045*** (0.013)
Age				0.003 (0.002)	0.001 (0.002)
Female				-0.022 (0.040)	-0.040 (0.039)
Single				-0.050 (0.040)	-0.033 (0.039)
Employed				-0.015 (0.049)	-0.011 (0.044)
Number of Children (log)				-0.002 (0.059)	-0.005 (0.048)
Family Income (log)				-0.029*** (0.010)	-0.020* (0.011)
HH Fin. Wealth (log)				0.008 (0.008)	0.011 (0.008)
HH Wealth Imputed				0.017 (0.102)	0.023 (0.091)
Financial Literacy					-0.025*** (0.009)
Risk Aversion					-0.013 (0.036)
Likelihood Insensitivity					0.163*** (0.040)
Random Slope: Stock	No	No	Yes	Yes	Yes
Observations (n)	1180	1180	1180	1180	1180
ICC of Random Effect u_i^b	0.15	0.16	0.13	0.09	0.06
$Var[\varepsilon_{i,s}^b]$, Error	0.260 (85%)	0.255 (83%)	0.230 (75%)	0.230 (75%)	0.230 (75%)
$Var[u_i^b]$, Random Constant	0.046 (15%)	0.047 (16%)	0.041 (14%)	0.029 (10%)	0.020 (7%)
$Var[v_{i,2}^a]$, Slope Stock	-	-	0.031 (10%)	0.031 (10%)	0.030 (10%)
$Var[\beta'D + \gamma'X]$, Observed	-	0.0036 (1%)	0.0036 (1%)	0.015 (5%)	0.024 (8%)

Online Appendix for

**Ambiguity Attitudes for Real-World Sources:
Field Evidence from a Large Sample of Investors**

Kanin Anantanasuwong, Roy Kouwenberg, Olivia S. Mitchell, and Kim Peijnenburg

September 23, 2022

Online Appendix A. Experimental Design and Instructions

The DHS survey module started with questions about financial literacy (see Online Appendix B) and investing, followed by choice lists for measuring risk and ambiguity attitudes. The introduction text for the risk and ambiguity questions was as follows:

INTRODUCTION

In the next few questions, you will be asked several times to make a choice between Option A and Option B. After completing the survey, one of the questions you answered will be selected randomly by the computer, and your winnings will be based on the choices you have made. You could win between 0 and 15 euro, in addition to your payment for answering the survey.

The order of the risk and ambiguity choice lists was randomized, with some respondents receiving the risk questions first, and others the ambiguity questions. One of the choice lists for eliciting risk aversion, with its instructions, is shown in Figure A1 as an example. In total there were four choice lists for risk, with chances of winning of 50%, 33%, 17%, and 83%. For the questions with a 33%, 17% and 83% chance of winning, a role of a die with six sides was used as the source of risk, rather than a coin toss like in the 50% question. The order of the risk choice lists was randomized.

One of the ambiguity choice lists for the AEX stock market index, with its instructions, is shown in Figure 1 of the main text. In total there were 24 choice lists for ambiguity, namely six choice lists each for four different investments (AEX, MSCI, familiar stock and Bitcoin), as explained in Section 2. The order of the four investments was randomized, as well as the order of the six events for each investment. The 24 ambiguity choice lists were always preceded by one practice question about the temperature in Amsterdam, shown in Figure A2.

The percentage change of the investments in the ambiguous event E_1 , E_2 and E_3 was set based on the approximate volatility of the assets: 15% for the AEX index and the MSCI World index, 40% for a typical individual stock, and 100% for Bitcoin (in February 2018). Given these volatilities, and assuming annualized mean returns of 5% for the AEX, MSCI World and the stock, and 30% for Bitcoin, the percentage change used in the ambiguity choice lists was set so the event E_3 (large positive return) had a probability of approximately 20% under a normal distribution.

Figure A1: First Choice List for Eliciting Risk Attitudes

In this question you can win a prize depending on the result of a random coin toss .There is a 50% chance that the coin will come up heads and a 50% chance it will come up tails. For each of the 18 rows below, please choose whether you prefer Option A or Option B.

Option A: pays off €15 if the coin comes up head (50% chance)

Option B: A certain pay off with the amount increasing down the rows of the table. For example, in row 1 the pay off is €0.00, in row 2 the pay off is €1.00, etc., until in row 18 the pay off is €15.00.

Please indicate whether you prefer Option A or Option B.

You do not have to make a choice in all of the 18 rows. If you select Option B in one particular row, then your choice in all following rows will automatically be set at Option B as well, and in all previous rows at Option A.

So you only have to select from which row onwards you prefer Option B.

It is also possible that you prefer Option A for every row. In that case if you select Option A in the last row, then your choice in all previous rows will automatically be set at Option A as well.

<p style="text-align: center;"><u>Option A</u></p> <p>You win €15 if the coin comes up heads (and nothing otherwise)</p>	<p style="text-align: center;">A</p>	<p style="text-align: center;">B</p>	<p style="text-align: center;"><u>Option B</u></p> <p>You win the following amount with certainty.</p>
<p>Heads (50% chance): You win €15. Tails (50% chance): You win nothing.</p>	X		A certain pay off of €0.00
	X		A certain pay off of €1.00
	X		A certain pay off of €2.00
	X		A certain pay off of €3.00
	X		A certain pay off of €4.00
	X		A certain pay off of €4.50
	X		A certain pay off of €5.00
	X		A certain pay off of €5.50
	X		A certain pay off of €6.00
	X		A certain pay off of €6.50
			X A certain pay off of €7.00
			X A certain pay off of €7.50
			X A certain pay off of €8.00
			X A certain pay off of €9.00
			X A certain pay off of €10.00
			X A certain pay off of €11.00
			X A certain pay off of €12.50
			X A certain pay off of €15.00

Figure A2: Ambiguity Practice Question

For each of the 15 rows below, please choose whether you prefer Option A or Option B.

Option A: pays off **15** euro if the temperature in Amsterdam 1 month from now at 3 p.m. is *more than 20 degrees Celsius*.

Option B: pays off **15** euro with a given chance, with the chance increasing down the rows of the table. For example, in row 1 the chance is 0%, in row 2 the chance is 2.5%, etc., until in row 15 the chance is 100%.

Note: any amount you win will be paid after one month, both for Option A and Option B.

Please indicate whether you prefer Option A or Option B.

You do not have to make a choice in all of the 15 rows. If you select Option B in one particular row, then your choice in all following rows will automatically be set at Option B as well, and in all previous rows at Option A. So you only have to select from which row onwards you prefer Option B. It is also possible that you prefer Option A for every row. In that case if you select Option A in the last row, then your choice in all previous rows will automatically be set at Option A as well

<p align="center"><u>Option A</u> You win €15 if the temperature in Amsterdam 1 month from now at 3pm is <i>more than 20 degree Celsius</i> (and nothing otherwise)</p>	A	B	<p align="center"><u>Option B</u> You win €15 in one month time with the following chance (and nothing otherwise)</p>
<p align="center">A: Win €15 if the temperature in Amsterdam 1 month from now at 3pm is <i>more than 20 degree Celsius</i> (and nothing otherwise)</p>	X		B: Win €15 with chance of 0%
	X		B: Win €15 with chance of 2.5%
	X		B: Win €15 with chance of 5%
	X		B: Win €15 with chance of 10%
	X		B: Win €15 with chance of 20%
	X		B: Win €15 with chance of 30%
	X		B: Win €15 with chance of 40%
	X		B: Win €15 with chance of 50%
		X	B: Win €15 with chance of 60%
		X	B: Win €15 with chance of 70%
		X	B: Win €15 with chance of 80%
		X	B: Win €15 with chance of 90%
		X	B: Win €15 with chance of 95%
		X	B: Win €15 with chance of 97.5%
		X	B: Win €15 with chance of 100%

Online Appendix B. Risk Aversion and Financial Literacy

Section B.1 defines the risk aversion measures used as control variables in the main text and discusses alternative measures used in robustness checks. Section B.2 lists the financial literacy questions in the DHS survey used to create a measure of financial literacy.

B.1 Risk Aversion Measures

The DHS module included four choice lists to measure risk attitudes (a screenshot appears in Online Appendix A, Figure A1). The first risk attitude choice list in Figure A1 elicited a certainty equivalent for a known 50% chance of winning €15, based on a fair coin toss. The other three choice lists elicited certainty equivalents for chances of winning of 33%, 17%, and 83%, respectively, using the throw of a die. Respondents could win real money for the risk questions, and the order of the risk and ambiguity question sets in the survey was randomized. Table B1 shows summary statistics of the respondents' risk premiums for the four questions. The mean risk premiums in Table B1 display risk aversion for moderate and high probabilities (50%, 87%), and risk seeking for low probabilities (17%, 33%), in line with common findings in the literature (see Fehr-Duda and Epper, 2011).

Table B1: Risk Premiums

The table shows summary statistics of the investors' risk premiums for the four risk questions. The choice lists elicited a certainty equivalent for a chance of winning a prize of €15 of 50%, 33%, 17% and 88%, respectively. A positive (negative) risk premium indicates that the respondent is risk averse (risk seeking), as his certainty equivalent for the risky prospect was below (above) the expected value of the prospect.

	Mean	Median	St dev	Min	Max
<i>Risk premiums</i>					
Question 1: chance of winning 50%	0.08	0.03	0.59	-1.00	1.00
Question 2: chance of winning 33%	-0.13	-0.05	0.77	-2.00	1.00
Question 3: chance of winning 17%	-0.77	-0.40	1.60	-5.00	1.00
Question 4: chance of winning 87%	0.32	0.24	0.41	-0.20	1.00

Following Abdellaoui et al. (2011), we estimate index b_r for risk as a measure of *Risk Aversion* and index a_r for risk as a measure of *Likelihood Insensitivity* (probability weighting). The underlying assumptions are as follows: risk preferences are modelled with a rank-dependent utility model using a neo-additive probability weighting function and a linear utility function.

In a rank-dependent utility model with utility function U and probability weighting function w , indifference between the sure amount CE_k and winning €15 with chance p_k implies:

$$(B1) \quad U(CE_k) = w(p_k)U(15) + (1 - w(p_k))U(0), \text{ for risk question } k = 1, 2, 3, 4.$$

As utility curvature is often close to linear for small amounts and risk aversion can be modelled with the probability weighting function w , we assume U is linear with $U(x) = x$:

$$(B2) \quad CE_k = w(p_k)15$$

The probability weighting function is of the neo-additive type as in Chateauneuf et al. (2007):

$$(B3) \quad w(p) = c + sp \text{ for } 0 < p < 1, \text{ with } w(0) = 0 \text{ and } w(1) = 1.$$

The expression for the certainty equivalent in Equation (B2) now reduces to:

$$(B4) \quad \frac{CE_k}{15} = c + sp_k.$$

The unknown parameters c and s in Equation (B4) are estimated with ordinary least squares, for each respondent separately, using the four certainty equivalents. Following Abdellaoui et al. (2011), index b_r and a_r for risk are then defined as follows, as functions of c and s :

$$(B5) \quad \text{Risk Aversion} = \text{index } b_r \text{ for risk} = 1 - s - 2c,$$

$$(B6) \quad \text{Likelihood Insensitivity} = \text{index } a_r \text{ for risk} = 1 - s.$$

The *Risk Aversion* measure captures the tendency to underweight all probabilities, originally denoted as *Pessimism* by Abdellaoui et al. (2011). As utility is assumed to be linear in the model above, the measure effectively captures the effect of risk aversion. The *Likelihood Insensitivity* measure of Abdellaoui et al. (2011) captures the tendency to overweight extreme good and bad events that occur with small known probabilities, or treating all probabilities as 50-50%, which is related to Inverse-S probability weighting. See Figure 2 in Abdellaoui et al. (2011) for a graphic illustration of these measures. The risk attitude measures above have the advantage that they are conceptually related to index b for ambiguity aversion and index a for a-insensitivity, while having an axiomatic foundation in the rank-dependent utility model with a neo-additive probability weighting function, see Cohen (1992), Chateauneuf et al. (2007), and Abdellaoui et al. (2011).

As a robustness check, we have also estimated two alternative, non-parametric, measures of risk attitudes. First, *Alt. Risk Aversion* is the average of the risk premiums for the two risk questions with 50% and 33% chance of winning. *Alt. Inverse-S* is defined as the difference in the risk premiums for the two questions with 83% and 17% chance of winning, similar to Dimmock, Kouwenberg, Mitchell and Peijnenburg (2021). Table B2 shows the correlations between these alternative measures and the risk measures used for the main paper. *Alt. Risk Aversion* has a strong correlation of $r = 0.9$ with *Risk Aversion*, implying that the two measures are highly similar. In addition, *Alt. Inverse-S* has a correlation of $r = 0.6$ with *Likelihood Insensitivity*.

All results reported in the main text are qualitatively similar to those obtained when using *Alt. Risk Aversion* and *Alt. Inverse-S* as the control variables. Table B3 shows the same analyses as Table 2 and Table 4 in the main text, while the models in columns (2) and (4) use the alternative risk attitude measures. For ambiguity aversion, the results in Column (2) of Table B3 with the alternative risk measures are effectively the same as the original results in Column (1). In both cases, risk aversion has a strong positive relation with ambiguity aversion (index b). For perceived ambiguity, the main difference is that the alternative measure of probability weighting in Column (4) of Table B3 has an insignificant relation with perceived ambiguity, different from the original results with index a_r for risk. This is likely the result of multicollinearity between risk seeking attitudes and the alternative measure of Inverse-S, as the correlation between *Alt Inverse-S* and *Alt. Risk Aversion* is -0.5 (see Table B2).

Table B2: Correlations of Alternative Risk Attitude Measures

The table shows correlations between the main risk attitude measures, *Risk Aversion* (index b_r for risk) and *Likelihood Insensitivity* (index a_r for risk), and two alternative non-parametric measures: *Alt. Risk Aversion* and *Alt. Inverse-S*, defined above. The sample consists of $n = 295$ investors.

	(1) <i>Risk Aversion</i> (b_r)	(2) <i>Alt. Risk Aversion</i>	(3) <i>Likelihood Insensitivity</i> (a_r)	(4) <i>Alt. Inverse-S</i>
<i>Risk Aversion</i> (b_r)	1.00			
<i>Alt. Risk Aversion</i>	0.90	1.00		
<i>Likelihood Insensitivity</i> (a_r)	0.28	0.02	1.00	
<i>Alt. Inverse-S</i>	-0.51	-0.51	0.59	1.00

Table B3: Analysis of Heterogeneity in Ambiguity Attitudes and Perceived Ambiguity

Columns (1) and (2) show estimation results for the regression model in Equation (7), with index b (ambiguity aversion) toward the four investments as the dependent variable. In Column (1), the control variables for risk attitudes are index b and a for risk, showing the same results as Table 2 in the main paper. In Column (2), as a robustness check, *Alt. Risk Aversion* and *Alt. Inverse-S* are used as risk attitude measures. Column (3) and (4) show results for the panel regression model in Equation (9), with index a as the dependent variable. Violations of monotonicity ($a_{i,s} > 1$) and negative values of index a ($a_{i,s} < 0$) are excluded, so index a can be interpreted as the perceived level of ambiguity. In Column (3), index b and a for risk are used as measures of risk attitudes, showing the same results as Table 4 in the main paper. In Column (4), as a robustness check, *Alt. Risk Aversion* and *Alt. Inverse-S* are used as the risk attitude measures. *, **, *** denote significant coefficients at the 10%, 5% and 1% level.

	(1)	(2)	(3)	(4)
	Index b	Index b	Index a	Index a
Constant	0.213	0.268	0.915***	0.968***
Dummy Familiar Stock	-0.012	-0.012	-0.103***	-0.102***
Dummy MSCI World	0.042**	0.042**	-0.016	-0.014
Dummy Bitcoin	0.007	0.007	0.011	0.014
Education	-0.018	-0.020	-0.034***	-0.036***
Age	0.003*	0.004*	0.002*	0.003**
Female	0.059	0.045	0.005	-0.001
Single	-0.090*	-0.084*	-0.045	-0.046
Employed	-0.042	-0.045	0.028	0.025
Number of Children (log)	0.048	0.035	-0.032	-0.037
Family Income (log)	0.016	0.013	-0.010	-0.012
HH Fin. Wealth (log)	-0.011*	-0.011	0.007	0.007
HH Wealth Imputed	-0.050	-0.057	0.069	0.064
Financial Literacy	-0.015	-0.015	-0.022**	-0.023***
Risk Aversion	0.466***		0.041	
Likelihood Insensitivity	-0.084*		0.087***	
Alt. Risk Aversion		0.306***		0.044
Alt. Inverse-S		-0.021		0.017
Random Slope: Bitcoin	Yes	Yes	Yes	Yes
Random Slope: Stock	No	No	Yes	Yes
N Observations	1180	1180	794	794
I Respondents	295	295	284	284
Number of Variables	15	15	15	15
Log-Likelihood	-414.645	-416.836	-97.594	-103.413
Chi-Square	127.777	123.999	114.137	86.751
P-Value	0.000	0.000	0.000	0.000
ICC of Random Effect u_i^b	0.65	0.66	0.41	0.43
$Var[\varepsilon_{i,s}]$, Error	0.061	0.061	0.047	0.046
$Var[u_i]$, Random Constant	0.112	0.114	0.031	0.033
$Var[v_{i,4}]$, Slope Bitcoin	0.012	0.011	0.004	0.004
$Var[v_{i,2}]$, Slope Stock	-	-	0.004	0.004
$Var[\beta'D + \gamma'X]$, Observed	0.056	0.056	0.014	0.012
%, Error	25.3%	25.2%	46.9%	46.6%
%, Random Constant	46.5%	47.1%	30.1%	32.8%
%, Slope Bitcoin	4.8%	4.7%	4.2%	3.9%
%, Slope Stock	-	-	4.4%	4.4%
%, Observed Variables	23.3%	23.1%	14.3%	12.2%

B.2 Financial Literacy Questions

The financial literacy questions are drawn from Lusardi and Mitchell (2007) and Van Rooij, Lusardi, and Alessie (2011). Responses to the financial literacy questions were provided by the DHS (Centerdata), collected in a 2017 survey. For respondents with missing financial literacy data, these questions were included in our own DHS survey module.

The questions were preceded by the following instructions: *“The following 12 questions are about financial knowledge and investments. Please do not look up information and do not use a calculator. Your initial thought matters.”* Apart from the possible answers shown below each question, respondents could also choose “I do not know” and “Refuse to answer” as a response. [Correct answers shown in bold.]

FL1: Suppose you had 100 euro in a savings account and the interest rate was 2% per year. After 5 years, how much do you think you would have in the account if you left the money to grow?

1. **More than 102 euro**
2. Exactly 102 euro
3. Less than 102 euro

FL2: Assume a friend inherits euro 10,000 today and his sibling inherits 10,000 euro 3 years from now. Who is richer because of the inheritance?

1. **My friend**
2. His sibling
3. They are equally rich

FL3: Suppose that in the year 2018, your income has doubled and prices of all goods have doubled too. In 2018, how much will you be able to buy with your income?

1. More than today
2. **The same**
3. Less than today

FL4: Suppose that you have 100 euro in a savings account and the interest is 20% per year, and you never withdraw the money or interest. How much do you have on the account after 5 years?

1. **More than 200 euro**
2. Exactly 200 euro
3. Less than 200 euro

FL5: Suppose the interest on your savings account is 1% per year and the inflation is 2% per year. After 1 year, can you buy more, exactly the same, or less than today with the money on the account?

1. More than today
2. Exactly the same as today
3. **Less than today**

FL6: Is the following statement true, or not true?

“A company stock usually provides a less risky return than an equity mutual fund.”

1. *True*
2. ***Not true***

FL7: Which of the following statements describes the main function of the stock market?

1. *The stock market helps to predict stock earnings*
2. *The stock market results in an increase in the price of stocks*
3. ***The stock market brings people who want to buy stocks together with those who want to sell stocks***
4. *None of the above*

FL8: Which of the following statements is correct? If somebody buys the stock of firm B in the stock market:

1. ***He owns a part of firm B***
2. *He has lent money to firm B*
3. *He is liable for firm B's debts*
4. *None of the above*

FL9: Which of the following statements is correct?

1. *If one invests in a mutual fund, one cannot withdraw the money in the first year*
2. ***Mutual funds can invest in several assets, for example invest in both stocks and bonds***
3. *Mutual funds pay a guaranteed rate of return which depends on their past performance*
4. *None of the above*

FL10: Normally, which asset displays the highest fluctuations over time: a savings account, bonds or stocks?

1. *Savings accounts*
2. *Bonds*
3. ***Stocks***

FL11: When an investor spreads his money among different assets, does the risk of losing money: increase, decrease, or stay the same?

1. *Increase*
2. ***Decrease***
3. *Stay the same*

FL12: Is the following statement true, or not true? 'Stocks are normally riskier than bonds.'

1. ***Yes***
2. *No*

Online Appendix C. Model Specification Tests

C.1 Testing Source-Specific Random Slopes for Ambiguity Aversion

Table C1 below reports the results of likelihood-ratio tests for including random slopes in the panel model for ambiguity aversion, shown in Equation (7) and Table 2 in the main text. Our estimation approach is as follows: first, we estimate a baseline panel model for ambiguity aversion with only a random constant, and then random slopes are added to the model one at a time, followed by a likelihood-ratio test for their significance. A model with a full set of 3 random slopes plus a random constant is too complex to estimate given that there are only 4 repeated measurements and such an approach would give infeasible coefficients. For this reason, we add random slopes one at a time, and then test for their significance. Further, if an estimated random slope model turns out to have insignificant variance ($\sigma_{v,s}^b = 0$), or perfect correlation with the random constant ($Cor(u_i^b, v_{i,s}^b) = 1$ or -1), then the model is considered invalid and not used. The results in Table C1 show that a model with a random slope for Bitcoin has significantly better fit than the baseline model with only a random constant ($p < 0.001$).

Table C1: Testing Random Slopes for Ambiguity Aversion

The table shows the results of likelihood-ratio tests for including random slopes in the panel model for ambiguity aversion (index b), Equation (7) in the main text. The first row shows the log-likelihood (LL) of a baseline model for index b with only a random constant and indicators for different investments, similar to Model 2 in Table 2 of the main text. The second, third and fourth row show the log-likelihood (LL) of the model after adding a random slope for the familiar stock, MSCI World and Bitcoin, respectively. The column “Chi-square rel. to baseline” shows the likelihood ratio test to see if the goodness of fit has increased significantly, with the “p-value” reported in the next column. The column “Par. Values feasible” indicates whether the estimated coefficient values are feasible (Yes or No): a random slope model with insignificant variance ($\sigma_{v,s}^b = 0$) or perfect correlation with the random constant ($Cor(u_i^b, v_{i,s}^b) = 1$ or -1) is invalid.

Model specification	LL	Chi-square rel. to baseline	p-value	Par. values feasible
Baseline model	-482.2			
Random slope for Stock	-482.2	0.002	0.999	No
Random slope for MSCI World	-482.1	0.234	0.889	No
Random slope for Bitcoin	-467.8	28.828	0.000	Yes

C.2 Testing Source-Specific Random Slopes for Perceived Ambiguity

Table C2 reports the results of likelihood-ratio tests for including random slopes in the panel model for perceived ambiguity, index a , shown in Equation (9) and Table 4 in the main text. The results show that a model with a random slope for the familiar stock has significantly better fit than the baseline model with only a random constant ($p = 0.006$), but the parameter values are infeasible. A model with a random slope for Bitcoin has marginally better fit than the baseline model ($p = 0.092$) and the parameter estimates are feasible. Next, we also estimate a model with both random slopes for the familiar stock and Bitcoin added, which has significantly better fit than the baseline model ($p = 0.013$) and feasible coefficient values. The model with two random slopes also has significantly better fit than the model with a random slope for Bitcoin only ($p = 0.021$, not reported in the table). In sum, the best fitting model for perceived ambiguity is the one with a random slope for both the familiar stock and Bitcoin.

Table C2: Testing Random Slopes for Perceived Ambiguity

The table shows the results of likelihood-ratio tests for including random slopes in the panel model for perceived ambiguity (index a), Equation (9) in the main text. Only values of index a between 0 and 1 are included, so index a can be interpreted as perceived ambiguity. The first row shows the log-likelihood (LL) of a baseline model for index a with only a random constant and indicators for different investments, similar to Model 2 in Table 4 of the main text. The second, third and fourth row show the log-likelihood (LL) of a model with a random slope for the familiar stock, MSCI World and Bitcoin, respectively. The fifth row shows the log-likelihood (LL) of a model with two random slopes for the familiar stock *and* Bitcoin. The column “Chi-square rel. to baseline” shows the likelihood ratio test to see if the model goodness of fit has increased significantly relative to the baseline model, with the “p-value” reported in the next column. The column “Par. Values feasible” indicates whether the estimated coefficient values are feasible (Yes or No): a random slope model with insignificant variance ($\sigma_{v,s}^b = 0$) or perfect correlation with the random constant ($Cor(u_i^b, v_{i,s}^b) = 1$ or -1) is invalid.

Model specification	LL	Chi-square rel. to baseline	p-value	Par. values feasible
Baseline model	-135.66			
Random slope for Stock	-130.58	10.176	0.006	No
Random slope for MSCI World	-135.49	0.337	0.845	No
Random slope for Bitcoin	-133.28	4.771	0.092	Yes
Random slope for Stock and Bitcoin	-128.41	14.499	0.013	Yes

C.3 Testing Random Effects and Source-Specific Slopes for Investments

Table C3 below reports the results of likelihood-ratio tests for including random effects in the panel probit model for investment in the familiar stock, MSCI World and Bitcoin, shown in Equation (10) and Table 5 in the main text. Our estimation approach is as follows: first, we estimate a baseline panel probit model for investment ownership, similar to Column (1) in Table 5 of the main text. Next, we add a random effect (random constant) to the model and test its significance with a likelihood ratio test, shown in the second row in Table C3. The results show that adding a random effect does not improve the model fit ($p = 0.250$). The reason is that asset ownership is not much correlated between different investments.

The baseline model for asset ownership in Column (1) of Table 5 in the main text assumes that the slope coefficients of index a and b (i.e., the effects of perceived ambiguity and ambiguity aversion) are the same for the familiar stock, MSCI World and Bitcoin. To test this assumption, we add 4 interaction terms between index b and a with dummies for MSCI World (d_3) and Bitcoin (d_4). The likelihood ratio test shown in the third row of Table C3 confirms that allowing index a and b to have a different impact on each investment does not improve the model fit ($p = 0.562$).

Finally, in rows 4 to 6 of Table C3 we repeat these specification tests for the model in Column (4) of Table 5, using the fitted values of index a and b as the main independent variables. The test conclusions are the same, namely that including random effects and different slope coefficients for a and b that vary across the investments do not add value to the model.

Table C3: Testing Random Effects and Interaction Effects for Investment

The table shows the results of likelihood-ratio tests for including random effects in the panel probit model for asset ownership shown in Equation (10) and Table 5 in the main text. The first row shows the log-likelihood (LL) of a baseline probit model for investments, the same as Column (1) in Table 5 in the main text. The second row shows the log-likelihood (LL) of the model after adding a random effect (constant) to the model. The third row shows the model log-likelihood (LL) after allowing the impact of a and b on asset ownership to differ across investments, using two interaction terms. The column “Chi-square rel. to baseline” shows the likelihood ratio test to see if the goodness of fit has increased significantly, with the “p-value” reported in the next column. Row 4-6 of the table repeat these tests for the model in Column (4) of Table 5 in the main text, using fitted values of index a and b .

Model specification	Chi-square		
	LL	rel. to baseline	p-value
Baseline model in Table 5, Column (1)	-228.78		
Random effect added	-228.55	0.454	0.250
Different slopes of a and b for MSCI World and Bitcoin	-227.29	2.977	0.562
Baseline model in Table 5, Column (4)	-152.43		
Random effect added	-152.43	0.000	0.498
Different slopes of a and b for MSCI World and Bitcoin	-149.94	5.000	0.287

Online Appendix D. Repeated Measurement of Index b with Single Events

The ambiguity aversion index b of Baillon et al. (2018b) is calculated using matching probabilities which are averaged over three events:

$$(D1) \quad b = 1 - \bar{m}_c - \bar{m}_s,$$

with $-1 \leq b \leq 1$. Here $\bar{m}_s = (m_1 + m_2 + m_3)/3$ denotes the average single-event matching probability, and $\bar{m}_c = (m_{12} + m_{13} + m_{23})/3$ is the average composite-event matching probability. The decision-maker is ambiguity averse for $b > 0$, ambiguity seeking for $b < 0$, and ambiguity neutral for $b = 0$.

The good measurement reliability for index b reported in the main text can arise from using natural sources rather than artificial ones, but also from averaging over three events. To investigate this issue, in this Online Appendix we redo the analysis using three separate estimates for index b per source, without averaging:

$$(D2) \quad b_1 = 1 - (m_1 + m_{23}),$$

$$(D3) \quad b_2 = 1 - (m_2 + m_{13}), \text{ and}$$

$$(D4) \quad b_3 = 1 - (m_3 + m_{12}).$$

Table D1 below shows summary statistics for the three separate b -indexes (ambiguity aversion), for the local stock market index (*aex*), a familiar company stock (*stock*), the MSCI World stock index (*msci*), and Bitcoin (*bitcoin*), for the set of $n = 295$ investors. The table also shows Hotelling's T^2 test for the null hypothesis that the means of the three b -indexes are equal, which cannot be rejected for each source. Further, Table D1 shows Cronbach's alpha, a proxy for measurement reliability based on the correlations between b_1 , b_2 , and b_3 , for each investment separately. Based on the values of Cronbach's alpha, ranging between 0.87 to 0.93, we conclude that measurement reliability for ambiguity aversion is high.

Table D2 below shows the correlations between the three measurements of index b for each source, as well as the between-source correlations. We note that the within-source correlations of the three b -indexes are especially high, ranging between 0.67 to 0.84, which is another indication of good measurement reliability. The between-source correlations range from 0.47 to 0.67, somewhat lower, but consistent with the main conclusion that ambiguity aversion for different sources is related and mainly driven by one underlying factor.

Next, we estimate an econometric model similar to Equation (7) in the main text, but with an additional "time dimension" j , representing the three measurements of index b for each source s :

$$(D5) \quad b_{i,j,s} = \beta_1 + \sum_{s=2}^4 (\beta_s + v_{i,s}^b) d_s + \sum_{k=1}^K \gamma_k^b X_{i,k} + u_i^b + \varepsilon_{i,j,s}^b,$$

$$i = 1, 2, \dots, I, s = 1, 2, 3, 4, j = 1, 2, 3$$

where $b_{i,j,s}$ is measurement $j = 1, 2, 3$, for index b (ambiguity aversion) of respondent i toward source s , for the AEX index ($s = 1$), the familiar stock ($s = 2$), the MSCI World index ($s = 3$), and Bitcoin ($s = 4$). One advantage of using 3 separate measurements of index b is that it is now feasible

and statistically significant to add a source-specific random slope $v_{i,s}^b$ for the familiar stock ($s = 2$), the MSCI World index ($s = 3$), and Bitcoin ($s = 4$), in addition to the random constant that captures individual heterogeneity in ambiguity aversion toward the AEX Index.

Table D3 below shows the estimation results. In Model 1, the constant is 0.18, indicating significant ambiguity aversion toward investments on average, similar to the results in Table 2. Model 2 shows that ambiguity aversion is higher for MSCI World, although only marginally so (the joint p-value is 0.054 for the four source dummies). Additional tests show that adding random slopes for all three sources, capturing source-specific individual heterogeneity in ambiguity aversion, improves the model significantly; they are added in Model 3. The estimation results for Model 3 confirm that most variation in ambiguity aversion is common to all four sources (61%), while source-specific ambiguity aversion toward Bitcoin explains 6.9%, followed by 3.2% for MSCI World, and 3.0% for the familiar stock. The ICC in Models 1, 2, and 3 ranges from 0.60 to 0.74, confirming that measurement reliability for index b is high, also when not averaging the measurements over three events.

In Model 4 of Table D3, observed socio-demographic variables are added, explaining 5% of the variation in ambiguity aversion. Younger investors and singles tend to be less ambiguity averse, similar to the results in Table 2 in the main text. Then in Model 5, financial literacy and risk attitudes are added, accounting for 14% (=19.4% - 5.3%) of the variation. All variables together explain 19% of the variation in index b in Table D3 when using three separate measurements, versus 23% in Table 2 in the main text after averaging over the measurements. Overall, based on these similar results, we conclude that the good measurement reliability for index b we report in the main text is mostly due to using real-world sources instead of artificial events, rather than due to averaging.

Table D1: Summary Statistics of Single-Event b -indexes for Ambiguity Aversion

The table shows summary statistics for the three separate b -indexes (ambiguity aversion), denoted b_1 , b_2 , and b_3 , for the local stock market index (*aex*), a familiar company stock (*stock*), the MSCI World stock index (*msci*) and Bitcoin (*bitcoin*). Each b -index is calculated using matching probabilities for a different single event and its complement, giving three repeated measurement for each source: b_1 , b_2 , and b_3 . For each investment source, the table also shows Hotelling's T^2 test for the null hypothesis that the means of the three b -indexes are equal. Further, for each investment, the table shows Cronbach's alpha, a proxy for measurement reliability based on the correlations between b_1 , b_2 , and b_3 . The sample consists of $n = 295$ investors.

	Mean	Median	St dev	Min	Max	n (obs.)
<u>AEX Index</u>						
b_{1_aex}	0.16	0.10	0.56	-1.00	1.00	295
b_{2_aex}	0.16	0.10	0.54	-1.00	1.00	295
b_{3_aex}	0.19	0.10	0.52	-1.00	1.00	295
Test of equal means: $T^2 = 1.94$, $p = 0.382$. Reliability: Cronbach's alpha = 0.87						
<u>Familiar Stock</u>						
b_{1_stock}	0.17	0.07	0.53	-1.00	1.00	295
b_{2_stock}	0.14	0.07	0.55	-1.00	1.00	295
b_{3_stock}	0.15	0.07	0.53	-1.00	1.00	295
Test of equal means: $T^2 = 1.83$, $p = 0.403$. Reliability: Cronbach's alpha = 0.88						
<u>MSCI World</u>						
b_{1_msci}	0.21	0.10	0.54	-1.00	1.00	295
b_{2_msci}	0.22	0.10	0.52	-1.00	1.00	295
b_{3_msci}	0.20	0.10	0.52	-1.00	1.00	295
Test of equal means: $T^2 = 1.21$, $p = 0.547$. Reliability: Cronbach's alpha = 0.90						
<u>Bitcoin</u>						
$b_{1_bitcoin}$	0.20	0.10	0.55	-1.00	1.00	295
$b_{2_bitcoin}$	0.17	0.10	0.54	-1.00	1.00	295
$b_{3_bitcoin}$	0.16	0.10	0.56	-1.00	1.00	295
Test of equal means: $T^2 = 4.19$, $p = 0.126$. Reliability: Cronbach's alpha = 0.93						

Table D2: Correlations of Single-Event b -indexes for Ambiguity Aversion

The table shows correlations for the three “single-event” b -indexes (ambiguity aversion), denoted b_1 , b_2 , and b_3 , for the local stock market index (*aex*), a familiar company stock (*stock*), the MSCI World stock index (*msci*), and Bitcoin (*bitcoin*). Each b -index is calculated using matching probabilities for a different single event and its complement, giving three repeated measurement for each source: b_1 , b_2 , and b_3 . The sample consists of $n = 295$ investors. Correlations between the three repeated measurements of index b for the same source are denoted in bold, with grey shading.

	AEX Index			Familiar stock			MSCI World			Bitcoin		
	b_1	b_2	b_3	b_1	b_2	b_3	b_1	b_2	b_3	b_1	b_2	b_3
b_{1_aex}	1.00											
b_{2_aex}	0.67	1.00										
b_{3_aex}	0.72	0.71	1.00									
b_{1_stock}	0.58	0.60	0.67	1.00								
b_{2_stock}	0.55	0.56	0.58	0.68	1.00							
b_{3_stock}	0.59	0.59	0.64	0.73	0.70	1.00						
b_{1_msci}	0.59	0.59	0.63	0.66	0.56	0.62	1.00					
b_{2_msci}	0.57	0.64	0.62	0.60	0.61	0.56	0.77	1.00				
b_{3_msci}	0.55	0.57	0.60	0.65	0.57	0.60	0.75	0.74	1.00			
$b_{1_bitcoin}$	0.52	0.58	0.63	0.58	0.56	0.58	0.55	0.53	0.54	1.00		
$b_{2_bitcoin}$	0.51	0.57	0.56	0.57	0.55	0.57	0.55	0.56	0.56	0.81	1.00	
$b_{3_bitcoin}$	0.47	0.51	0.57	0.53	0.49	0.55	0.52	0.49	0.51	0.84	0.81	1.00

Table D3: Analysis of Heterogeneity in Single-Event b -indexes for Ambiguity Aversion

The table shows estimation results for the regression model in Equation (D5) above, with index $b_{i,j,s}$ (ambiguity aversion) toward the four investments as the dependent variable. Three separate measures of index b are used for each investment source. In Models 3, 4, and 5, three random slopes are included to capture heterogeneity in ambiguity aversion toward Bitcoin, the familiar stock and MSCI World, which are jointly significant based on a likelihood ratio test (not reported here). Model 4 includes observed socio-demographic variables: education, age, gender, single, an indicator for employment, the logarithm of the number of children living at home, family income, and household financial wealth, plus a dummy for missing wealth. Model 5 adds variables for financial literacy, risk aversion, and likelihood insensitivity. The sample consists of $n = 295$ investors. *, **, *** denote significant coefficients at the 10%, 5% and 1% level.

	Model 1	Model 2	Model 3	Model 4	Model 5
	Index b	Index b	Index b	Index b	Index b
Constant	0.177***	0.168***	0.168***	0.144	0.202
Dummy familiar stock		-0.012	-0.012	-0.012	-0.012
Dummy MSCI World		0.042**	0.042**	0.042**	0.042**
Dummy Bitcoin		0.007	0.007	0.007	0.007
Education				-0.010	-0.017
Age				0.006***	0.003*
Female				0.072	0.060
Single				-0.118**	-0.093*
Employed				-0.041	-0.043
Number of Children (log)				0.060	0.050
Family Income (log)				-0.011	0.015
HH Fin. Wealth (log)				-0.016*	-0.011*
HH Wealth Imputed				-0.130	-0.047
Financial Literacy					-0.014
Risk Aversion					0.467***
Likelihood Insensitivity					-0.083*
N observations	3540	3540	3540	3540	3540
I respondents	295	295	295	295	295
Number of variables	0	3	3	12	15
Log-Likelihood	-1638.455	-1632.330	-1391.678	-1379.143	-1338.296
Chi-Square	-	7.645	7.645	46.263	129.668
p-value	-	0.054	0.054	0.000	0.000
ICC of random effect u_i^b	0.60	0.60	0.74	0.72	0.68
$Var[\varepsilon_{i,s}^b]$, error	0.116	0.115	0.074	0.074	0.074
$Var[u_i^b]$, random constant	0.174	0.174	0.177	0.163	0.124
$Var[v_{i,4}^b]$, slope Bitcoin	-	-	0.020	0.020	0.019
$Var[v_{i,3}^b]$, slope MSCI	-	-	0.009	0.009	0.009
$Var[v_{i,2}^b]$, slope Stock	-	-	0.009	0.008	0.007
$Var[\beta'D + \gamma'X]$, observed	-	0.0004	0.0004	0.015	0.056
%, error	39.9%	39.8%	25.6%	25.5%	25.5%
%, random constant	60.1%	60.1%	61.2%	56.4%	42.8%
%, slope Bitcoin	-	-	6.9%	7.1%	6.7%
%, slope MSCI	-	-	3.2%	3.0%	3.0%
%, slope Stock	-	-	3.0%	2.8%	2.5%
%, observed variables	-	0.1%	0.1%	5.3%	19.4%

Online Appendix E. Robustness Checks

Section E.1 and E.2 first presents the main results of the paper for ambiguity attitudes after screening out investors who violate monotonicity conditions. Then, as a robustness check, Section E.3 reports the main results after screening out investors who make several mistakes on the ambiguity questions, selecting dominated rows. Further, Section E.4 excludes investors who spent less than 10 minutes on the survey module. In Section E.5, the asset ownership regressions are repeated for each investment separately, with a limited set of control variables.

E.1 Excluding investors who violate weak monotonicity

As a robustness check, we repeat the analysis of heterogeneity in ambiguity aversion in Table 2 after excluding values of $b_{i,s}$ for which $a_{i,s} > 1$, that is, after excluding violations of so-called weak monotonicity. Summary statistics of index b after excluding such violations appear in Table E1. The mean of b_{avg} in the restricted sample is 0.17, similar to the value of 0.18 in the full sample. Further tests show that, for all four investments, the mean of index b is not significantly different between those investors who violate monotonicity and those who do not. The proportions of ambiguity averse, seeking, and neutral investors based on b_{avg} in the restricted sample are 63%, 9%, and 28%, the same as in the full sample.

Estimation results for the panel models appear in Table E2. After excluding monotonicity violations, the average number of b -index observations per respondent reduces from 4 to 3.1, but only three investors have to be dropped ($n = 292$) for having insufficient data to estimate the model. The ICC in Table E2 is 0.73 (in Model 2), slightly higher than the ICC of 0.69 in the full sample. The percentage of variation explained by individual characteristics is 28% in Table E2, higher than the 23% explained in the full sample. Ambiguity aversion is positively related to risk aversion and age, and higher for MSCI World.

Overall, the full-sample results for index b in Table 2 and the results in Table E2 after screening out violations of monotonicity are similar, with the main difference being a moderate increase in measurement reliability and the percentage of variation explained by observed variables. We conclude that violations of monotonicity have limited impact on the measurement of ambiguity aversion (index b). Rather, monotonicity violations more strongly affect a-insensitivity (index a) and perceived ambiguity, as shown in the main text, as index a is measured from differences in matching probabilities between composite and single events ($\bar{m}_c - \bar{m}_s$).

Table E1: Summary Statistics of b -index after Excluding Monotonicity Violations

The table shows summary statistics for ambiguity aversion (index b), similar to Table 1 of the main text, after excluding observations for which monotonicity was violated based on $a > 1$.

	Mean	Median	St dev	Min	Max	n (obs.)
b_{aex}	0.14	0.08	0.50	-1.00	1.00	218
b_{stock}	0.17	0.10	0.50	-1.00	1.00	229
b_{msci}	0.20	0.14	0.50	-1.00	1.00	228
$b_{bitcoin}$	0.20	0.16	0.54	-1.00	1.00	221
b_{avg}	0.17	0.13	0.43	-1.00	1.00	235

Table E2: Econometric Models for b -index after Excluding Monotonicity Violations

The table shows estimation results for the panel regression model in Equation (7), with index b (ambiguity aversion) as the dependent variable, similar to Table 2 in the main text, but after excluding violations of monotonicity based on $a > 1$.

	Model 1	Model 2	Model 3	Model 4	Model 5
	Index b	Index b	Index b	Index b	Index b
Constant	0.177***	0.147***	0.148***	0.229	0.237
Dummy Familiar Stock		0.018	0.015	0.015	0.016
Dummy MSCI World		0.057**	0.055**	0.056**	0.058**
Dummy Bitcoin		0.045*	0.045*	0.045*	0.045*
Education				-0.008	-0.016
Age				0.007***	0.004**
Female				0.089	0.084
Single				-0.119*	-0.089*
Employed				0.020	0.024
Number of Children (log)				0.081	0.072
Family Income (log)				-0.037***	-0.008
HH Fin. Wealth (log)				-0.017*	-0.013*
HH Wealth Imputed				-0.152	-0.065
Financial Literacy					-0.012
Risk Aversion					0.512***
Likelihood Insensitivity					-0.059
Random Slope: Bitcoin	No	No	Yes	Yes	Yes
N Observations	896	896	896	896	896
I Respondents	292	292	292	292	292
Number of Variables	0	3	3	12	15
Log-Likelihood	-377.364	-374.351	-365.070	-352.332	-306.543
Chi-Square	-	7.894	8.056	51.159	158.412
P-Value	-	0.048	0.045	0.000	0.000
ICC of Random Effect u_i^b	0.73	0.73	0.77	0.75	0.67
$Var[\varepsilon_{i,s}^b]$, Error	0.067	0.066	0.054	0.054	0.054
$Var[u_i^b]$, Random Constant	0.179	0.179	0.180	0.163	0.113
$Var[v_{i,4}^b]$, Slope Bitcoin	-	-	0.011	0.012	0.013
$Var[\beta'D + \gamma'X]$, Observed	-	0.0005	0.0005	0.018	0.069
%, Error	27.2%	27.0%	22.1%	21.9%	21.8%
%, Random Constant	72.8%	72.8%	73.3%	65.9%	45.3%
%, Slope Bitcoin	-	-	4.5%	4.9%	5.2%
%, Observed Variables	-	0.2%	0.2%	7.2%	27.7%

E.2 Excluding investors with many set-inclusion monotonicity violations

Panel A of Table E3 reports set-inclusion monotonicity violations ($m_s > m_c$) for each source, when a respondent's matching probability for a single event is larger than for a composite event that includes the single event. Respondents could make up to 6 such violations for each investment source. This restriction is stricter than $a > 1$ analyzed previously. Table E3 shows that set-inclusion monotonicity is violated about 1.3 times out of 6 on average, at a rate of 22.7%. Similar rates are reported by Li et al. (2017), ranging from 14% to 28%.

As a robustness check, we exclude values of index b and a when investors violate the set-inclusion monotonicity conditions more than two times for a source. Table E3 shows summary statistics for the ambiguity attitude measures. In the restricted sample, the mean level of ambiguity aversion (index b) is the same as in the full sample, about 0.18 on average. A-insensitivity is significantly lower: the mean of a -index in Table E3 is 0.66, versus 0.79 in the full sample, after screening out respondents with many monotonicity violations.

Table E4 and E5 show the econometric analysis of heterogeneity in ambiguity aversion and perceived ambiguity, restricted to values of index b and a with two or less violations of set-inclusion monotonicity. Overall, the results are similar as in Table 2 and Table 4 in the main text. One minor difference is that the dummy for MSCI World is no longer significant in Table E4. Ambiguity aversion for MSCI World ($b = 0.20$) is still about 25% higher than for the domestic AEX index ($b = 0.15$), displaying home bias, but this difference is no longer statistically significant in the smaller sample size after screening in Table E4.

In Table E4, most variation in ambiguity aversion is driven by a general ambiguity aversion factor, the random constant, explaining 72% of the variation, while source-specific ambiguity aversion toward Bitcoin (the random slope) explains only 5%. Observed socio-demographic variables explain 7% of the variation in ambiguity aversion. Specifically, younger investors, singles, and investors with higher financial wealth tend to be less ambiguity averse. The percentage increases to 25% after including risk attitudes and financial literacy, with risk aversion having the strongest relation with ambiguity aversion. Overall, these results are similar to the full sample in Table 2.

For perceived ambiguity, the results in Table E5 after excluding those with many violations, are similar to Table 4 for the full sample in the main paper. The main conclusion is that compared to ambiguity aversion (index b), perceived ambiguity varies more between sources and ICC is lower. The main drivers of perceived ambiguity are education, financial literacy and likelihood insensitivity (probability weighting), suggesting it is a cognitive component.

Table E3: Descriptive Statistics for Ambiguity Measures – Restricted Sample

Panel A shows the average number of set-inclusion monotonicity violations for each source, with a maximum of six possible violations. Panel B shows summary statistics for ambiguity aversion (index b) and Panel C for a-insensitivity (index a), after excluding values of b and a when set-monotonicity was violated more than two times for a particular source. The average b -index (b_avg) and the average a -index (a_avg) are calculated using subjects who have b and a index values for at least 3 out of 4 sources after excluding sources with more than two set-inclusion monotonicity violations. The sample consists of $n = 295$ investors.

Panel A: Number of Set-Inclusion Monotonicity Violations

	<i>Max possible number of violations</i>	<i>Average number of violations</i>	<i>% of Max</i>
<i>AEA index</i>	6	1.48	24.6%
<i>Familiar stock</i>	6	1.32	21.9%
<i>MSCI World index</i>	6	1.37	22.8%
<i>Bitcoin</i>	6	1.29	21.6%
<i>All four investments</i>	24	5.46	22.7%

Panel B: Ambiguity Aversion, for Investors with Two or Fewer Violations

	Mean	Median	St dev	Min	Max	<i>n (obs.)</i>
<i>b_aex</i>	0.15	0.09	0.50	-1.00	1.00	227
<i>b_stock</i>	0.15	0.07	0.50	-1.00	1.00	245
<i>b_msci</i>	0.20	0.14	0.50	-1.00	1.00	240
<i>b_bitcoin</i>	0.21	0.16	0.54	-1.00	1.00	233
<i>b_avg</i>	0.18	0.12	0.45	-1.00	1.00	227

Panel C: A-Insensitivity, for Investors with Two or Fewer Violations

	Mean	Median	St dev	Min	Max	<i>n (obs.)</i>
<i>a_aex</i>	0.66	0.83	0.44	-0.70	1.45	227
<i>a_stock</i>	0.56	0.65	0.59	-1.81	2.00	245
<i>a_msci</i>	0.67	0.81	0.48	-1.51	2.00	240
<i>a_bitcoin</i>	0.72	0.98	0.45	-1.02	2.00	233
<i>a_avg</i>	0.66	0.72	0.37	-0.53	1.73	227

Table E4: Analysis of Heterogeneity in Ambiguity Aversion, Two or Fewer Violations

The table shows estimation results for the panel regression model in Equation (7), with index b (ambiguity aversion) as the dependent variable, similar to Table 2 in the main text, but only including index b values when the respondent violated set-inclusion monotonicity two times or fewer on the six choice lists for a particular source.

	Dependent variable: Ambiguity aversion (Index b)				
	Model 1	Model 2	Model 3	Model 4	Model 5
Constant	0.176*** (0.026)	0.159*** (0.030)	0.161*** (0.030)	0.146 (0.224)	0.170 (0.245)
Dummy Familiar Stock		0.002 (0.024)	-0.001 (0.023)	-0.001 (0.023)	-0.001 (0.023)
Dummy MSCI World		0.037 (0.023)	0.036 (0.023)	0.036 (0.023)	0.038 (0.023)
Dummy Bitcoin		0.029 (0.027)	0.027 (0.027)	0.027 (0.027)	0.028 (0.027)
Education				-0.011 (0.018)	-0.020 (0.018)
Age				0.007*** (0.002)	0.004** (0.002)
Female				0.083 (0.065)	0.072 (0.056)
Single				-0.126** (0.062)	-0.099* (0.053)
Employed				0.005 (0.073)	0.006 (0.061)
Number of Children (log)				0.057 (0.064)	0.043 (0.059)
Family Income (log)				-0.018 (0.014)	0.009 (0.016)
HH Fin. Wealth (log)				-0.018* (0.009)	-0.014** (0.007)
HH Wealth Imputed				-0.150 (0.120)	-0.072 (0.095)
Financial Literacy					-0.011 (0.018)
Risk Aversion					0.479*** (0.067)
Likelihood Insensitivity					-0.075 (0.051)
Random Slope: Bitcoin	No	No	Yes	Yes	Yes
Observations n	945	945	945	945	945
ICC of Random Effect u_i^b	0.71	0.71	0.76	0.74	0.67
$Var[\varepsilon_{i,s}^b]$, Error	0.073 (29%)	0.073 (29%)	0.059 (23%)	0.059 (23%)	0.059 (23%)
$Var[u_i^b]$, Random Constant	0.178 (71%)	0.178 (71%)	0.180 (72%)	0.163 (65%)	0.120 (47%)
$Var[v_{i,4}^b]$, Slope Bitcoin	-	-	0.013 (5%)	0.013 (5%)	0.013 (5%)
$Var[\beta'D + \gamma'X]$, Observed	-	0.000 (0%)	0.000 (0%)	0.017 (7%)	0.062 (25%)

Table E5: Analysis of Heterogeneity in Perceived Ambiguity, Two or Fewer Violations

The table shows estimation results for the panel regression model in Equation (9), with index a (perceived ambiguity) as the dependent variable, similar to Table 4 in the main text, including only observations of index a when the respondent violated set-inclusion monotonicity two or fewer times on the six choice lists for a source. Similar to Table 4, only values of index a between 0 and 1 are included, so index a can be interpreted as perceived ambiguity.

	Dependent variable: Perceived ambiguity (Index a , between 0 and 1)				
	Model 1	Model 2	Model 3	Model 4	Model 5
Constant	0.687*** (0.016)	0.711*** (0.021)	0.716*** (0.021)	0.801*** (0.125)	0.942*** (0.151)
Dummy Familiar Stock		-0.093*** (0.027)	-0.103*** (0.026)	-0.104*** (0.026)	-0.105*** (0.026)
Dummy MSCI World		-0.018 (0.024)	-0.021 (0.024)	-0.020 (0.023)	-0.021 (0.024)
Dummy Bitcoin		0.008 (0.025)	0.009 (0.026)	0.008 (0.026)	0.008 (0.025)
Education				-0.040*** (0.010)	-0.033*** (0.010)
Age				0.003*** (0.001)	0.002* (0.001)
Female				0.021 (0.032)	0.004 (0.033)
Single				-0.062* (0.033)	-0.047 (0.031)
Employed				0.029 (0.039)	0.030 (0.037)
Number of Children (log)				-0.033 (0.040)	-0.037 (0.038)
Family Income (log)				-0.019** (0.009)	-0.009 (0.010)
HH Fin. Wealth (log)				0.003 (0.006)	0.006 (0.006)
HH Wealth Imputed				0.051 (0.058)	0.056 (0.064)
Financial Literacy					-0.025*** (0.009)
Risk Aversion					0.052 (0.032)
Likelihood Insensitivity					0.081** (0.033)
Random Slope: Stock/Bitcoin	No	No	Yes	Yes	Yes
Observations n	749	749	749	749	749
ICC of Random Effect u_i^b	0.47	0.47	0.52	0.47	0.44
$Var[\varepsilon_{i,s}^a]$, Error	0.056 (53%)	0.054 (52%)	0.046 (43%)	0.046 (44%)	0.047 (45%)
$Var[u_i^a]$, Random Constant	0.049 (47%)	0.048 (47%)	0.048 (45%)	0.039 (37%)	0.034 (33%)
$Var[v_{i,4}^a]$, Slope Bitcoin	-	-	0.004 (4%)	0.004 (4%)	0.003 (3%)
$Var[v_{i,2}^a]$, Slope Stock	-	-	0.006 (6%)	0.006 (6%)	0.005 (5%)
$Var[\alpha'D + \gamma'X]$, Observed	-	0.002 (2%)	0.002 (2%)	0.010 (9%)	0.014 (14%)

E.3 Excluding investors who make many errors on the ambiguity questions

As a robustness check, we now exclude investors who make many errors on the choice lists when measuring ambiguity attitudes. Respondents could make two errors on each choice list: always choosing Option A, or always choosing Option B. Respondents who always select Option A act as if the ambiguous event has a 100% chance of occurring, while respondents who always select Option B act as if the chance is 0%. Although such beliefs are possible, these responses tend to become inconsistent when made repeatedly for the six related events. Panel A of Table E6 shows the percentage of investors making zero mistakes, 1 or 2 errors, 3 or 4 errors, and 5 or 6 errors, on the six choice lists. We note that the majority of investors make no mistakes, ranging from 69% to 75% depending on the source. However, there is also a small group of respondents who make many mistakes. As a robustness check, we now exclude investors who make three or more mistakes on the six ambiguity choice lists for a particular source, using pairwise deletion.

The proportion of ambiguity averse, neutral, and seeking respondents are 60%, 9%, 31%, respectively, based on b_{avg} , with $n = 221$ observations. These proportions are not significantly different compared to the full sample (63%, 9%, 28%). This illustrates that ambiguity averse and ambiguity seeking attitudes are not driven by respondents making many errors on the choice lists.

Table E6 shows summary statistics for the ambiguity attitude measures. In the restricted sample, the mean level of ambiguity aversion (index b) is significantly lower at 0.12, versus 0.18 in the full sample. Investors making many errors on the ambiguity questions have higher matching probabilities and larger values of index b , driven by the error of preferring unambiguous Option B on every row of the choice list. The mean of index b therefore drops, after excluding these most ambiguity averse choices. For a-insensitivity and perceived ambiguity, there is no significant difference between those making more or fewer mistakes: the mean of a -index in Table E6 is 0.77, versus 0.79 in the full sample.

Table E7 shows the econometric analysis of heterogeneity in ambiguity aversion, after excluding values of index b when three or more errors were made. In this restricted sample, the measurement reliability of ambiguity aversion is similar to the full sample, with ICC's ranging from 0.66 to 0.72. Most of the variation in ambiguity aversion is driven by a general ambiguity aversion factor, the random constant, explaining 69% of the variation, while source-specific ambiguity aversion toward Bitcoin (the random slope) explains only 4%. Observed socio-demographic variables explain 6% of the variation in ambiguity aversion. Specifically, younger investors and investors with higher financial wealth tend to be less ambiguity averse. The percentage increases to 18% after including risk attitudes and financial literacy, with risk aversion having the strongest relation with ambiguity aversion. Overall, these results are similar to the full sample in Table 2.

For perceived ambiguity, the results in Table E8 after excluding those who make many mistakes, are similar to Table 4 for the full sample in the main paper. The main conclusion is that compared to ambiguity aversion (index b), perceived ambiguity varies more between sources and ICC is lower. The main drivers of perceived ambiguity are education, financial literacy and likelihood insensitivity (probability weighting), suggesting it is a cognitive component. The percentage of variation in perceived ambiguity explained by observable variables is 16% in Table E8, slightly higher than the 14% in the full sample.

Table E6: Descriptive Statistics for Ambiguity Measures – Restricted Sample

Panel A shows the percentage of investors making zero mistakes, 1 or 2 mistakes, 3 or 4 mistakes, and 5 or 6 mistakes, on the six choice lists for a particular investment. Panel B shows summary statistics for ambiguity attitudes regarding the local stock market index (*b_aex*), a familiar company stock (*b_stock*), the MSCI World stock index (*b_msci*) and Bitcoin (*b_bitcoin*), as well as the average of the four b-indexes (*b_avg*), including only observations when the respondent made two or fewer mistakes on the six choice lists for a particular investment. Panel C shows summary statistics of a-insensitivity for the local stock market index (*a_aex*), a familiar company stock (*a_stock*), the MSCI World stock index (*a_msci*) and Bitcoin (*a_bitcoin*), as well as the average of the four *a*-indexes (*a_avg*).

Panel A: Number of Mistakes on the Six Choice Lists

	No Mistake	1-2 Errors	3-4 Errors	5-6 Errors	<i>n</i> (obs.)
<i>aex</i>	73.9%	10.5%	6.8%	8.8%	295
<i>stock</i>	69.2%	13.6%	7.5%	9.8%	295
<i>msci</i>	74.9%	10.8%	5.4%	8.8%	295
<i>bitcoin</i>	73.2%	9.5%	5.4%	11.9%	295

Panel B: Ambiguity Aversion, for Investors Making Two or Fewer Errors

	Mean	Median	St dev	Min	Max	<i>n</i> (obs.)
<i>b_aex</i>	0.11	0.09	0.43	-0.98	0.98	249
<i>b_stock</i>	0.12	0.06	0.43	-0.98	0.98	244
<i>b_msci</i>	0.16	0.13	0.42	-0.98	0.98	253
<i>b_bitcoin</i>	0.13	0.10	0.44	-0.98	0.98	244
<i>b_avg</i>	0.12	0.10	0.37	-0.98	0.98	221

Panel C: A-Insensitivity, for Investors Making Two or Fewer Errors

	Mean	Median	St dev	Min	Max	<i>n</i> (obs.)
<i>a_aex</i>	0.81	0.96	0.51	-0.70	2.19	249
<i>a_stock</i>	0.69	0.80	0.63	-1.81	2.90	244
<i>a_msci</i>	0.76	0.85	0.53	-1.51	2.80	253
<i>a_bitcoin</i>	0.85	1.00	0.48	-0.99	2.61	244
<i>a_avg</i>	0.77	0.86	0.35	-0.29	1.73	221

Table E7: Analysis of Heterogeneity in Ambiguity Aversion, Investors Making Two or Fewer Errors
The table shows estimation results for the panel regression model in Equation (7), with index b (ambiguity aversion) as the dependent variable, similar to Table 2 in the main text, including only observations of index b when the respondent made two or fewer errors on the six choice list for a particular investment.

	Model 1	Model 2	Model 3	Model 4	Model 5
	Index b	Index b	Index b	Index b	Index b
Constant	0.129***	0.109***	0.110***	0.277	0.352
Dummy Familiar Stock		0.004	0.003	0.003	0.002
Dummy MSCI World		0.052**	0.051**	0.052**	0.051**
Dummy Bitcoin		0.024	0.022	0.023	0.023
Education				-0.001	-0.008
Age				0.005**	0.003*
Female				0.037	0.050
Single				-0.103*	-0.080*
Employed				-0.011	-0.028
Number of Children (log)				0.007	0.017
Family Income (log)				-0.030*	-0.008
HH Fin. Wealth (log)				-0.019**	-0.013**
HH Wealth Imputed				-0.103	-0.024
Financial Literacy					-0.015
Risk Aversion					0.396***
Likelihood Insensitivity					-0.081*
Random Slope: Bitcoin	No	No	Yes	Yes	Yes
N Observations	990	990	990	990	990
I Respondents	272	272	272	272	272
Number of Variables	0	3	3	12	15
Log-Likelihood	-321.528	-318.226	-306.245	-294.778	-266.845
Chi-Square	.	8.080	7.930	42.617	86.985
P-Value	.	0.044	0.047	0.000	0.000
ICC of Random Effect u_i^b	0.66	0.66	0.72	0.70	0.66
$Var[\varepsilon_{i,s}^b]$, Error	0.064	0.063	0.051	0.051	0.051
$Var[u_i^b]$, Random Constant	0.124	0.124	0.129	0.116	0.094
$Var[v_{i,4}^b]$, Slope Bitcoin	-	-	0.007	0.008	0.008
$Var[\beta'D + \gamma'X]$, Observed	-	0.0004	0.0004	0.012	0.034
%, Error	34.0%	33.7%	27.3%	27.2%	27.3%
%, Random Constant	66.0%	66.1%	68.6%	61.9%	50.2%
%, Slope Bitcoin	-	-	4.0%	4.5%	4.2%
%, Observed Variables	-	0.2%	0.2%	6.4%	18.3%

Table E8: Analysis of Heterogeneity in Perceived Ambiguity, Investors Making Two or Fewer Errors

The table shows estimation results for the panel regression model in Equation (9), with index a (perceived ambiguity) as the dependent variable, similar to Table 4 in the main text, including only observations of index a when the respondent made two or fewer errors on the six choice lists for a particular investment. Further, similar to Table 4, only values of index a between 0 and 1 are included, so index a can be interpreted as perceived ambiguity.

	Model 1	Model 2	Model 3	Model 4	Model 5
	Index a	Index a	Index a	Index a	Index a
Constant	0.666***	0.698***	0.701***	0.861***	0.952***
Dummy Familiar Stock		-0.111***	-0.118***	-0.122***	-0.122***
Dummy MSCI World		-0.026	-0.028	-0.030	-0.031
Dummy Bitcoin		-0.000	-0.001	-0.004	-0.006
Education				-0.042***	-0.035***
Age				0.002*	0.001
Female				0.019	0.008
Single				-0.056*	-0.044
Employed				0.003	0.003
Number of Children (log)				-0.052	-0.050
Family Income (log)				-0.024***	-0.017
HH Fin. Wealth (log)				0.010	0.012**
HH Wealth Imputed				0.089*	0.062
Financial Literacy					-0.019**
Risk Aversion					-0.014
Likelihood Insensitivity					0.124***
Random Slope: Bitcoin	No	No	Yes	Yes	Yes
Random Slope: Stock	No	No	Yes	Yes	Yes
N Observations	659	659	659	659	659
I Respondents	258	258	258	258	258
Number of Variables	0	3	3	12	15
Log-Likelihood	-128.437	-118.045	-110.318	-91.381	-79.592
Chi-Square	.	20.849	25.055	80.406	115.251
P-Value	.	0.000	0.000	0.000	0.000
ICC of Random Effect u_i^a	0.42	0.44	0.51	0.47	0.43
$Var[\varepsilon_{i,s}^a]$, Error	0.058	0.056	0.044	0.044	0.045
$Var[u_i^a]$, Random Constant	0.043	0.043	0.044	0.035	0.029
$Var[v_{i,4}^a]$, Slope Bitcoin	-	-	0.006	0.006	0.007
$Var[v_{i,2}^a]$, Slope Stock	-	-	0.004	0.004	0.003
$Var[\alpha'D + \gamma'X]$, Observed	-	0.002	0.002	0.011	0.016
%, Error	57.7%	55.2%	43.9%	43.6%	44.8%
%, Random Constant	42.3%	42.8%	43.8%	35.1%	29.5%
%, Slope Bitcoin	-	-	6.2%	6.4%	6.6%
%, Slope Stock	-	-	3.9%	4.0%	2.9%
%, Observed Variables	-	2.0%	2.2%	10.9%	16.2%

E.4 Excluding investors who spent less than 10 minutes on the survey module

As a robustness check, we exclude 30 investors who spent less than ten minutes answering the questions in our DHS survey module. As spending fewer than ten minutes overall implies having 15 seconds or less per choice list (or question) on average, it provides a more direct measure for identifying respondents who devoted insufficient attention to the questions. Table E9 shows that the 30 investors who spent fewer than 10 minutes have a-insensitivity close to 1 on average. They were about 3 times more likely to always select the same row on each of the 6 choice lists for a source, which tends to give a -index close to 1.

Next, we exclude these 30 quick respondents and then repeat the main analyses in Table E10, E11 and E12. The results in the restricted sample are very similar to those shown in the main text, and support the expected relations formulated in Section 5. Hence, the results are not driven by the small group of respondents who spent less than 10 minutes on the ambiguity module questions.

Table E9: Descriptive Statistics for Ambiguity Measures – Quick Respondents

Panel A and B shows summary statistics for ambiguity aversion (index b) and for a-insensitivity (index a), including only 30 investors who spent less than 10 minutes answering the ambiguity survey module questions.

Panel A: Ambiguity Aversion, for Investors Spending less than 10 Minutes

	Mean	Median	St dev	Min	Max	n (obs.)
b_{aex}	0.22	0.10	0.56	-1.00	1.00	30
b_{stock}	0.18	0.11	0.58	-1.00	1.00	30
b_{msci}	0.24	0.10	0.55	-1.00	1.00	30
$b_{bitcoin}$	0.11	0.03	0.58	-1.00	1.00	30
b_{avg}	0.19	0.10	0.55	-1.00	1.00	30

Panel B: A-Insensitivity, for Investors Spending less than 10 Minutes

	Mean	Median	St dev	Min	Max	n (obs.)
a_{aex}	1.02	1.00	0.28	0.17	1.55	30
a_{stock}	1.00	1.00	0.28	0.40	1.98	30
a_{msci}	0.93	1.00	0.51	-0.86	2.10	30
$a_{bitcoin}$	0.98	1.00	0.46	0.10	2.51	30
a_{avg}	0.98	1.00	0.23	0.33	1.73	30

Table E10: Descriptive Statistics for Ambiguity Measures – Restricted Sample

Panel A and B shows summary statistics for ambiguity aversion (index *b*) and for a-insensitivity (index *a*), including only 265 investors who spent at least 10 minutes answering the ambiguity survey module questions.

Panel A: Ambiguity Aversion, for Investors Spending at Least 10 Minutes

	Mean	Median	St dev	Min	Max	<i>n</i> (obs.)
<i>b_aex</i>	0.16	0.10	0.47	-0.98	1.00	265
<i>b_stock</i>	0.15	0.07	0.47	-1.00	1.00	265
<i>b_msci</i>	0.21	0.16	0.47	-1.00	1.00	265
<i>b_bitcoin</i>	0.18	0.16	0.51	-1.00	1.00	265
<i>b_avg</i>	0.18	0.16	0.41	-0.99	1.00	265

Panel B: A-Insensitivity, for Investors Spending at Least 10 Minutes

	Mean	Median	St dev	Min	Max	<i>n</i> (obs.)
<i>a_aex</i>	0.80	0.96	0.55	-0.70	2.99	265
<i>a_stock</i>	0.65	0.79	0.66	-1.81	2.90	265
<i>a_msci</i>	0.76	0.90	0.52	-1.51	2.80	265
<i>a_bitcoin</i>	0.83	1.00	0.50	-1.02	2.61	265
<i>a_avg</i>	0.76	0.83	0.34	-0.29	1.62	265

Table E11: Analysis of Heterogeneity in Ambiguity Aversion, Spent at Least 10 Minutes

The table shows estimation results for the panel regression model in Equation (7), with index b (ambiguity aversion) as the dependent variable, similar to Table 2 in the main text, after excluding 30 respondents who spent less than 10 minutes answering the ambiguity survey module questions.

	Dependent variable: Ambiguity aversion (Index b)				
	Model 1	Model 2	Model 3	Model 4	Model 5
Constant	0.176*** (0.025)	0.162*** (0.029)	0.162*** (0.029)	0.147 (0.22)	0.341 (0.258)
Dummy Familiar Stock		-0.009 (0.022)	-0.009 (0.022)	-0.009 (0.022)	-0.009 (0.022)
Dummy MSCI World		0.045** (0.022)	0.045** (0.022)	0.045** (0.022)	0.045** (0.022)
Dummy Bitcoin		0.020 (0.027)	0.020 (0.027)	0.020 (0.027)	0.020 (0.027)
Education				-0.007 (0.018)	-0.017 (0.018)
Age				0.005** (0.002)	0.003 (0.002)
Female				0.023 (0.065)	0.023 (0.056)
Single				-0.129** (0.059)	-0.093* (0.052)
Employed				-0.005 (0.070)	-0.004 (0.058)
Number of Children (log)				-0.021 (0.061)	0.000 (0.06)
Family Income (log)				-0.006 (0.015)	0.024 (0.019)
HH Fin. Wealth (log)				-0.015* (0.008)	-0.009 (0.007)
HH Wealth Imputed				-0.140 (0.117)	-0.076 (0.095)
Financial Literacy					-0.031 (0.020)
Risk Aversion					0.438*** (0.072)
Likelihood Insensitivity					-0.088* (0.051)
Random Slope: Bitcoin	No	No	Yes	Yes	Yes
Observations n	1060	1060	1060	1060	1060
ICC of Random Effect u_i^b	0.65	0.65	0.71	0.69	0.63
$Var[\varepsilon_{i,s}^b]$, Error	0.080 (35%)	0.080 (34%)	0.064 (28%)	0.064 (28%)	0.064 (28%)
$Var[u_i^b]$, Random Constant	0.151 (65%)	0.151 (65%)	0.155 (67%)	0.142 (61%)	0.108 (47%)
$Var[v_{i,4}^b]$, Slope Bitcoin	-	-	0.013 (5%)	0.014 (6%)	0.013 (6%)
$Var[\beta'D + \gamma'X]$, Observed	-	0.000 (0%)	0.000 (0%)	0.012 (5%)	0.047 (20%)

Table E12: Analysis of Heterogeneity in Perceived Ambiguity, Spent at Least 10 Minutes

The table shows estimation results for the panel regression model in Equation (9), with index a (perceived ambiguity) as the dependent variable, similar to Table 4 in the main text, after excluding 30 respondents who spent less than 10 minutes answering the ambiguity survey module questions. Similar to Table 4, only values of index a between 0 and 1 are included, so index a can be interpreted as perceived ambiguity.

	Dependent variable: Perceived ambiguity (Index a , between 0 and 1)				
	Model 1	Model 2	Model 3	Model 4	Model 5
Constant	0.679*** (0.016)	0.702*** (0.022)	0.702*** (0.022)	0.762*** (0.132)	0.845*** (0.158)
Dummy Familiar Stock		-0.107*** (0.028)	-0.107*** (0.028)	-0.110*** (0.028)	-0.112*** (0.028)
Dummy MSCI World		-0.012 (0.026)	-0.012 (0.026)	-0.013 (0.025)	-0.015 (0.026)
Dummy Bitcoin		0.021 (0.027)	0.021 (0.027)	0.019 (0.027)	0.019 (0.027)
Education				-0.035*** (0.011)	-0.030*** (0.010)
Age				0.004*** (0.001)	0.003** (0.001)
Female				0.057 (0.033)	0.047 (0.033)
Single				-0.068** (0.034)	-0.056* (0.032)
Employed				-0.008 (0.039)	0.004 (0.037)
Number of Children (log)				-0.025 (0.041)	-0.022 (0.040)
Family Income (log)				-0.020 (0.013)	-0.013 (0.014)
HH Fin. Wealth (log)				0.004 (0.006)	0.006 (0.006)
HH Wealth Imputed				0.078 (0.050)	0.079 (0.056)
Financial Literacy					-0.018** (0.009)
Risk Aversion					0.038 (0.035)
Likelihood Insensitivity					0.092*** (0.033)
Random Constant	No	No	Yes	Yes	Yes
Observations n	705	705	705	705	705
ICC of Random Effect u_i^b	0.41	0.42	0.42	0.35	0.32
$Var[\varepsilon_{i,s}^a]$, Error	0.061 (59%)	0.058 (57%)	0.058 (57%)	0.058 (57%)	0.059 (57%)
$Var[u_i^a]$, Random Constant	0.042 (41%)	0.042 (41%)	0.042 (41%)	0.032 (31%)	0.027 (27%)
$Var[\alpha'D + \gamma'X]$, Observed	-	0.002 (2%)	0.002 (2%)	0.012 (12%)	0.016 (16%)

E.5 Asset Ownership Regressions for Each Investment Separately

Table 5 in the main text shows results for a probit model that explain *Invests in the Familiar Stock*, *Invests in MSCI World*, and *Invests in Crypto-Currencies* with ambiguity aversion (index b) and perceived ambiguity (index a), using a panel regression approach where the regression slope coefficients are assumed constant across investments. In this appendix, as a robustness check, we repeat the analysis for each asset separately. We first note that due to the small number of investors owning MSCI World and crypto-currencies, including a full set of socio-demographic control variables is infeasible, as it gives rise to perfect separation of the binary dependent variable. This is also the foremost reason that in the main text we apply a panel estimation approach.

Table E13 reports the estimation results for separate probit models to explain *Invests in the Familiar Stock*, *Invests in MSCI World*, and *Invests in Crypto-Currencies* in Columns (1), (2) and (3). The main independent variables are the predicted values $\hat{b}_{i,s}$ and $\hat{a}_{i,s}$ of ambiguity aversion and perceived ambiguity from the estimated panel models in Table 2 and Table 4 (Model 3), to reduce the impact of measurement error. First, in columns (1a), (2a), and (3a), only $\hat{b}_{i,s}$ and $\hat{a}_{i,s}$ and a constant are included in the model, to show the total effect of fitted perceived ambiguity and fitted ambiguity aversion. Then in columns (1b), (2b), and (3b) of Table E6 we add controls for household financial wealth and education, two key socio-demographic variables relevant for investment. Subsequently, in columns (1c), (2c), and (3c), we try to add controls for risk attitudes and financial literacy. We note that in Column (2c) for MSCI World, financial literacy could not be included as it led to perfect separation of the dependent variable, as all those who invest in MSCI World have a full score for financial literacy.

The results in Table E13 show that perceived ambiguity has a significant negative relation with investing in MSCI World and Bitcoin, but not with investing in the familiar stock. Ambiguity aversion has a negative relation with investing in Bitcoin only. As mentioned before, the full set of control variables could not be included due to the small number of investors who own MSCI World and Bitcoin. We chose to include education, wealth, financial literacy, risk aversion and insensitivity, as they are relevant for investments and potentially related to ambiguity attitudes.

Table E13: Investment in the Familiar Stock, MSCI World and Crypto-Currencies, with Controls

This table reports estimation results for a probit model explaining asset ownership with perceived ambiguity (fitted index a) and ambiguity aversion (fitted index b), similar to Table 5 in the main text, but estimated for each asset separately. The numbers displayed are estimated probit coefficients. In columns (1a), (1b), and (1c), the dependent variable is 1 if the respondent invests in the familiar individual stock and 0 otherwise. In columns (2a), (2b), and (2c), the dependent variable is 1 if the respondent invests in funds tracking the MSCI World equity index and 0 otherwise. In columns (3a), (3b), and (3c), the dependent variable is 1 if the respondent invests in crypto-currency and 0 otherwise. The main independent variables are ambiguity aversion and the perceived level of ambiguity about the asset, using fitted values from the panel regression models in Table 2 and Table 4 (specification Model 3 with random slopes). Only observations with $0 \leq a \leq 1$ are included and for this reason the sample size n varies in each column. In column (1b), (2b) and (3b), control variables for (log) household financial wealth and education are added. In column (1c), (2c) and (3c), controls for financial literacy, risk aversion and likelihood insensitivity are included. *, **, *** denote significant probit coefficients at the 10%, 5% and 1% level.

	Invests in Familiar Stock			Invests in MSCI World			Invests in Crypto-Currencies		
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)	(3a)	(3b)	(3c)
Perc. Ambiguity (fitted)	-0.693*	-0.555	-0.644	-3.163***	-3.705***	-3.259**	-2.350**	-1.661*	-2.053**
Amb. Aversion (fitted)	-0.077	-0.057	-0.038	0.486	0.238	0.379	-0.751**	-0.896**	-0.959*
Education		0.082			-0.234			0.500***	
HH Fin. Wealth (log)		0.016			0.019			-0.086	
Risk Aversion			0.209			0.187			0.186
Likelihood Insensitivity			0.212			0.079			-0.466
Financial Literacy			0.144**			---			0.009
N observations	192	192	192	205	205	205	205	205	205
I respondents	192	192	192	205	205	205	205	205	205
Number of variables	2	4	5	2	4	4	2	4	5
Log-Likelihood	-112.353	-111.608	-108.462	-13.608	-12.687	-13.560	-23.974	-20.976	-23.461
Chi-Square	3.502	4.851	9.748	13.515	28.784	30.057	6.499	15.501	15.335
P-value	0.174	0.303	0.083	0.001	0.000	0.000	0.039	0.004	0.009
Pseudo R-square	0.015	0.022	0.049	0.131	0.189	0.134	0.115	0.226	0.134

Online Appendix F. Results for Non-Investors

Our survey was also given to a random sample of 304 non-investors, with 230 complete and valid responses (76%). Summary statistics of their socio-demographic variables appear in Table F1. Compared to the investors, the non-investors are younger, less educated, more often female, have less financial wealth, and lower financial literacy. Only 18% of the non-investors know a company stock that they are familiar with.

Table F2 displays summary statistics of ambiguity attitudes in the non-investor group. As expected, a-insensitivity is significantly higher among non-investors on average: $a_{avg} = 0.86$ for non-investors vs. $a_{avg} = 0.79$ for investors ($p = 0.017$). Specifically, investors have significantly lower a-insensitivity for the familiar stock ($a_{stock} = 0.80$ vs. 0.69 , $p = 0.032$) and for the MSCI index ($a_{msci} = 0.87$ vs. 0.78 , $p = 0.038$).

The proportion of ambiguity averse, neutral, and seeking subjects are 65%, 11%, and 24%, based on b_{avg} , which is not significantly different from the investor group (63%, 9%, 28%). The mean level of aversion is similar for the groups of non-investors and investors: $b_{avg} = 0.20$ among non-investors, versus $b_{avg} = 0.18$ for investors ($p = 0.65$). In sum, ambiguity aversion toward investments is not so different between investors and non-investors on average, but a-insensitivity is significantly higher among non-investors. Hence, competence effects are most pronounced in a-insensitivity (and perceived ambiguity), the cognitive component of ambiguity attitudes.

The econometric models in Table F3 show that in the non-investor group, heterogeneity in ambiguity aversion is driven by a single random constant explaining 77% of the variation, while random slopes for Bitcoin and other sources are not significant. Further, there is no significant difference in the mean level of ambiguity aversion toward the four sources. Hence in the non-investor group, ambiguity aversion toward investments is driven by a single underlying factor, without distinction between sources. Measurement reliability is high, with ICC of 0.77. Further, higher ambiguity aversion is mainly explained by higher risk aversion and older age, with all observed variables jointly explaining up to 25% of the variation. Different from investors, non-investors with higher financial literacy tend to be less ambiguity averse.

The results for perceived ambiguity in Table F4 reveal that in the non-investor group, perceived ambiguity toward different investment is also driven largely by one underlying factor explaining 48% of the variation, while source-specific ambiguity about Bitcoin explains only 3%. The random slope for the familiar stock is not significant (different from Table 4), and there are no significant differences in the mean level of perceived ambiguity toward the four investments. Hence, non-investors indicate little distinction in perceived ambiguity between different types of investments.

Further, in the group of non-investors, education and financial literacy do not have a significant relation with perceived ambiguity in Table F4, different from the investor results in Table 4. Overall, observable variables explain only 7.5% of the variation in perceived ambiguity in the non-investor group. This supports our overall conclusion that, among non-investors, there is less variation in perceived ambiguity between investments and respondents, probably driven by this groups' overall unfamiliarity with investments.

Table F1: Descriptive Statistics of the Non-Investor Sample

This table reports summary statistics of the socio-demographics, risk preferences, financial literacy, and asset ownership of non-investor group in the DHS panel who indicated that they did not invest in financial assets as of 31 December 2016 (in the October 2017 DHS survey of wealth and assets). Sample size is $n = 230$. Family income (monthly, after tax) and household financial wealth are measured in euros. The reference category for employment status is either unemployed or not actively seeking work (21%).

	Mean	Median	St dev	Min	Max
<i><u>Socio-demographics</u></i>					
Age	55.96	57	16.11	19	93
Female	0.49	0	0.50	0	1
Single	0.29	0	0.45	0	1
Number of Children	0.66	0	1.08	0	6
Education	3.68	4	1.54	1	6
Employed	0.50	1	0.50	0	1
Retired	0.29	0	0.46	0	1
Household Income	2,938	2,681	1,474	0	10,000
Household Financial Wealth	44,001	17,578	85,582	0	956,470
<i><u>Risk Preferences</u></i>					
Risk Aversion (b_r)	0.12	0.12	0.49	-1.00	1.00
Indicator for Risk Aversion > 0	0.66	1.00	0.48	0.00	1.00
Likelihood Insensitivity (a_r)	0.67	0.76	0.53	-0.62	2.56
Indicator for LL. Insensitivity > 0	0.88	1.00	0.32	0.00	1.00
<i><u>Financial Literacy and Investments</u></i>					
Financial Literacy	8.55	9	3.02	0	12
Knows a Familiar Company Stock	0.183	1	0.39	0	1
Invests in Familiar Stock	0.030	0	0.17	0	1
Invests in Crypto-Currencies	0.026	0	0.16	0	1
Invests in MSCI World	0	0	0	0	0

Table F2: Descriptive Statistics for Ambiguity Measures – Non-Investor Sample

Panel A shows summary statistics for ambiguity attitudes regarding the local stock market index (b_{aex}), a familiar company stock (b_{stock}), the MSCI World stock index (b_{msci}), and Bitcoin ($b_{bitcoin}$), as well as the average of the four b -indexes (b_{avg}). Positive values of the b -index denote ambiguity aversion, and negative values indicate ambiguity seeking. The sample consists of $n = 230$ non-investors. Panel B shows summary statistics for a-insensitivity regarding the local stock market index (a_{aex}), a familiar company stock (a_{stock}), the MSCI World stock index (a_{msci}), and Bitcoin ($a_{bitcoin}$), as well as the average of the four a -indexes (a_{avg}). In Panel A, Hotelling's T^2 tests the null hypothesis that the means of the four ambiguity attitude measures are equal for b_{aex} , b_{stock} , b_{msci} , and $b_{bitcoin}$. In Panel B, Hotelling's T^2 tests whether the means of the four a-insensitivity measures are equal for a_{aex} , a_{stock} , a_{msci} , and $a_{bitcoin}$.

Panel A: Ambiguity Aversion

	Mean	Median	St dev	Min	Max	n (obs.)
b_{aex}	0.20	0.17	0.50	-1.00	1.00	230
b_{stock}	0.22	0.23	0.54	-1.00	1.00	230
b_{msci}	0.19	0.15	0.51	-1.00	1.00	230
$b_{bitcoin}$	0.17	0.10	0.54	-1.00	1.00	230
b_{avg}	0.20	0.17	0.48	-1.00	1.00	230
Test of equal means: Hotelling's $T^2 = 5.11, p = 0.170$						

Panel B: A-Insensitivity

	Mean	Median	St dev	Min	Max	n (obs.)
a_{aex}	0.88	1.00	0.53	-1.00	2.35	230
a_{stock}	0.80	1.00	0.54	-0.95	2.38	230
a_{msci}	0.87	1.00	0.45	-0.74	2.14	230
$a_{bitcoin}$	0.87	1.00	0.52	-0.81	2.95	230
a_{avg}	0.86	0.95	0.33	-0.18	1.84	230
Test of equal means: Hotelling's $T^2 = 4.09, p = 0.259$						

Table F3: Analysis of Heterogeneity in Ambiguity Aversion, Non-Investors

The table shows estimation results for the panel regression model in Equation (9), with index b (ambiguity aversion) as the dependent variable, similar to Table 2 in the main text but now using the sample of $n = 230$ non-investors. Random slopes capturing individual-level source-specific variation in ambiguity aversion for the familiar stock, MSCI World, and Bitcoin were tested but found not to improve model fit significantly, so no random slopes are included.

	Model 1	Model 2	Model 3	Model 4
	Index b	Index b	Index b	Index b
Constant	0.195***	0.196***	0.139	0.152
Dummy Familiar Stock		0.028	0.028	0.028
Dummy MSCI World		-0.007	-0.007	-0.007
Dummy Bitcoin		-0.025	-0.025	-0.025
Education			-0.039*	-0.015
Age			0.005*	0.007***
Female			0.018	0.026
Single			-0.022	-0.037
Employed			-0.039	0.054
Number of Children (log)			0.008	0.035
Family Income (log)			0.009	0.006
HH Fin. Wealth (log)			-0.016	-0.012
HH Wealth Imputed			-0.145	-0.024
Financial Literacy				-0.026***
Risk Aversion				0.433***
Likelihood Insensitivity				-0.105*
Random Slopes:	No	No	No	No
N Observations	920	920	920	920
I Respondents	230	230	230	230
Number of Variables	0	3	12	15
Log-Likelihood	-349.184	-346.623	-337.051	-306.263
Chi-Square	.	5.108	24.782	101.189
P-Value	.	0.164	0.016	0.000
ICC of Random Effect u_i^b	0.77	0.77	0.75	0.69
$Var[\varepsilon_{i,s}^b]$, Error	0.065	0.064	0.064	0.064
$Var[u_i^b]$, Random Constant	0.211	0.211	0.193	0.144
$Var[\beta'D + \gamma'X]$, Observed	-	0.0004	0.0185	0.068
%, Error	23.4%	23.2%	23.2%	23.2%
%, Random Constant	76.6%	76.6%	70.0%	52.2%
%, Observed Variables	-	0.1%	6.7%	24.6%

Table F4: Analysis of Heterogeneity in Perceived Ambiguity, Non-Investors

The table shows estimation results for the panel regression model in Equation (9), with index a (perceived ambiguity) as the dependent variable, similar to Table 4 in the main text but now using the sample of $n = 230$ non-investors. Violations of monotonicity ($a_{i,s} > 1$) and negative values of index a ($a_{i,s} < 0$) are excluded from the sample, so index a can be interpreted as the perceived level of ambiguity.

	Model 1	Model 2	Model 3	Model 4	Model 5
	Index a	Index a	Index a	Index a	Index a
Constant	0.759***	0.745***	0.745***	1.053***	1.051***
Dummy Familiar Stock		0.005	0.003	0.002	0.002
Dummy MSCI World		0.024	0.024	0.022	0.023
Dummy Bitcoin		0.020	0.024	0.023	0.023
Education				-0.022*	-0.013
Age				0.001	0.001
Female				0.000	-0.003
Single				0.021	0.003
Employed				0.086**	0.096**
Number of Children (log)				-0.033	-0.032
Family Income (log)				-0.028***	-0.027***
HH Fin. Wealth (log)				-0.013**	-0.009
HH Wealth Imputed				0.041	0.038
Financial Literacy					-0.011*
Risk Aversion					0.022
Likelihood Insensitivity					0.042
Random Slope: Bitcoin	No	No	Yes	Yes	Yes
N Observations	631	631	631	631	631
I Respondents	221	221	221	221	221
Number of Variables	0	3	3	12	15
Log-Likelihood	-74.151	-73.556	-70.656	-61.578	-58.083
Chi-Square	.	1.238	1.536	37.822	47.592
P-Value	.	0.744	0.674	0.000	0.000
ICC of Random Effect u_i^a	0.45	0.45	0.52	0.49	0.48
$Var[\varepsilon_{i,s}^a]$, Error	0.049	0.049	0.043	0.043	0.043
$Var[u_i^a]$, Random Constant	0.040	0.040	0.043	0.038	0.036
$Var[v_{i,4}^a]$, Slope Bitcoin	-	-	0.003	0.003	0.003
$Var[\alpha'D + \gamma'X]$, Observed	-	0.0001	0.0001	0.005	0.007
%, Error	55.5%	55.2%	48.2%	48.8%	48.8%
%, Random Constant	44.5%	44.7%	48.4%	42.3%	40.4%
%, Slope Bitcoin	-	-	3.3%	3.4%	3.3%
%, Observed Variables	-	0.1%	0.1%	5.5%	7.5%

Online Appendix G. The Effect of Naming a Familiar Company Stock

Before beginning the questions about the individual stock, each respondent was first asked to name a familiar company stock; subsequently, that stock name was used in the six choice lists shown to the respondent. For respondents who did not know any familiar company stock, we used Philips, a well-known Dutch consumer electronics brand.

As an additional test, we now distinguish between investors who mentioned a particular familiar stock (55% of the investor sample) and those who did not (45%). In the regression model (7), we replace the stock dummy d_2 by a “Particular Stock” dummy $d_{2,Particular}$ that is equal to one when $s = 2$ and the subject mentioned a particular stock, and a “Philips Stock” dummy $d_{2,Philips}$ that is equal to one when $s = 2$ and the subject did *not* mention a familiar stock. Note: $d_2 = d_{2,Particular} + d_{2,Philips}$. We then estimate the following model:

$$(G1) \quad b_{i,s} = \beta_1 + \beta_{2,Particular}d_{2,Particular} + \beta_{2,Philips}d_{2,Philips} + \beta_3d_3 + \beta_4d_4 + u_i^b + \varepsilon_{i,s}^b, \\ i = 1, 2, \dots, I, \text{ and } s = 1, 2, 3, 4,$$

where $b_{i,s}$ is index b of respondent i toward source s , for the AEX index ($s = 1$), the stock ($s = 2$), the MSCI World index ($s = 3$), and Bitcoin ($s = 4$). The constant β_1 represents ambiguity aversion for the AEX index, whereas the coefficients $\beta_{2,Particular}$, $\beta_{2,Philips}$, β_3 and β_4 represent differences in mean ambiguity aversion for the particular familiar stock mentioned by the investor, the stock Philips, MSCI World and Bitcoin. Similar to the main text, we also add and test random slopes one at a time, but now separately for the particular stock mentioned ($v_{i,2,Particular}^b$), Philips ($v_{i,2,Philips}^b$), MSCI World ($v_{i,3}^b$) and Bitcoin ($v_{i,4}^b$). Further, we also estimate a version of the model with a full set of control variables.

Table G1 below shows the estimation results for ambiguity aversion ($b_{i,s}$) in Column (1) and (2), and the results for perceived ambiguity ($0 \leq a_{i,s} \leq 1$) in Column (3) and (4). The results show that investors who named a particular familiar stock are slightly less ambiguity averse about it (compared to other investments), but the effect is small and insignificant. However, these investors do perceive substantially lower ambiguity about their familiar stock (-0.14; $p < 0.01$). Hence, in line with the conclusions in the main text, this suggests that perceived ambiguity is more source-dependent and more influenced by familiarity, in comparison to ambiguity aversion.

In Column (4) with a full set of controls, those answering questions about Philips perceive less ambiguity about it (-0.054; $p=0.046$) compared to the AEX index, MSCI World and Bitcoin. An additional test for the difference in $\beta_{2,Particular}$ and $\beta_{2,Philips}$ confirms that investors naming a familiar stock on average perceive significantly less ambiguity about it (-0.087; $p=0.027$) than investors answering questions about Philips.

Table G1: Ambiguity Aversion and Perceived Ambiguity for Named Stocks and Philips

Columns (1) and (2) show results for the model in Equation (G1), explaining index b (ambiguity aversion) as the dependent variable, while distinguishing between investors who named a particular familiar stock and those who did not (and filled in choice lists about Philips). In Column (3) and (4), perceived ambiguity ($0 \leq a \leq 1$) is the dependent variable. The model for ambiguity aversion in Column (1) and (2) includes a random slope for Bitcoin. The model for perceived ambiguity in Column (3) and (4) includes random slopes for the Particular Stock dummy and for Bitcoin, which are significant based on a chi-square test. *, **, *** denote significant coefficients at the 10%, 5% and 1% level.

	(1)	(2)	(3)	(4)
	Ambiguity aversion (Index b)		Perceived Ambiguity (Index a)	
	Model 3	Model 5	Model 3	Model 5
Constant	0.168***	0.205	0.717***	0.913***
Dummy Particular Stock	-0.029	-0.026	-0.142***	-0.141***
Dummy Philips Stock	0.010	0.006	-0.043	-0.054**
Dummy MSCI World	0.042**	0.042**	-0.010	-0.013
Dummy Bitcoin	0.007	0.007	0.019	0.016
Education		-0.018		-0.034***
Age		0.003*		0.002**
Female		0.058		0.005
Single		-0.089*		-0.043
Employed		-0.041		0.029
Number of Children (log)		0.048		-0.030
Family Income (log)		0.016		-0.010
HH Fin. Wealth (log)		-0.011*		0.006
HH Wealth Imputed		-0.053		0.063
Financial Literacy		-0.014		-0.022**
Risk Aversion		0.465***		0.041
Likelihood Insensitivity		-0.083*		0.089***
Random Slope: Bitcoin	Yes	Yes	Yes	Yes
Random Slope: Part. Stock	No	No	Yes	Yes
Observations n	1180	1180	794	794
ICC of Random Effect u_i^b	0.74	0.65	0.57	0.49
<i>Var</i> , Error	0.061 (25%)	0.061 (25%)	0.041 (41%)	0.041 (41%)
<i>Var</i> , Random Constant	0.167 (70%)	0.112 (47%)	0.047 (47%)	0.034 (34%)
<i>Var</i> , Slope Bitcoin	0.012 (5%)	0.012 (5%)	0.004 (4%)	0.004 (4%)
<i>Var</i> , Slope Particular Stock	-	-	0.006 (6%)	0.005 (5%)
<i>Var</i> , Observed	0.0005 (0%)	0.056 (23%)	0.002 (2%)	0.016 (16%)

Online Appendix References

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