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 is the first to measure ambiguity attitudes for real-world sources 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. Ambiguity aversion and perceived ambiguity are related to actual investment choices, validating the measures.

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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 (Tversky & Kahneman, 1992).

One limitation of the available evidence on ambiguity attitudes that it has been mostly 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. So far, this new method has been applied in laboratory settings with convenience student samples.

Our paper is the first 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, we first conduct an econometric analysis with panel models. Correlations between repeated measures of ambiguity aversion are moderate to high, in the 0.6 to 0.8 range. Individual characteristics also display significant and plausible correlations with ambiguity attitudes. Demographics, income, wealth, and risk aversion explain 28% of individual-level variation in ambiguity aversion and 14% of perceived ambiguity. This is an improvement over previous studies that used artificial urn experiments to measure ambiguity, where individual characteristics explained only up to 3% of the variation in ambiguity aversion (see Dimmock, et al., 2015; l'Haridon et al., 2018). We find that perceived ambiguity is lower for investors with higher financial literacy and better education. This is intuitive, as better knowledge should help mitigate perceived ambiguity. For ambiguity aversion, we find that risk aversion can explain the largest share of its variation, but it is only weakly related to financial knowledge and education. This suggests that ambiguity aversion is a preference, not driven by lack of knowledge or low levels of sophistication.

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. Third, we confirm that insensitivity to the likelihood of ambiguous events is an important second component of ambiguity attitudes, displayed by a large majority of investors. Insensitivity refers to the tendency to treat all ambiguous events as if they are 50/50% (Tversky & Fox, 1995; Abdellaoui et al., 2011), which is conceptually related to perceiving high levels of ambiguity (Dimmock et al. 2015, and Baillon et al., 2018a). Insensitivity also implies ambiguity seeking behavior for unlikely events, such as new ventures that offer a large payoff with a small unknown probability.

Our data also allow us to test whether ambiguity aversion and perceived ambiguity (insensitivity) 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

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 & Wakker (2011), Trautmann & van de Kuilen (2015), Dimmock et al. (2015), Dimmock, Kouwenberg & Wakker (2016), Cubitt et al. (2018), and Kocher et al. (2018).

between sources, while 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 highly related and mostly driven by one underlying preference 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 company stock but perceive 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 & Tallon, 2019; and Kostopoulos & Meyer, 2019). Our paper is the first to confirm such a link with measures of non-artificial ambiguity directly relevant for the investments.

We contribute to the empirical literature on ambiguity by measuring ambiguity attitudes toward naturally occurring sources in a large sample of investors. We analyze the reliability of the new elicitation method of Baillon et al. (2018b) applied in the field, 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 in laboratory experiments (Baillon et al., 2018b; Li et al., 2019) and a field study with students (Li, 2017).[3] Compared to ambiguity experiments 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] 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 to explore the relation between ambiguity attitudes and income 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 provide more evidence on the source-dependence of both ambiguity aversion and perceived ambiguity for real-world sources, for the first time using subjects from the general population. In this way, we build on earlier work by Abdellaoui et al. (2011), Baillon & Bleichrodt (2015), and Li et al. (2017). In another related study, Brenner & Izhakian (2018) analyzed aggregate U.S. stock market data to measure ambiguity attitudes for a representative investor using a different methodology; in the present paper, we measure ambiguity attitudes at the individual level.

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.[4] The survey is computer-based and subjects can participate from their home. To limit selection bias, households lacking internet access at the recruiting stage were provided with a set-top box for their television set (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 custom-designed 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).

Our questionnaire was targeted at all DHS panel members who indicated that they invested in financial assets, defined to include mutual funds (about 67% of the investors), individual company stocks (50%), bonds (10%), or options (3%).[5] Our survey module was fielded from 27 April-14 May 2018, yielding 295 complete and valid responses.[6] Our survey was also given to a random sample of non-investors from the general population, with 230 complete responses. The non-investors sample allows us to compare the ambiguity attitudes of investors and non-investors, which we do in Section 5.3. For our main results, we focus only on investors, as our goal is to

[4] Additional information on the DHS is available at https://www.centerdata.nl/en/databank/dhs-data-access.

[5] Asset ownership as of 31 December 2016, based on the October 2017 DHS survey of wealth and assets.

[6] Out of 391 DHS panel members who indicated that they invested in financial assets, 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.

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 investments with the measurement method for real-world events 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.[7] 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, and defined as:

$E_1 = (-\infty, -4\%]$: the AEX index decreases by 4% or more

$E_2 = (-4\%, +4\%)$: the AEX index decreases or increases by less than 4%

$E_3 = [+4\%, \infty)$: the AEX index increases by 4% or more.

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 €15 if Event E_1 happens) and Option B (winning €15 with known chance p).[8] We approximate the matching probability by taking the average of the probabilities p in the two rows that define the

[7] The AEX is a stock market index composed of the shares of 25 companies traded on the Amsterdam stock market.
[8] 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.

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 compliment of each event:

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

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 Figure 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*, after averaging over the three events, as follows:

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

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 $b = 0$.

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

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

with $-2 \leq a \leq 4$. For ambiguity neutral decision-makers, $a = 0$, while $a > 0$ denotes a-insensitivity, the typical finding in empirical studies. Negative values, $a < 0$, indicate that the decision-maker is overly sensitive to changes in the likelihood of ambiguous events, 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 ($\overline{m}_c \geq \overline{m}_s$). However, in practice, respondents can make errors and violate monotonicity, leading to $a > 1$.

The measurement method above has one major advantage: using events and their complements in the calculation of indexes *b* and *a* ensures that the unknown subjective probabilities drop out of the equation (see Baillon et al., 2018b). Accordingly, we can measure ambiguity aversion without knowing respondents' subjective probabilities. 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 support and explain the interpretation of the measures, we now show that in the context of the α-MaxMin model, index *b* and *a* can be interpreted, respectively, as *ambiguity aversion* and the *perceived level of ambiguity* (see Dimmock et al. 2015, and Baillon et al., 2018a). 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_E0 denote a two-outcome prospect that pays amount $x \geq 0$ if the ambiguous event E occurs, and 0 otherwise. The α-MaxMin model (Hurwicz, 1951; Ghirardato et al., 2004) evaluates the ambiguous prospect x_E0 as follows:

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

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

A tractable set of prior distributions for the α-MaxMin model can be specified with the neo-additive model axiomatized by Chateauneuf, Eichberger, and Grant (2007). The model assumes that the decision-maker has a reference probability for the event, $\pi(E)$, an 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 the reference probability π, 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 compliment of E, this gives rise to the following interval $I_{E,\delta}$ of possible probabilities for event E:

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

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 α-MaxMin model with prior set $I_{E,\delta}$ evaluates Option A as:

$$(5) \qquad \alpha\, min_{p\in[(1-\delta)\pi_1,(1-\delta)\pi_1+\delta]}\, pU(15) + (1-\alpha) max_{p\in[(1-\delta)\pi_1,(1-\delta)\pi_1+\delta]}\, pU(15)$$
$$= \big((1-\delta)\pi_1 + (1-\alpha)\delta\big)U(15),$$

where $\pi_1 = \pi(E_1)$ is the respondent's reference probability for E_1. Option B offers a known probability p of winning \$15 and is evaluated with expected utility: $pU(15)$. The matching probability m_1 is the known probability p that makes the respondent indifferent between Option A and Option B:

$$(6) \qquad m_1 = (1-\delta)\pi_1 + (1-\alpha)\delta\ .$$

We note that U has canceled out in the comparison between Options A and B, so we do not need to estimate utility function parameters (or risk aversion) to measure people's ambiguity attitudes (see Dimmock, Kouwenberg & Wakker, 2016).

Our survey module also elicits a matching probability for the complement event E_{23}, shown in Figure 2. Using the same derivation, the matching probability 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:

$$(7) \qquad b = 1 - (m_1 + m_{23}) = 1 - (1-\delta)(\pi_1 + \pi_{23}) - 2(1-\alpha)\delta = 2\big(\alpha - \tfrac{1}{2}\big)\delta.$$

Note that π_1 and π_{23} have dropped out in (7), as $\pi_1 + \pi_{23} = 1$, hence we can measure ambiguity aversion with index b without having information about the decision-maker's subjective probabilities. This result also applies to the definition of index b in (1), which is based on the average over three events. Further, Equation (7) also shows that index b is a rescaled version of α, ranging from $-\delta$ to δ (Baillon et al., 2018b).[9]

Similarly, for the a-insensitivity index a, we can derive the following expression in the α-MaxMin model with prior set $I_{E,\delta}$:

$$(8) \qquad a = 3 \times \left(\tfrac{1}{3} - (\overline{m}_c - \overline{m}_s)\right) = \left(1 - (1-\delta)(\pi_{23} + \pi_{13} + \pi_{12} - (\pi_1 + \pi_2 + \pi_3)\right)$$
$$= \left(1 - (1-\delta)((1-\pi_1) + (1-\pi_2) + (1-\pi_3) - 1)\right) = \left(1 - (1-\delta)\right) = \delta.$$

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

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 Index and the MSCI World Index, the event E_1 (E_3) represented a return of 4% (-4%) in one month.

[9] 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 $a = 0$.

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.[10]

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 for risk as a measure of *Risk Aversion*.[11] We use index a 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. We refer to Online Appendix B for more details about these measures. These two risk attitude measures are conceptually related to index b for ambiguity aversion and index a for a-insensitivity (Abdellaoui et al. 2011), while also having an axiomatic foundation in rank-dependent utility.

Appendix Table A1 shows that on average investors are risk averse (mean > 0) but with strong heterogeneity, and about one third of the investors are risk seeking. Further, the *Likelihood Insensitivity* measure is positive for 85% of the investors, displaying a tendency to overweight small probabilities, which is in line with the findings of previous studies (see, e.g., Fehr-Duda & Epper, 2011 and Dimmock et al., 2020).

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 DHS one month after the end of the survey, when the changes in the asset values were known. As

[10] 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.

[11] Index b is a measure of pessimism, the tendency to underweight all probabilities. We assume a linear utility function, as utility is typically close to linear for small payoffs. In that case index b captures risk aversion. See Online App. B.

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 this proxy for financial knowledge relates to ambiguity attitudes. To measure this, we use 12 questions from Lusardi & Mitchell (2007) and van Rooij et al. (2011), who devised both basic and advanced financial literacy questions. Online Appendix B provides the list of financial literacy questions, and the variable *Financial Literacy* is the combined number of correct responses to the 12 questions. The average number of correct answers to the literacy questions was 10.6 out of 12 (see Appendix Table A1).[12]

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. About one-third of investors did hold the familiar stock (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% of the DHS investors, respectively. Finally, none of the investors in the sample owns funds tracking the domestic AEX stock index.

3. Results for ambiguity attitudes

3.1. Descriptive statistics

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

[12] 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).

neutral.[13] About 58% of the respondents are ambiguity averse, while 30% are ambiguity seeking, a pattern that is similar across the sources of financial ambiguity. Furthermore, ambiguity neutrality is less common (12%), implying that only few investors' choices are 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 Ellsberg urns) 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 appear to display somewhat 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). There is 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 statistic[14] 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.

Dimmock, Kouwenberg, & Wakker (2016) measured index *b* with Ellsberg urns in a large sample of the Dutch population (similar to the DHS panel, but no overlapping respondents). 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.[15] This suggests that the mean level of ambiguity aversion is not 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 has relatively high ambiguity aversion toward one specific financial source (e.g., the AEX index), he also tends to display high ambiguity aversion toward the other three investments. A factor analysis shows that

[13] 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.

[14] 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.

[15] 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 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 Stahl (2014) and l'Haridon et al. (2018) found high levels of unexplained heterogeneity and noise in ambiguity attitudes, measured with Ellsberg urns. An open question is: to what extent does using relevant natural events such as 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:

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

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 $Var[\varepsilon_{i,s}^b] = (\sigma_\varepsilon^b)^2$. The random effect u_i^b represents unobserved heterogeneity in ambiguity aversion, which is independent of the error term and uncorrelated between individuals, with $Var[u_i^b] = (\sigma_u^b)^2$. The total variance of ambiguity attitudes can now be decomposed as follows:

(10) $$Var[b_{i,s}] = Var[\beta' D + \gamma^{b\prime} X] + Var[u_i^b] + Var[\varepsilon_{i,s}^b],$$

with the three right-hand-side components representing variance explained by observed variables ($Var[\beta' D + \gamma^{b\prime} X]$), unobserved heterogeneity in ambiguity at the individual level ($Var[u_i^b]$), and error variance ($Var[\varepsilon_{i,s}^b]$).

In l'Haridon et al. (2018), a main finding was that observed individual characteristics like gender and age could explain at most 3% of the variation in ambiguity attitudes. Further, that study suggested that unobserved heterogeneity (random effects) may be driven by noise as well, as the interclass correlation coefficient (ICC) for repeated ambiguity measurements was only 0.15 to 0.18. ICC measures how strong different measures of ambiguity at the individual level are correlated with each other.[16] In our dataset, ICC captures the correlation of the ambiguity aversion measures for the four investment sources.

The panel data model in (9) can be extended to capture source-specific heterogeneity in ambiguity aversion at the individual level, by introducing additional random effects $v_{i,s}^b$ for each source separately as "random slopes:"

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

with $Var[v_{i,s}^b] = (\sigma_{v,s}^b)^2$, for $s = 2, 3, 4$. The random effect $v_{i,s}^b$ is know as a "random slope", as it changes the beta coefficient 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. The correlation between the random effects (u_i^b , $v_{i,s}^b$) is also estimated as part of the model.

Our estimation approach is as follows: first, we estimate the baseline model (9) 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).[17] 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 attitudes

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 when the respondent violates monotonicity or makes other errors, to show the impact of noise in the data. In line with the journal style requirements, Table 2 shows estimated coefficients with standard errors in parentheses, and no stars for significance levels. Model 1 in Table 2 includes only a random effect,

[16] 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.
[17] 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.

capturing individual heterogeneity in ambiguity aversion that is common to the four investments. The constant in the model is 0.177 ($p < 0.001$), implying that investors on average are ambiguity averse toward the investments. The interclass correlation coefficient (ICC) is 0.69, indicating that ambiguity aversion for the four investments is strongly correlated at the individual level. 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 next added to the model, 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 ($p < 0.001$). Model 3 in Table 2 shows that heterogeneity in ambiguity aversion toward Bitcoin (the random slope) explains 5% of the total variation, on top of the 70% captured by ambiguity aversion toward all four sources (the 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. Ambiguity aversion toward investments is lower for younger investors ($p = 0.008$) and singles ($p = 0.044$). Overall, observed individual characteristics explain about 6% of the total variance. In Model 5, proxies for financial literacy and risk attitudes are added, which account for an additional 17% of the variation in ambiguity aversion (= 23% - 6%). Specifically, ambiguity aversion toward investments and risk aversion have a strong positive relation ($p < 0.001$). Ambiguity aversion is not related to education ($p = 0.263$) and financial literacy ($p = 0.401$). These findings suggest that ambiguity aversion is a component of preferences, rather than driven by cognitive errors.

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 artificial sources (Ellsberg urns), versus 6% here for socio-demographic variables, and up to 23% when risk attitudes and financial literacy are also included. Further, in l'Haridon et al. (2018), the correlation between repeated measurements of ambiguity aversion is only 0.15-0.18, versus ICC = 0.69 using real-world sources here. Related, Dimmock et al. (2015) estimated ambiguity aversion with artificial urns in the U.S. population: a large set of observed variables explain only 2.2% of the variation, and ICC is 0.30.

This suggests that ambiguity aversion for natural sources measured with the Baillon et al. (2018b) method has higher reliability compared to traditional measures based on Ellsberg urns.

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 separate b-indexes is 0.74. Further, the ICC using the 12 measurements of index b 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 violate monotonicity, $\bar{m}_s > \bar{m}_c$, which implies $a > 1$. About 25% violate monotonicity when looking at each investment separately, and 20% after averaging over the four investments ($a\_avg > 1$). 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 in Table 3 are high, but similar to those in previous ambiguity studies.

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%. Overall, the coefficient estimates are similar and the original results for index b in Table 2 are robust to screening out violations of monotonicity.

4. Results for perceived ambiguity

4.1. Descriptive statistics

We now summarize the a-index values. As we aim to interpret index a as a proxy for perceived ambiguity, which is only feasible if a is between 0 and 1, we first analyze how often index a falls outside these boundaries. Panel A in Table 3 shows that 22% to 26% of the a-index values are larger than one and violate monotonicity, as discussed above. Further, about 5% to 12.5% have negative a-index values, implying that the decision-maker is overly sensitive to changes in the likelihood of ambiguous events. Overall, the majority of investors are insensitive to the likelihood of ambiguous events ($a > 0$) for these investment sources, confirming results for Ellsberg urns in Dimmock et al. (2015) and Dimmock, Kouwenberg, & Wakker (2016). From now on we exclude monotonicity violations ($a > 1$) and negative values of a, using pairwise deletion, in order to interpret index a as a measure of perceived ambiguity. As a robustness check, later in Section 4.4 we also report estimation results for a-insensitivity, using all values of index a.

Panel B of Table 3 shows descriptive statistics for the level of perceived ambiguity toward the four investments. On average, investors perceive 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). Hotelling's T-squared test rejects the null hypothesis that all means are equal ($T^2 = 15.76$; p-value = 0.003). A follow-up analysis with paired t-tests shows that the mean a-index for the familiar stock is significantly lower than perceived ambiguity for the other three investments. For comparison, in Dimmock, Kouwenberg, & Wakker (2016) perceived ambiguity toward Ellsberg urns on average is 0.35, considerably lower than the average a-index value of 0.71 for investments. This confirms that the mean of perceived ambiguity is source-dependent, also between artificial and real-world sources. Further, perceived ambiguity about investments is relatively high.

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.[18]

4.2. Analysis of heterogeneity in perceived ambiguity

We analyze the variance in index a, using a similar panel model estimation:

[18] 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).

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

(13) $Var[a_{i,s}] = Var[\alpha' D + \gamma^{a\prime} X] + Var[u_i^a + v_{i,s}^a] + Var[\varepsilon_{i,s}^a]$,

where $a_{i,s}$ is index a (perceived ambiguity) of respondent i toward source *s*. 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 mean perceived ambiguity relative to the AEX index. The random effect and the error term for perceived ambiguity are denoted by u_i^a and $\varepsilon_{i,s}^a$, respectively. Further, random slopes $v_{i,s}^a$ are tested and added to capture source-specific heterogeneity in perceived ambiguity, if significant based on a likelihood ratio test. As before, violations of monotonicity ($a_{i,s} > 1$) and negative values of index *a* ($a_{i,s} < 0$) are excluded from the estimation sample, so index *a* can be interpreted as the perceived level of ambiguity.

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 total variation in index *a*. Model 2 shows that on average investors perceive less ambiguity about the familiar stock: λ_2 = -0.091 ($p < 0.001$), relative to perceived ambiguity of λ_1 = 0.718 for the AEX index and the other investments. The interclass correlation coefficient (ICC) of the random effect is 0.45, implying that levels of perceived ambiguity toward different investments have a moderate positive correlation.

Random slopes are added to the model to capture heterogeneity in source-specific ambiguity, and a chi-square test (see Online Appendix C.2) shows that including random slopes for the familiar stock and Bitcoin leads to a significant improvement of the model fit ($p < 0.001$). Model 3 in Table 4 shows that individual variation in perceived ambiguity toward the familiar stock explains 6% of the total variation, versus 4% for Bitcoin, on top of the 43% that is captured by general perceived ambiguity about all investments (the random constant). Hence, whereas ambiguity aversion toward investments 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

In Model 4, observed individual socio-demographic variables are added to the model, explaining 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% of the variance (= 14% - 10%). Specifically, investors with better financial literacy perceive less ambiguity (p = 0.011). Further, perceived ambiguity is positively related to index *a* for risk (p = 0.005), a proxy for likelihood insensitivity. All variables together can explain up to 14% of the variation in perceived ambiguity, whereas 39% is unobserved heterogeneity (captured by random effects), and 47% is error. All of the above indicates that measurement reliability for perceived ambiguity about investments is reasonable, although clearly lower than for ambiguity aversion. A possible reason is that index *a* is measured from small differences in matching probabilities between composite and single events, 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. The correlations between the *a*-indexes for the four investments are low, ranging from 0.10 to 0.24. A factor analysis shows that the first component accounts for only 37% of the cross-sectional variation (versus 60% for perceived ambiguity), thus a-insensitivity is not very correlated across the four investment sources. When estimating the econometric model (12), the ICC is only 0.16 and measurement error is high (75% of the variation).[19]

These analyses provide two important 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 reason is that index *a* is measured off differences in matching probabilities between composite events and single events that are multiplied by a factor 3, see Equation (2), making the measure more sensitive to errors and violations of monotonicity than index *b*.

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 if they relate to other variables in the expected way. 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 & van de Kuilen (2015). Similarly, we expect that likelihood insensitivity (overweighting of small

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

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 expected relations ($p < 0.01$).[20] 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 investment knowledge reduces the level of perceived ambiguity.

The expected relation between ambiguity *aversion* and financial knowledge (or education) is less clear. On the one hand, if ambiguity aversion is a rational response to high uncertainty that can protect people from unexpected losses such as market crashes, financial knowledge (or education) is expected to be positively related to ambiguity aversion. On the other hand, if we consider all deviations from ambiguity neutrality as irrational, then better knowledge would be associated with both lower ambiguity aversion and less ambiguity seeking. The results in Table 2 show that ambiguity aversion is not significantly related to education, nor to financial literacy.

Together, these results suggest that ambiguity aversion is a preference component, given its positive relation with risk aversion. On the other hand, perceived ambiguity is mitigated by financial literacy and education, suggesting it is a cognitive component.

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).[21] 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):

$$(14) \quad P[DI_{i,s} = 1] = \mu_s d_s + \theta_1 b_{i,s} + \theta_2 a_{i,s} + \sum_{k=1}^{K} \theta_{k+2} X_{i,k} + \epsilon_{i,s}, \; i = 1, 2, \ldots, I, \, s = 2, 3, 4,$$

where $b_{i,s}$ is index b and $a_{i,s}$ is index a of respondent i, for the familiar stock (s = 2), the MSCI World index (s = 3), and Bitcoin (s = 4), with coefficients θ_1 and θ_2. The constant μ_2 represents

[20] The correlations between risk preferences and ambiguity attitudes are moderate (0.07 to 0.49), confirming that risk and ambiguity attitudes are separate concepts, as suggested by Abdellaoui et al. (2011) and Dimmock, Kouwenberg, Mitchell, & Peijnenburg (2015, 2016).

[21] 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.

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 invest in a fund tracking the AEX. The model includes K observable individual characteristics $X_{i,k}$ as control variables, with regression slope coefficients θ_{k+2}, for $k = 1, 2, \ldots, K$.

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). We note that the estimated effect of index a becomes smaller as more controls are added in Models 2 and 3, as index a is related to education and financial literacy. In Models 4 to 6 of Table 5 the 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 Tables 2 and 4 (Model 3), to reduce the impact of measurement error.[22] Using the predicted values, we effectively remove the error terms $\hat{\varepsilon}^{b}_{i,s}$ and $\hat{\varepsilon}^{a}_{i,s}$ 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 confirm that investors who perceive more ambiguity about an asset are less likely to invest in it (p = 0.004), while ambiguity aversion is not significant (p = 0.460).

Online Appendix C.3 shows results for several model specification tests. First, adding a random effect to the panel probit model (14) does not add value, because ownership of different investments is not much correlated. Second, allowing ambiguity aversion and perceived ambiguity 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 robustness checks for our main results, which are reported in Online Appendix E of the paper. First, we repeat 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

[22] Predicted values are based on fitted values of the random effects ($\hat{u}^b_i$, $\hat{u}^a_i$) and random slopes ($\hat{v}^b_{4,s}$,$\hat{v}^a_{2,s}$, $\hat{v}^a_{4,s}$) for each investor, as well as differences in means of index b and a between sources ($\hat{\beta}_s$, λ_s), from Model 3 in Tables 2 and 4.

Option B on every row of the choice list; this results in high values of index *b*. 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.

Online Appendix F presents results for the group of 230 non-investors who own no financial assets. As expected, perceived ambiguity is higher in this group, while ambiguity preferences on average are not different. In this 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, while source-specific ambiguity about Bitcoin explains only 3%. 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 unfamiliarity.

6. Conclusion

This paper is the first to measure ambiguity attitudes for relevant real-world sources of ambiguity in a large representative sample of investors, while controlling for unknown probability beliefs. One concern raised in the literature is that ambiguity measurements for artificial events such as Ellsberg urns are often noisy, and not much 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 with 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 have significant correlations with ambiguity attitudes: 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 sources 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 are the first to 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.

In addition, our research contributes to the literature on portfolio choice under ambiguity, by providing insight on how to model ambiguity attitudes.[23] 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 & 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, & Peijnenberg (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.

Tentatively, our results suggest that policies aimed at reducing perceived ambiguity (the cognitive component) appear to be more promising for stimulating equity market participation than are policies targeting ambiguity aversion (the preference component). To confirm these conjectures, an interesting avenue for future research would be to reduce perceived ambiguity through an experimental intervention, and then to measure the subsequent impact on actual investments.

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Table 1: Descriptive Statistics for Ambiguity Attitudes

The table 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* = 295 investors.

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

Table 2: Analysis of Heterogeneity in Ambiguity Attitudes

The table shows estimation results for the panel regression model in Equation (11), 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	0.168	0.168	0.153	0.213
	(0.025)	(0.028)	(0.028)	(0.219)	(0.240)
Dummy Familiar Stock		-0.012	-0.012	-0.012	-0.012
		(0.020)	(0.020)	(0.020)	(0.020)
Dummy MSCI World		0.042	0.042	0.042	0.042
		(0.021)	(0.021)	(0.021)	(0.021)
Dummy Bitcoin		0.007	0.007	0.007	0.007
		(0.024)	(0.024)	(0.024)	(0.024)
Education				-0.010	-0.018
				(0.017)	(0.016)
Age				0.006	0.003
				(0.002)	(0.002)
Female				0.072	0.059
				(0.062)	(0.053)
Single				-0.116	-0.090
				(0.058)	(0.049)
Employed				-0.040	-0.042
				(0.070)	(0.058)
Number of Children (log)				0.059	0.048
				(0.062)	(0.057)
Family Income (log)				-0.011	0.016
				(0.014)	(0.016)
HH Fin. Wealth (log)				-0.016	-0.011
				(0.009)	(0.007)
HH Wealth Imputed				-0.130	-0.050
				(0.115)	(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

	Within limits for perceived ambiguity % with $0 \leq a \leq 1$	*Over-sensitive to likelihoods* % with $a < 0$	*Violation of monotonicity* % 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 (12), 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	0.718	0.721	0.796	0.915
	(0.015)	(0.021)	(0.021)	(0.117)	(0.143)
Dummy Familiar Stock		-0.091	-0.099	-0.102	-0.103
		(0.026)	(0.025)	(0.025)	(0.025)
Dummy MSCI World		-0.011	-0.013	-0.014	-0.016
		(0.023)	(0.023)	(0.023)	(0.023)
Dummy Bitcoin		0.013	0.014	0.013	0.011
		(0.025)	(0.025)	(0.025)	(0.025)
Education				-0.041	-0.034
				(0.010)	(0.009)
Age				0.003	0.002
				(0.001)	(0.001)
Female				0.019	0.005
				(0.030)	(0.030)
Single				-0.059	-0.045
				(0.032)	(0.030)
Employed				0.027	0.028
				(0.036)	(0.034)
Number of Children (log)				-0.029	-0.032
				(0.038)	(0.037)
Family Income (log)				-0.019	-0.010
				(0.008)	(0.010)
HH Fin. Wealth (log)				0.005	0.007
				(0.006)	(0.006)
HH Wealth Imputed				0.068	0.069
				(0.049)	(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 (14). 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 (14) 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	-0.033	-0.029			
	(0.015)	(0.015)	(0.015)			
Amb. Aversion (index b)	-0.035	-0.020	-0.028			
	(0.019)	(0.019)	(0.022)			
Perc. Ambiguity (fitted $\hat{a}$)				-0.135	-0.097	-0.089
				(0.047)	(0.046)	(0.052)
Amb. Aversion (fitted $\hat{b}$)				-0.018	-0.004	-0.018
				(0.025)	(0.026)	(0.033)
Dummy MSCI World	-0.242	-0.242	-0.242	-0.214	-0.219	-0.220
	(0.028)	(0.027)	(0.027)	(0.034)	(0.032)	(0.032)
Dummy Bitcoin	-0.205	-0.207	-0.208	-0.169	-0.176	-0.179
	(0.024)	(0.022)	(0.022)	(0.028)	(0.025)	(0.025)
Education		0.011	0.008		0.008	0.005
		(0.007)	(0.007)		(0.008)	(0.008)
Age		0.000	0.000		0.000	0.000
		(0.001)	(0.001)		(0.001)	(0.001)
Female		-0.058	-0.048		-0.063	-0.050
		(0.024)	(0.024)		(0.028)	(0.028)
Single		0.008	0.002		-0.015	-0.020
		(0.022)	(0.021)		(0.025)	(0.024)
Employed		0.051	0.053		0.059	0.059
		(0.025)	(0.024)		(0.027)	(0.026)
Number of Children (log)		0.001	0.003		-0.025	-0.020
		(0.025)	(0.025)		(0.031)	(0.031)
Family Income (log)		0.002	0.000		-0.003	-0.005
		(0.009)	(0.009)		(0.009)	(0.009)
HH Fin. Wealth (log)		0.001	0.000		-0.001	-0.002
		(0.004)	(0.003)		(0.004)	(0.004)
HH Wealth Imputed		-0.063	-0.060		-0.055	-0.042
		(0.047)	(0.047)		(0.052)	(0.051)
Financial Literacy			0.016			0.015
			(0.007)			(0.008)
Risk Aversion			0.018			0.019
			(0.024)			(0.030)
Likelihood Insensitivity			-0.007			0.015
			(0.018)			(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.

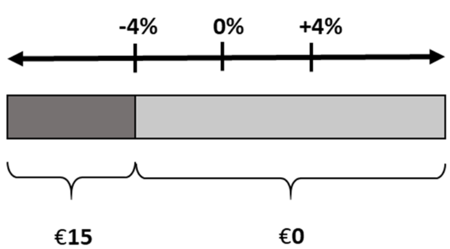
Option A You win €15 if the AEX *decreases by 4% or more* in one month time compared to what the index value is today (and nothing otherwise)	A	B	**Option B** You win €15 in one month time with the following chance (and nothing otherwise)
A: Win €15 if the AEX *decreases by 4% or more* in 1 month time  	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 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.

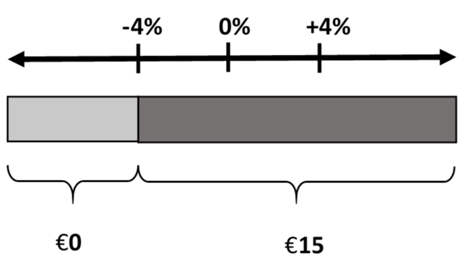
<table>
<tr><th>Option A
You win €15 if the AEX does
not decrease by 4% or more in one month time compared to what the index value is today (and nothing otherwise)</th><th>A</th><th>B</th><th>Option B
You win €15 in one month time with the following chance
(and nothing otherwise)</th></tr>
<tr><td rowspan="15">A: Win €15 if the AEX does
not decrease by 4% or more
in 1 month time

</td><td>X</td><td></td><td>B: Win €15 with chance of 0%</td></tr>
<tr><td>X</td><td></td><td>B: Win €15 with chance of 2.5%</td></tr>
<tr><td>X</td><td></td><td>B: Win €15 with chance of 5%</td></tr>
<tr><td>X</td><td></td><td>B: Win €15 with chance of 10%</td></tr>
<tr><td>X</td><td></td><td>B: Win €15 with chance of 20%</td></tr>
<tr><td>X</td><td></td><td>B: Win €15 with chance of 30%</td></tr>
<tr><td>X</td><td></td><td>B: Win €15 with chance of 40%</td></tr>
<tr><td>X</td><td></td><td>B: Win €15 with chance of 50%</td></tr>
<tr><td></td><td>X</td><td>B: Win €15 with chance of 60%</td></tr>
<tr><td></td><td>X</td><td>B: Win €15 with chance of 70%</td></tr>
<tr><td></td><td>X</td><td>B: Win €15 with chance of 80%</td></tr>
<tr><td></td><td>X</td><td>B: Win €15 with chance of 90%</td></tr>
<tr><td></td><td>X</td><td>B: Win €15 with chance of 95%</td></tr>
<tr><td></td><td>X</td><td>B: Win €15 with chance of 97.5%</td></tr>
<tr><td></td><td>X</td><td>B: Win €15 with chance of 100%</td></tr>
</table>

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

This Figure shows the percent of investors who are ambiguity averse (*b*-index > 0, significant at 5%), ambiguity neutral (cannot reject *b*-index = 0), and ambiguity seeking (*b*-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.

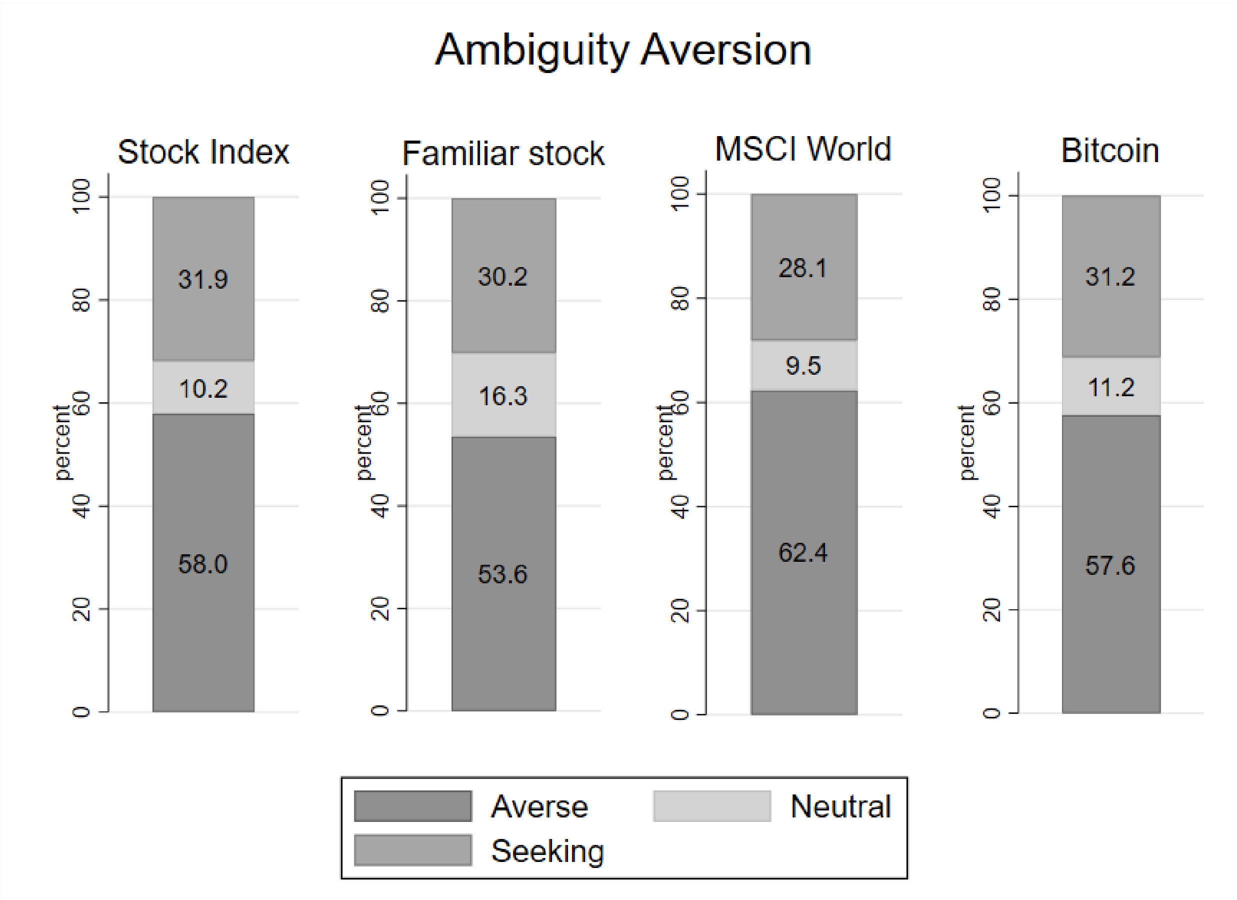


Figure 4: Scatter Plots of Ambiguity Attitudes toward Different Financial Sources

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.

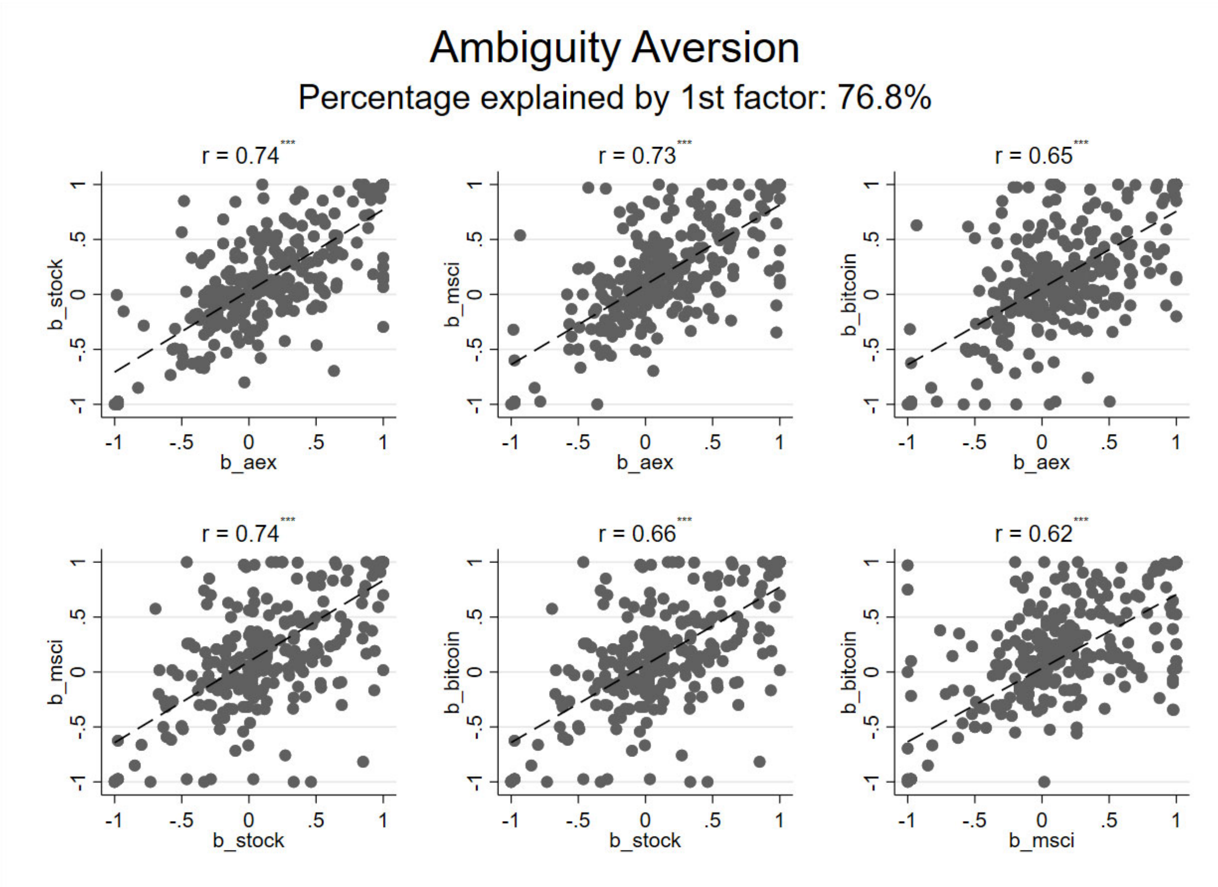
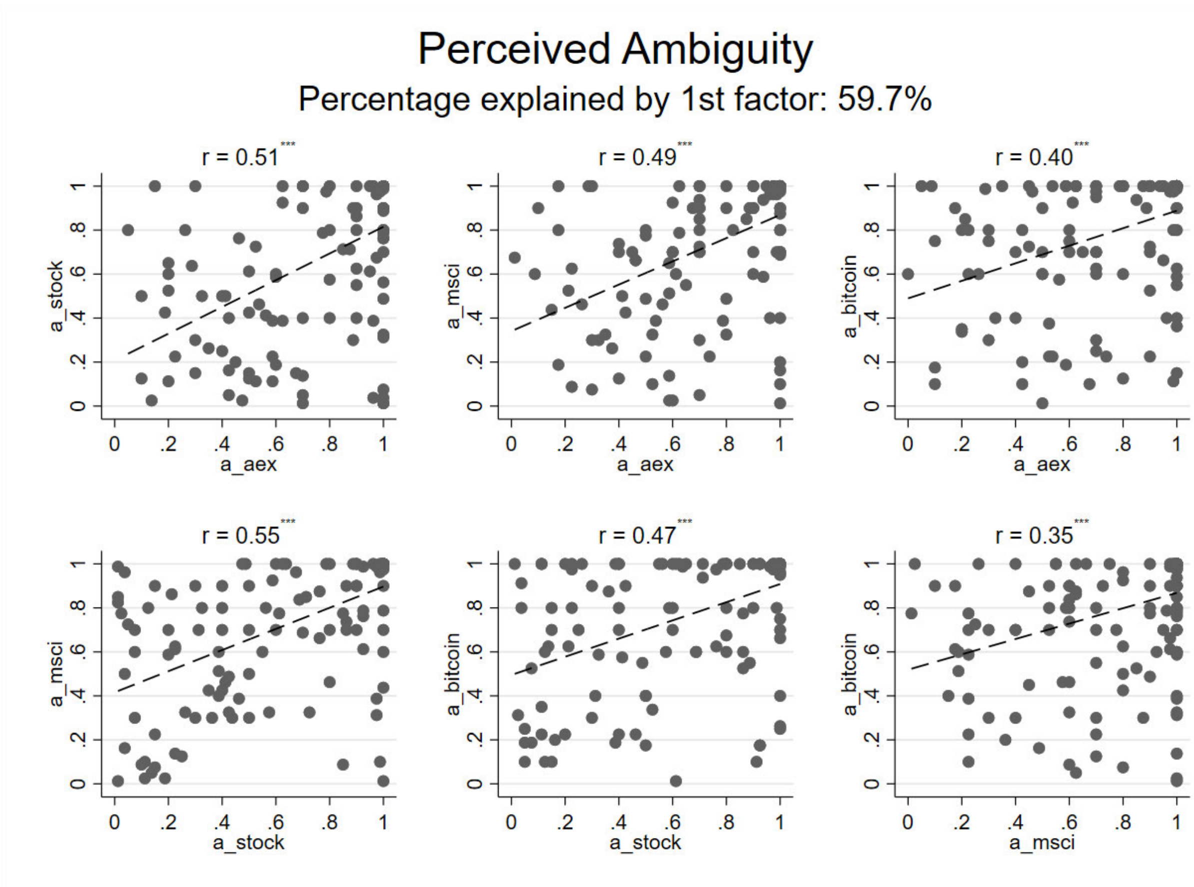


Figure 5: Scatter Plots of Perceived Ambiguity about Different Financial Sources

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
Socio-demographics					
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
Risk Preferences					
Risk Aversion	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	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
Financial Literacy and Investments					
Financial Literacy	10.56	11	1.70	3	12
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 B1: Summary Statistics of Index *a*

The table shows summary statistics for index a (a-insensitivity), similar to Panel B in Table 3 of the main text, but including all values of index a (also when $a < 0$ or $a > 1$) for n = 295 investors.

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

Table B2: Analysis of Heterogeneity in A-Insensitivity

The table shows estimation results for Equation (12) 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	0.826	0.826	1.077	1.177
	(0.019)	(0.031)	(0.031)	(0.171)	(0.183)
Dummy Familiar Stock		-0.136	-0.136	-0.136	-0.136
		(0.044)	(0.044)	(0.044)	(0.044)
Dummy MSCI World		-0.046	-0.046	-0.046	-0.046
		(0.04)	(0.04)	(0.04)	(0.04)
Dummy Bitcoin		0.019	0.019	0.019	0.019
		(0.04)	(0.04)	(0.04)	(0.04)
Education				-0.056	-0.045
				(0.013)	(0.013)
Age				0.003	0.001
				(0.002)	(0.002)
Female				-0.022	-0.040
				(0.04)	(0.039)
Single				-0.050	-0.033
				(0.04)	(0.039)
Employed				-0.015	-0.011
				(0.049)	(0.044)
Number of Children (log)				-0.002	-0.005
				(0.059)	(0.05)
Family Income (log)				-0.029	-0.020
				(0.01)	(0.011)
HH Fin. Wealth (log)				0.008	0.011
				(0.008)	(0.008)
HH Wealth Imputed				0.017	0.023
				(0.102)	(0.091)
Financial Literacy					-0.025
					(0.009)
Risk Aversion					-0.013
					(0.036)
Likelihood Insensitivity					0.163
					(0.04)
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

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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.

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.

Option A You win €15 if the coin comes up heads (and nothing otherwise)	A	B	**Option B** You win the following amount with certainty.
Heads (50% chance): You win €15. Tails (50% chance): You win nothing.	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

Option A You win €15 if the temperature in Amsterdam 1 month from now at 3pm is *more than 20 degree Celsius* (and nothing otherwise)	A	B	**Option B** You win €15 in one month time with the following chance (and nothing otherwise)
A: Win €15 if the temperature in Amsterdam 1 month from now at 3pm is *more than 20 degree Celsius* (and nothing otherwise)	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
Risk premiums					
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* for risk as a measure of *Risk Aversion* and index *a* 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) $U(CE_k) = w(p_k)U(15) + \big(1 - w(p_k)\big)U(0)$, 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) $CE_k = w(p_k)15$

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

(B3) $w(p) = c + sp$ for $0 < p < 1$, with $w(0) = 0$ and $w(1) = 1$.

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

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

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* and *a* for risk are then defined as follows, as functions of c and s:

(B5) *Risk Aversion* = index b for risk $= 1 - s - 2c$,

(B6) *Likelihood Insensitivity* = index a 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, & Peijnenburg (2020). 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* 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* for risk) and *Likelihood Insensitivity* (index *a* 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) *Risk Aversion*	(2) *Alt. Risk Aversion*	(3) *Likelihood Insensitivity*	(4) *Alt. Inverse-S*
Risk Aversion	1.00			
Alt. Risk Aversion	0.90	1.00		
Likelihood Insensitivity	0.28	0.02	1.00	
Alt. Inverse-S	-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 (11), 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 (12), 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) Index b	(2) Index b	(3) Index a	(4) 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 (11) 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 (11) 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 (12) 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 (12) 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 (14) 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 (14) 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	LL	Chi-square 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) $$b = 1 - \bar{m}_c - \bar{m}_s,$$

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

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

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

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 (11) in the main text, but with an additional "time dimension" j, representing the three measurements of index b for each source s:

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

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

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 towards 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 towards 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.)
AEX Index						
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						
Familiar Stock						
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						
MSCI World						
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						
Bitcoin						
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 Index *b*	Model 2 Index *b*	Model 3 Index *b*	Model 4 Index *b*	Model 5 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 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.2 reports the main results after screening out investors who make several mistakes on the ambiguity questions. In Section E.3, the asset ownership regressions are repeated for each investment separately, with a limited set of control variables.

E.1 Excluding investors who violate 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 monotonicity. Summary statistics of index b after excluding monotonicity 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 ($\overline{m}_c - \overline{m}_s$).

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 (11), 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 Index b	Model 2 Index b	Model 3 Index b	Model 4 Index b	Model 5 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 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 E3 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 E3 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 the row of the choice list. The mean of index b therefore drops, after excluding these most ambiguity averse choices. For perceived ambiguity, there is no significant difference between those making more or fewer mistakes: the mean of a-index in Table E3 is 0.69, versus 0.71 in the full sample, and the same result also holds for a-insensitivity.

Table E4 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 towards 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 E5 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 E5, slightly higher than the 14% in the full sample.

Table E3: 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 for the perceived ambiguity indexes 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*). The sample in Panel C includes only observations when the respondent made two or fewer mistakes on the six choice lists for a particular investment, and further when $0 \leq a \leq 1$, so index a can be interpreted as perceived ambiguity.

Panel A: Number of Mistakes on the Six Choice Lists

	No Mistake	1-2 Errors	3-4 Errors	5-6 Errors	*n* (obs.)
aex	73.9%	10.5%	6.8%	8.8%	295
stock	69.2%	13.6%	7.5%	9.8%	295
msci	74.9%	10.8%	5.4%	8.8%	295
bitcoin	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	*n* (obs.)
b_aex	0.11	0.09	0.43	-0.98	0.98	249
b_stock	0.12	0.06	0.43	-0.98	0.98	244
b_msci	0.16	0.13	0.42	-0.98	0.98	253
b_bitcoin	0.13	0.10	0.44	-0.98	0.98	244
b_avg	0.12	0.10	0.37	-0.98	0.98	221

Panel C: Perceived Ambiguity, for Investors Making Two or Fewer Errors

	Mean	Median	St dev	Min	Max	*n* (obs.)
a_aex	0.71	0.80	0.30	0.00	1.00	162
a_stock	0.60	0.62	0.35	0.01	1.00	156
a_msci	0.68	0.75	0.31	0.00	1.00	174
a_bitcoin	0.71	0.80	0.31	0.01	1.00	167
a_avg	0.69	0.73	0.27	0.02	1.00	170

Table E4: Analysis of Heterogeneity in Ambiguity Aversion, Investors Making Two or Fewer Errors
The table shows estimation results for the panel regression model in Equation (11), 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 Index *b*	Model 2 Index *b*	Model 3 Index *b*	Model 4 Index *b*	Model 5 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 E5: Analysis of Heterogeneity in Perceived Ambiguity, Investors Making Two or Fewer Errors
The table shows estimation results for the panel regression model in Equation (12), 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 list 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 Index *a*	Model 2 Index *a*	Model 3 Index *a*	Model 4 Index *a*	Model 5 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.3 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 E6 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 E6 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 E6: 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.

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%). Table F2 displays summary statistics of ambiguity attitudes in the non-investor group. The mean level of aversion is similar for the groups of non-investors and investors. For example, the mean of *b_avg* is 0.20 among non-investors, versus 0.18 for investors ($p = 0.65$). However, the average level of perceived ambiguity (*a_avg*) is slightly higher for non-investors (0.76 vs. 0.71, $p = 0.08$), as expected. Hence ambiguity aversion toward financial assets is not significantly different between investors and non-investors on average, but the level of perceived ambiguity is slightly higher for non-investors.

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 towards 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 towards 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 towards 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
Socio-demographics					
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
Risk Preferences					
Risk Aversion	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	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
Financial Literacy and Investments					
Financial Literacy	8.55	9	3.02	0	12
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 the perceived ambiguity indexes 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*). Positive values of the *a*-index denote perceived ambiguity. In Panel B, the sample has been restricted to only those observations with values of index *a* 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. 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 perceived ambiguity 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 = 0.1704						

Panel B: Perceived Ambiguity

	Mean	Median	St dev	Min	Max	*n* (obs.)
a_aex	0.76	0.93	0.31	0.01	1.00	147
a_stock	0.77	0.98	0.30	0.00	1.00	151
a_msci	0.78	0.99	0.29	0.00	1.00	163
a_bitcoin	0.78	0.96	0.29	0.00	1.00	170
a_avg	0.76	0.85	0.25	0.14	1.00	162
Test of equal means: Hotelling's T^2 = 1.31, p = 0.7363						

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

The table shows estimation results for the panel regression model in Equation (11), 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 Index *b*	Model 2 Index *b*	Model 3 Index *b*	Model 4 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 (12), 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 Index *a*	Model 2 Index *a*	Model 3 Index *a*	Model 4 Index *a*	Model 5 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%

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