THE IMPACTS OF FINANCIAL LITERACY ON FINANCIAL DECISIONS AND BIASES

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ABSTRACT

Using the data from large representative surveys fielded in the United States and Netherlands, this thesis aims to examine the impacts of financial literacy on real-world financial decisions, through various behavioral factors. In this thesis, there are three studies, each addressing different financial problems that commonly arise due to improper decision making, irrationality, and behavioral biases.

The first study measures investors' ambiguity attitudes toward various investments: a domestic stock index, a foreign stock index, a familiar stock, and BitCoin. We find that ambiguity aversion is not universal, which means there both are ambiguity averse investors and ambiguity seeking investors. However, within the same person, ambiguity aversion is constant regardless of the source of uncertainty. The perceived level of ambiguity, on the other hand, is source dependent. The study also finds that ambiguity aversion is related to risk aversion and perceived ambiguity is related to financial literacy. This suggests ambiguity aversion is a preference component and perceived ambiguity is a cognitive component.

The second study examines the lack of retirement savings among U.S. households. We find that present bias and exponential growth bias can explain this lack of savings very well. The results suggest that better financial literacy is related to lower exponential growth bias. In addition, financial literacy helps to mitigate the impact of present bias on the amount of savings. Thus, financial literate people exhibit a lower degree of biases and are more resilient to them.

The last study looks into the relationship between financial literacy and overconfidence. In this study, overconfidence is measured directly. We divide overconfidence into three different aspects: volatility estimation, miscalibration, and better-than-average thinking. Unlike the previous findings in the literature, we find limited evidence that men are more overconfident than women. Financially literate people perceive less volatility and more humbly evaluate their financial literacy. However, we find no evidence that overconfidence explain deviations from rationality in financial decision making such as underdiversification and excessive trading.

KEY WORDS: FINANCIAL LITERACY/ OVERCONFIDENCE/ EXPONENTIAL GROWTH BIAS RETIREMENT SAVINGS/ PRESENT BIAS/ AMBIGUITY ATTITUDE/ INVESTOR BEHAVIOR

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CHAPTER I
INTRODUCTION

The purpose of this dissertation is to investigate how financial literacy impacts financial decision making. Traditional portfolio theory suggests that investors should buy and hold a well-diversified portfolio and avoid unnecessary trading. Yet, deviations from this suggestion are very common and widespread. Empirical evidence that investors ignore this wisdom and experience unnecessarily losses is well documented in the literature. For example, Odean (1998), amongst others (Barber and Odean, 2001; Grinblatt and Keloharju, 2000; Barber et al., 2009; Barber et al., 2014) reports that individual investors trade excessively and suffer losses as a result. Excessive trading cannot be explained by rational motives such as portfolio rebalancing or tax reduction. The amount of losses due to speculative trading are estimated up to 2 percent of GDP, and are thus tremendous (Barber and Odean, 2000). Polkovnichenko (2005) and Goetzmann and Kumar (2008) document that individual investors hold poorly diversified portfolios. Kumar (2009) finds a preference for stocks with low expected returns and high idiosyncratic risk. Given the extensive evidence of deviations from the normative portfolio theory, this leads to a big question why investors prefer choices that are hazardous to their wealth.

Traditional theories usually assume that the decision-makers have the properties of Homo Economicus. Being Homo Economicus means that they need to have unbounded knowledge and unlimited cognitive capacities to evaluate outcomes. Moreover, they must be in an environment that their decisions can be made independently from emotions and are not influenced by other individuals. This assumption is too strict to hold in reality. Individual investors are just ordinary people whose decisions are bounded by their knowledge and cognitive ability. For example, the possible scope of investment choices that an individual investor has is limited to what he knows. Therefore, given that he is rational, his choice would be an investment among what he knows, and the choice may or may not be the same as other investors who possess different sets of knowledge. We consider this individual investors' decision as "boundedly rational," since the decision can be optimal within the bounded scope of his knowledge. Therefore, the investor's capability is also an important factor that impacts investment decisions and possibly keeps the investor from making an investment choice that portfolio theory considers optimal.

In this dissertation, I will focus on an aspect of investor's capability called *financial literacy*. Financial literacy is an important ability that greatly impacts people's decisions both in the context of investment and personal finance. Van Rooji, Lusardi, and Alessie (2011) find that households with higher financial literacy are more likely to invest in stocks. They argue that low financial literacy prevents households from participating in the equity market. Muller and Weber (2010) document that financial literacy improves investment decisions. They find that individual investors with higher financial literacy are more likely to be aware of ETFs or index funds, and choose to invest in mutual funds with lower expenses. Guiso and Jappelli (2008) propose that financial literacy is one of the major factors that explain the lack of diversification in household portfolios. Despite its importance, lack of financial literacy is widespread and well-documented (Lusardi and Mitchell, 2007a, 2007b, 2008; van Rooji, Lusardi, and Alessie, 2007; Agnew and Szykman, 2005; Bernheim, 1995, 1998). Therefore, it is not surprising that many people around the world make financial decisions based on the limited financial knowledge they have, and those decisions are only boundedly rational.

This dissertation consist of three research studies regarding how financial literacy influences financial decision making in various situations. Each of the three research studies will be discussed in detail in the following chapters. The three chapters are as follow,

1. Ambiguity attitudes for real-world investment sources.
2. How financial literacy impacts retirement savings: the role of present bias and exponential growth bias
3. Financial literacy and overconfidence

In CHAPTER II, we measure investors' ambiguity attitudes about real-world investment sources of uncertainty using a newly developed methodology by Baillon et al. (2018). This study elicits both ambiguity aversion and perceived ambiguity toward four different investments: a domestic stock index, a foreign stock index, a familiar stock, and BitCoin. The results show that investors have the same level of ambiguity aversion toward all investments, however, they perceive different levels of ambiguity for each investment. Ambiguity aversion is related to risk aversion, while perceived ambiguity is associated with financial literacy. This indicates that ambiguity aversion is a preference component and perceived ambiguity is a cognitive component. Investors who perceived less ambiguity toward an investment have higher tendency to invest in that asset, which also helps to validate the measures.

In CHAPTER III, the study looks into the lack of retirement savings among U.S. households in the ALP panel. The results show that lack of retirement savings and planning is widespread. Two main behavioral biases that can explain this lack of savings are present bias and exponential growth bias. Although financial literacy is not directly related to the lack of savings, this study shows that better financial literacy is associated with lower exponential growth bias. That is, people with higher financial literacy have more accurate perception about the growth of their savings in the long run, and thus, accumulate more wealth. Moreover, financial literacy can mitigate the impact of present bias on savings. Thus, they save money despise exhibiting the bias. This study has important implications for developing a policy to promote retirement savings among individuals.

The study in CHAPTER IV investigates the impact of financial literacy on overconfidence. Using a combined sample from two DHS surveys in the Netherlands, this study directly measures the three aspects of overconfidence: volatility estimation, micalibration, and better-than-average thinking. These three aspects are proved to be different components of overconfidence and largely unrelated. Contrary to the findings from previous studies, men are not more overconfident than women. The study also finds that better financial literacy is associated with a better estimation of volatility, but not related to better-than-average thinking. Due to low test power, however, we find no evidence that these aspects of overconfidence lead to detrimental behaviors in the stock market such as underdiversification, excessive trading, and being a day trader.

CHAPTER II
AMBIGUITY ATTITUDES FOR REAL-WORLD SOURCES

2.1 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 and van de Kuilen, 2015). These show that people's choices do 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 and Kahneman, 1992).

One concern raised in the empirical literature is that measures of ambiguity aversion are rather 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). Most existing empirical studies measure ambiguity attitudes 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 and more difficult to understand for subjects, which may help explain the high levels of noise in ambiguity measurements. Recently, Baillon, Huang, Selim, and Wakker (2018b) developed a novel method to measure ambiguity for naturally

[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.

occurring sources that controls for unknown probability beliefs. So far, this new method has been applied in laboratory settings with convenience samples of students.

Our paper is the first to measure ambiguity attitudes for relevant real-world sources in a large sample of investors. In particular, households often confront financial decision problems such as saving, investment and insurance, where the probability distribution of future outcomes is not known precisely. 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, 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 highest 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, on average, about 60% of the investors 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 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) depend on the decision maker and the source of ambiguity. Popular theoretical models of ambiguity such as the smooth model (Klibanoff, Marinacci and Mukerji, 2005) and the alpha-MaxMin model (Ghirardato et. al, 2004) assume that ambiguity aversion is subject-dependent but constant 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 each asset and cannot be summarized by a single measure. Thus, 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 testing 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 (Dimmock, Kouwenberg, and Wakker 2016; Dimmock, Kouwenberg, Mitchell, and Peijnenburg 2016; Bianchi and Tallon

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

2019; and Kostopoulos and Meyer 2019) have measured ambiguity attitudes with Ellsberg urns to avoid issues with subjective beliefs and then related these measures to portfolio choices. Our paper is the first to confirm such a link with measures of non-artificial ambiguity directly relevant for the investments.

Our paper contributes 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, Turmunk, and Wakker, 2019) and a field study with students (Li, 2017).[3] Compared to ambiguity experiments using artificial events (Dimmock et al. 2015; and 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. Although considerable noise and monotonicity violations are still present in the data, the results suggest that measurement problems are at least *mitigated* when using real-world sources.

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 we build on earlier work by Abdellaoui et al. (2011), Baillon and Bleichrodt (2015) and Li, Müller, Wakker, and Wang (2017). In another related study, Brenner and 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.

In what follows, in Section 2.2 we first describe our dataset and how we elicit ambiguity attitudes. Next, in Section 2.3, we analyze the heterogeneity in investors' ambiguity aversion, followed by perceived ambiguity in Section 2.4. Then in Section 2.5 we validate the ambiguity measures by testing how they relate to risk

[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, Turmunk, and Wakker (2019) measure ambiguity aversion about the actions of other subjects in a trust game.

preferences, financial literacy, education and investment decisions. A short discussion concludes.

2.2 Data and elicitation methods

2.2.1 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, Sapienza, and Zingales, 2008; Van Rooij, Lusardi, and Alessie, 2011; Von Gaudecker, 2015).

Our questionnaire was targeted at all DHS panel members who indicated that they invested in financial assets as of 31 December 2016, based on the October 2017 DHS survey of wealth and assets. Investors in the DHS are defined as individuals who own mutual funds (about 67% of the investors), individual company stocks (50%), bonds (10%), or options (3%). Our survey module was fielded from 27 April-14 May 2018, yielding 295 complete and valid responses.[5] Our survey was also given to a random sample of 304 non-investors, with 230 complete responses (76%). This non-investor sample allows us to compare the ambiguity attitudes of investors and non-investors, which we do in Section 5.3 and Appendix E. For our main results,

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

[5] Out of 391 DHS panel members who indicated that they invested in financial assets as of 31 December 2016, 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.

we focus on investors, as our goal is to assess ambiguity attitudes of investors in financial markets, and to validate our measures by confirming that ambiguity attitudes are associated with investment decisions.

Summary statistics on the DHS investor sample appear in Table 2.1. *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 2.1 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, and Cox, Kamolsareeratana and Kouwenberg, 2019).

Table 2.1 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

Table 2.1 Descriptive Statistics of the DHS Investor Dataset (cont.)

	Mean	Median	St dev	Min	Max
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

2.2.2 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.[6] 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

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

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.[7] 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 respondent's switching point from Option A to B.

We also elicit matching probabilities 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 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 ($m_1 + m_{23} < 1$). 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 and Fox, 1995; Abdellaoui et al., 2011). For unlikely events, a-insensitivity

[7] We use the choice list approach instead of a willingness to pay method (WTP), as the latter produces less reliable results (Trautmann, Vieider, and Wakker, 2011).

[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.

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 and van de Kuilen, 2015; Dimmock, Kouwenberg and 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. Monotonicity requires $a \leq 1$, as the average matching probability of the composite events should exceed the average for the single events $(\bar{m}_c \geq \bar{m}_s)$. However, in practice, respondents can make errors and violate monotonicity, leading to $a > 1$.

The Baillon et al. (2018b) method has two major advantages. First, 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, and Appendix F). 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. Second, we also need not know the respondent's utility functions, as we use matching probabilities and a fixed price of €15 for both Options A and B, which ensures that utility drops out of the equation as well (see Dimmock, Kouwenberg and Wakker, 2016).

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). We refer to Appendix F for a full derivation, while here we only provide a brief summary. Ambiguity occurs when the decision-maker does not know the exact probability of the event E, but considers an interval I_E of possible probabilities for event E. Let $x_E 0$ denote a two-outcome prospect that pays amount $x \geq 0$ if the ambiguous event E occurs, and 0 otherwise. The α-MaxMin model (Hurwicz, 1951; Ghirardato, Maccheroni, and Marinacci, 2004) evaluates the ambiguous prospect $x_E 0$ as follows:

(3) $\alpha\ min_{p \in I_E} \{pU(x)\} + (1-\alpha) max_{p \in I_E} \{pU(x)\}$, 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. Within the context of the neo-additive model axiomatized by Chateauneuf, Eichberger, and Grant (2007), it can be shown that index *a* measures the length of the probability interval I_E, and thus is a measure of perceived ambiguity. Index *b* is a rescaled version of α, ranging from -*a* to *a*, and measures ambiguity aversion.[9] We note that interpretation of index *a* as a proxy for perceived ambiguity requires $0 \leq a \leq 1$, and we will later analyze how often index *a* falls within these boundaries.

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. For the individual stock

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[9] Namely: $b = 2\left(\alpha - \frac{1}{2}\right)a$. 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 problems as b/a is not defined for $a = 0$.

the percentage change was set to 8% and for Bitcoin to 30%, to reflect the higher historical volatility of these investments.[10]

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%

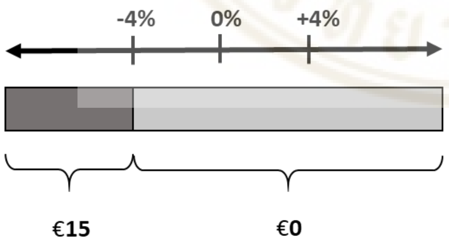
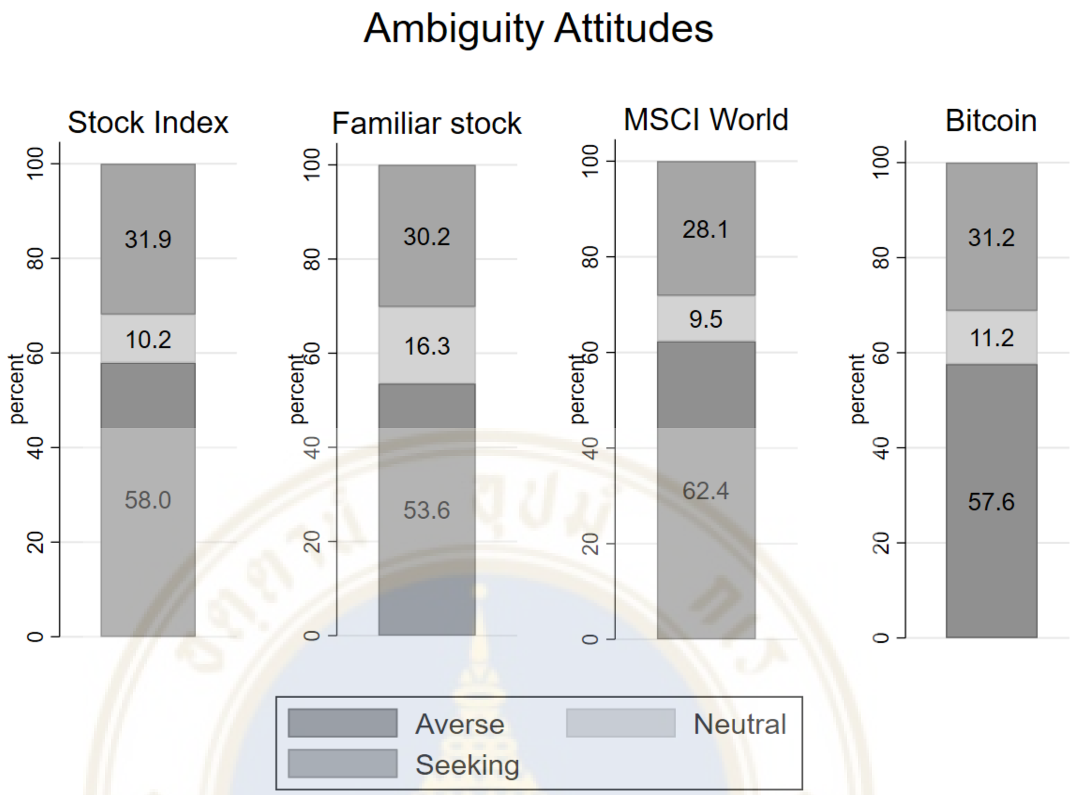


Figure 2.1 Example of a choice list for eliciting ambiguity attitudes

[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.



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 2.2 Ambiguity Attitudes toward Financial

Sources: Averse, Neutral and Seeking

2.2.3 Elicitation of risk attitudes

The DHS module also included four separate choice lists to measure risk attitudes (a screenshot is provided in 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 of the risk and ambiguity question sets in the survey was randomized. 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 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.

Table 2.1 shows that on average investors are risk averse (mean > 0), but with strong heterogeneity, and about one thirds 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 other studies (see, e.g., Fehr-Duda and Epper, 2011 and Dimmock et al., 2018).

2.2.4 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 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.

2.2.5 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 and Mitchell (2007) and Van Rooij et al. (2011), who devised both basic and advanced financial literacy questions. Appendix B provides the list of financial literacy questions, and the variable *Financial*

[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.

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 Table 2.1).[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 Table 2.1). *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.

2.3 Results for ambiguity attitudes

2.3.1 Descriptive statistics

Figure 2.2 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 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

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[12] The average financial literacy score is relatively high because our sample consists of investors. Among a sample of 230 non-investors in the DHS panel (See Appendix E), the average score is only 8.6 out of 12.

[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. We thank a reviewer for pointing this out.

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 (Ellsberg urns), such as Dimmock et al. (2015), Dimmock, Kouwenberg, and Wakker (2016), and Kocher, Lahno, and Trautmann (2018), showing that ambiguity seeking choices are not limited to Ellsberg urns.

Table 2.2 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), but the p-value is close. This implies that the mean level of ambiguity aversion does not depend strongly on the source of financial uncertainty.

Dimmock, Kouwenberg, and 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 used by Dimmock et al. (2016) 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 2.3 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 the first factor explains 77%

[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.

of the cross-sectional variation in the four ambiguity aversion measures, indicating that a single underlying preference variable is driving most of the variation.

Table 2.2 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

2.3.2 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:

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

for $i = 1, 2, \ldots, I$ 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:

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

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), one of the main findings is that observed individual characteristics like gender and age can explain at most 3% of the variation in ambiguity attitudes. Further, l'Haridon et al. (2018) suggest 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 (4) 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:"

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

i =1, 2, …, *I*, and s=1, 2, 3, 4

[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.

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, the baseline model (4) with only a random constant is estimated, 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 ($\widehat{Stdev}[v_{i,s}^b] = 0$), or perfect correlation with the random constant ($\widehat{Cor}(u_i^b, v_{i,s}^b)$ = 1 or -1), then it is considered invalid and not used.

2.3.3 Analysis of heterogeneity in ambiguity attitudes

The estimation results for index *b*, ambiguity aversion, appear in Table 2.3. 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. Model 1 in Table 2.3 includes only a random effect, 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. In Model 2, dummies are added to allow for differences in the mean level of ambiguity aversion toward the four investments. The dummy for the foreign stock index MSCI World is positive and significant at the 5% level ($p = 0.042$), suggesting that investors are more ambiguity averse for the foreign stock index.

[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.

Random slopes for source-specific ambiguity aversion are next added to the model, and a chi-square test (not shown in Table 2.3) shows that only adding a random slope for Bitcoin leads to a significant improvement of model fit ($p < 0.001$). Model 3 in Table 2.3 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.

Table 2.3 Analysis of Heterogeneity in Ambiguity Attitudes

The table shows estimation results for the panel regression model in Equation (6), 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 that is common to all sources. Model 2 adds dummies for differences in the mean of index *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 (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***	0.153	0.212
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	-0.018
Age				0.006***	0.003*
Female				0.072	0.059

Table 2.3 Analysis of Heterogeneity in Ambiguity Attitudes (cont.)

	Model 1 Index *b*	**Model 2 Index *b***	**Model 3 Index *b***	**Model 4 Index *b***	**Model 5 Index *b***
Single				-0.116**	-0.090*
Employed				-0.040	-0.042
Number of Children (log)				0.059	0.048
Family Income (log)				-0.011	0.016
HH Fin. Wealth (log)				-0.016*	-0.011*
HH Wealth Imputed				-0.130	-0.050
Financial Literacy					-0.015
Risk Aversion					0.466***
Likelihood Insensitivity					-0.084*
Random Slope: Bitcoin	No	No	Yes	Yes	Yes
N Observations	1180	1180	1180	1180	1180
I Respondents	295	295	295	295	295
Number of Variables	0	3	3	12	15
Log-Likelihood	-485.323	-482.191	-467.777	-455.351	-414.645
Chi-Square	-	7.645	7.645	46.080	127.777
P-Value	-	0.054	0.054	0.000	0.000
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	0.075	0.061	0.061	0.061
$Var[u_i^b]$, Random Constant	0.165	0.165	0.167	0.152	0.112
$Var[v_{i,4}^b]$, Slope Bitcoin	-	-	0.011	0.012	0.012
$Var[\beta'D + \gamma'X]$, Observed	-	0.0004	0.0004	0.015	0.056
%, Error	31.4%	31.2%	25.4%	25.3%	25.3%
%, Random Constant	68.6%	68.6%	69.7%	63.2%	46.5%
%, Slope Bitcoin	-	-	4.8%	5.1%	4.8%
%, Observed Variables	-	0.2%	0.2%	6.4%	23.3%

2.3.4 Variation in ambiguity attitudes explained by individual characteristics

In Model 4 in Table 2.3, observed individual socio-demographic variables are added, such as age, gender, education, employment, income, and financial assets. Ambiguity aversion toward investments is lower for younger investors and singles. 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 (= 23.3% - 6.4%). Specifically, ambiguity aversion toward investments and risk aversion have a strong positive relation. Ambiguity aversion is not significantly related to education and financial literacy. 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.

2.3.5 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 Appendix C 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.

Table 2.4 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 *a*-index 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

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

2.3.6 Monotonicity violations

Panel A in Table 2.4 shows the percentage of investors who violate monotonicity, $\overline{m}_s > \overline{m}_c$, 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, and Wakker (2016), using Ellsberg urns, 25.4% of investors violate monotonicity. Overall, the rates of monotonicity violations in Table 2.4 are high, but similar to previous ambiguity studies.

As a robustness check, in Appendix D we repeat the analysis in Table 2.3 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 2.3 are robust to screening out violations of monotonicity.

2.4 Results for perceived ambiguity

2.4.1 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 2.4 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 large 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 and 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 results for a-insensitivity, using all values of index *a*.

Panel B of Table 2.4 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 (075). 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, and 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 2.4 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]

2.4.2 Analysis of heterogeneity in perceived ambiguity

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

(7) $a_{i,s} = \alpha_1 + \sum_{s=2}^{4}(\alpha_s + v_{i,s}^a)d_s + \sum_{k=1}^{K}\gamma_k^a X_{i,k} + u_i^a + \varepsilon_{i,s}^a,$

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

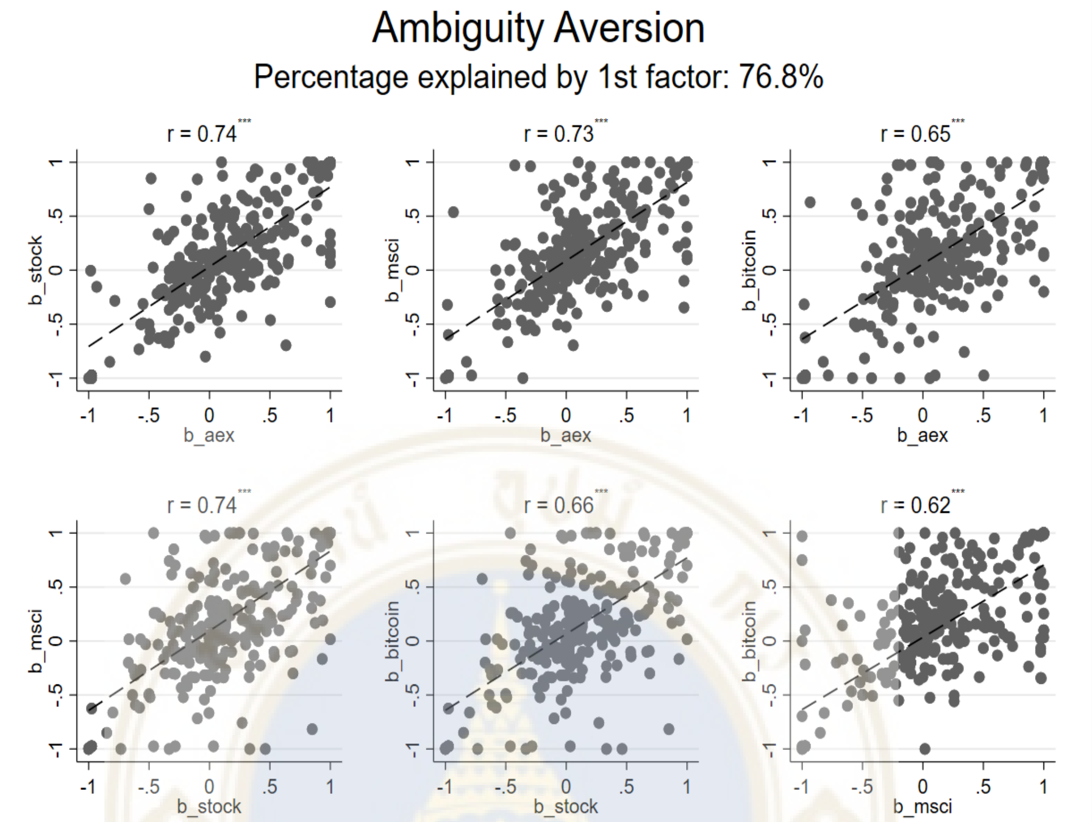
[18] Further, the correlations between index *b* and *a* are low, ranging from 0.11 to 0.32, indicating that ambiguity aversion and perceived ambiguity are two separate aspects of ambiguity attitudes (in line with evidence in Abdellaoui et al., 2011; Dimmock et al., 2015; Dimmock et al., 2016; Baillon et al., 2018b).

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

where $a_{i,s}$ is index *a* (perceived ambiguity) of respondent *i* toward source *s*. The 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.

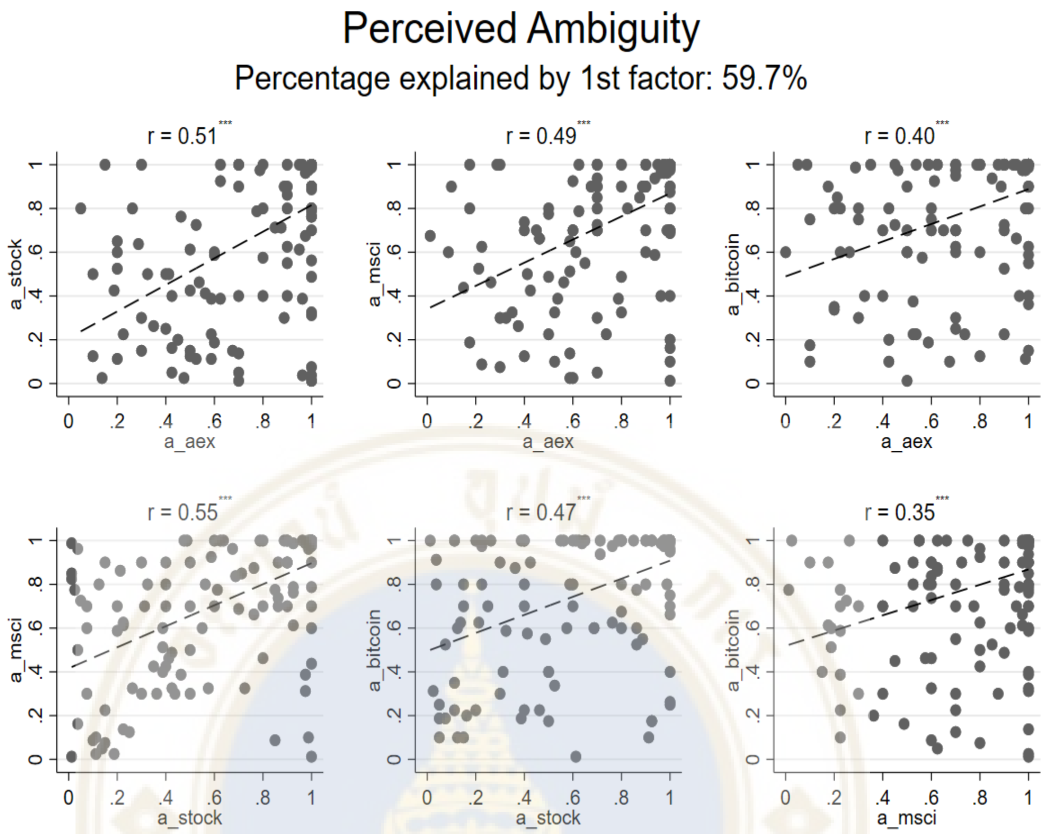
Table 2.5 shows the estimation results. Model 1 includes only a random effect, capturing individual heterogeneity in perceived ambiguity that is common to the four sources, which explains 44% of the total variation in index *a*. Model 2 shows that on average investors perceive less ambiguity about the familiar stock: α_2 = -0.091, relative to perceived ambiguity of α_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 (not shown in Table 2.5) 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 2.5 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.



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 2.3 Scatter Plots of Ambiguity Attitudes toward 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.

Figure 2.4 Scatter Plots of Perceived Ambiguity about Different Financial Sources

Table 2.5 Analysis of Heterogeneity in Perceived Ambiguity

The table shows estimation results for the panel regression model in Equation (7), with index *a* toward the four investments as the dependent variable. 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 includes a constant and a random effect for individual-level heterogeneity in perceived ambiguity that is common to all sources. Model 2 adds dummies for differences in the mean of perceived ambiguity between the four investments. Model 3 includes a random slope to capture heterogeneity in perceived ambiguity toward the familiar stock and Bitcoin, shown to be significant by 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. *, **, *** denote significance at the 10%, 5% and 1% level.

	Model 1 **Index *a***	**Model 2** **Index *a***	**Model 3** **Index *a***	**Model 4** **Index *a***	**Model 5** **Index *a***
Constant	0.696***	0.718***	0.721***	0.796***	0.915***
Dummy Familiar Stock		-0.091***	-0.099***	-0.102***	-0.103***
Dummy MSCI World		-0.011	-0.013	-0.014	-0.016
Dummy Bitcoin		0.013	0.014	0.013	0.011
Education				-0.041***	-0.034***
Age				0.003***	0.002*
Female				0.019	0.005
Single				-0.059*	-0.045
Employed				0.027	0.028
Number of Children (log)				-0.029	-0.032
Family Income (log)				-0.019**	-0.010
HH Fin. Wealth (log)				0.005	0.007
HH Wealth Imputed				0.068	0.069

Table 2.5 Analysis of Heterogeneity in Perceived Ambiguity (cont.)

	Model 1 Index *a*	**Model 2 Index *a***	**Model 3 Index *a***	**Model 4 Index *a***	**Model 5 Index *a***
Financial Literacy					-0.022**
Risk Aversion					0.041
Likelihood Insensitivity					0.087***
Random Slope: Bitcoin	No	No	Yes	Yes	Yes
Random Slope: Stock	No	No	Yes	Yes	Yes
N Observations	794	794	794	794	794
I Respondents	284	284	284	284	284
Number of Variables	0	3	3	12	15
Log-Likelihood	-146.296	-135.663	-128.414	-108.790	-97.594
Chi-Square	-	20.056	24.832	76.608	114.137
P-Value	-	0.000	0.000	0.000	0.000
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	0.055	0.046	0.046	0.047
$Var[u_i^a]$, Random Constant	0.044	0.044	0.044	0.035	0.031
$Var[v_{i,4}^a]$, Slope Bitcoin	-	-	0.004	0.005	0.004
$Var[v_{i,2}^a]$, Slope Stock	-	-	0.006	0.006	0.004
$Var[\alpha'D + \gamma'X]$, Observed	-	0.002	0.002	0.010	0.014
%, Error	56.2%	54.5%	45.4%	45.6%	46.9%
%, Random Constant	43.8%	43.9%	42.7%	34.4%	30.1%
%, Slope Bitcoin	-	-	4.2%	4.5%	4.2%
%, Slope Stock	-	-	5.7%	5.6%	4.4%
%, Observed Variables	-	1.6%	1.9%	9.9%	14.3%

2.4.3 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 (= 9.9% - 1.9%) in perceived ambiguity. Older investors perceive more ambiguity about investments, whereas investors with higher education and more income perceive less ambiguity. Model 5 adds proxies for financial literacy and risk attitudes, which explain an additional 4.4% of the variance (= 14.3% - 9.9%). Specifically, investors with better financial literacy perceive less ambiguity. Further, perceived ambiguity is positively related to index *a* for risk, 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 off small differences in matching probabilities between composite events and single events, as discussed below.

2.4.4 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 related between the four investment sources. When estimating the econometric model (7), 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*.

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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.

2.5 Validity of the measures

2.5.1 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. Similarly, we expect that likelihood insensitivity (overweighting of small probabilities) is positively related to a-insensitivity (overweighting of unlikely events), and thus to perceived ambiguity. The results in Table 2.3 and Table 2.5 clearly confirm these expected relations, with strong statistical significance ($p < 0.01$). [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 2.5 confirms both of these relations, 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 2.3 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.

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[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 et al. (2016).

2.5.2 External validation: The relation with 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.

In Table 2.6 we report marginal effects for probit regression models 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*), as before including only observations with $0 \leq a_{i,s} \leq 1$. We could not conduct a similar analysis for the AEX index, as none in our sample invest in a fund tracking the AEX. The results in Column (2) show that higher perceived ambiguity about MSCI World is negatively related to investing in it. In Column (3) higher ambiguity aversion and perceived ambiguity about Bitcoin have a negative relation with investing in crypto-currencies, but only marginally and the model is not significant.

To investigate the impact of measurement error in ambiguity attitudes, in Column (4)-(6) of Table 2.6 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 (Tables 2.3 and 2.5, Model 3). The predicted values are based on the fitted values of the random effects ($\hat{u}_i^b$, $\hat{u}_i^a$) and the random slopes ($\hat{v}_{4,s}^b$,$\hat{v}_{2,s}^a$, $\hat{v}_{4,s}^a$) for each investor in the sample, as well as differences in means of index *b* and *a* between sources ($\hat{\beta}_s$, $\hat{\alpha}_s$). Using the predicted values, we effectively remove the error terms $\hat{\varepsilon}_{i,s}^b$ and $\hat{\varepsilon}_{i,s}^a$ from index *b* and *a*. The results in Table 2.6 show that the fitted values better explain asset investment than the original indexes, as indicated by higher pseudo R-squares. Investors who perceive more ambiguity about a familiar stock and the MSCI World are less likely to invest in these assets. For bitcoin in Column (6), both ambiguity aversion and perceived ambiguity have a significant negative effect on investment.

Overall, these results suggest that the panel model has been able to separate out some of the noise in the measurements, and that individual heterogeneity

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[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.

in perceived ambiguity (the random effects) has a negative relation with actual investments. For investments in Bitcoin, ambiguity aversion also has a negative impact. These results support the validity of the ambiguity measures.

2.5.3 Robustness tests

We performed several robustness checks for our main results, reported in Appendix D 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 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.

We have also conducted a robustness check to assess if the relations between ambiguity attitudes and investments in Table 2.6 are driven by omitted variables such as risk aversion, financial wealth, education and financial literacy. In Appendix D we include these variables as control variables in the regression models. The main impact is a slight decrease in the effect of perceived ambiguity on investments in the familiar stock and Bitcoin. Perceived ambiguity still has a negative relation with investment in the foreign MSCI World index, and ambiguity aversion has negative relation with investing in Bitcoin.

Table 2.6 Investment in the Familiar Stock, MSCI World and Crypto-Currencies

This table reports estimation results for a probit model explaining asset ownership with perceived ambiguity (index *a*) and ambiguity aversion (index *b*). Only observations with $0 \leq a \leq 1$ are included so that index *a* can be interpreted as perceived ambiguity, and for this reason the sample size *n* varies in each column. The numbers displayed are estimated marginal effects. In columns (1) and (4), the dependent variable is 1 if the respondent invests in the familiar individual stock and 0 otherwise. In columns (2) and (5), the dependent variable is 1 if the respondent invests in funds tracking the MSCI World equity index and 0 otherwise. In columns (3) and (6), the dependent variable is 1 if the respondent invests in crypto-currency and 0 otherwise. The independent variables are ambiguity aversion and the perceived level of ambiguity about the specific asset: *a_stock* and *b_stock* in column (1), *a_msci* and *b_msci* in column (2), *a_bitcoin* and *b_bitcoin* in column (3). In column (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. Control variables are excluded from the probit models below to avoid problems with complete separation and over-fitting the data, due to the small number of investors owning crypto-currencies and investing in MSCI World. *, **, *** denote significant coefficients at the 10%, 5% and 1% level.

	(1) Invests in Familiar Stock	**(2) Invests in MSCI World**	**(3) Invests in Bitcoin**	**(4) Invest in Familiar Stock**	**(5) Invest in MSCI World**	**(6) Invests in Bitcoin**
Perc. ambiguity (index *a*)	-0.147	-0.035***	-0.053*			
Amb. Aversion (index *b*)	0.009	-0.009	-0.035*			
Perc. ambiguity (fitted)				-0.239*	-0.093**	-0.143**
Amb. aversion (fitted)				-0.004	-0.002	-0.046**
N observations	192	205	205	192	205	205
I respondents	192	205	205	192	205	205
Number of variables	2	2	2	2	2	2
Log-Likelihood	-112.813	-14.628	-24.883	-112.405	-13.727	-23.840

Table 2.6 Investment in the Familiar Stock, MSCI World and Crypto-Currencies (cont.)

	(1) Invests in Familiar Stock	(2) Invests in MSCI World	(3) Invests in Bitcoin	(4) Invest in Familiar Stock	(5) Invest in MSCI World	(6) Invests in Bitcoin
Chi-Square	2.499	10.456	4.178	3.486	6.860	6.206
P-value	0.287	0.005	0.124	0.175	0.032	0.045
Pseudo R-square	0.011	0.065	0.082	0.015	0.123	0.120

In Appendix E we present results for the group of 230 non-investors, who do not own financial assets. As expected, perceived ambiguity is higher in this group, while ambiguity preferences on average are not different. In the non-investor group, heterogeneity in ambiguity aversion is driven by a single underlying factor, while random slopes for Bitcoin and other sources are not significant. Further, perceived ambiguity toward different investment is also largely driven by one underlying factor explaining 48% of the variation, 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.

2.6 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 earlier empirical studies using Ellsberg urns is that ambiguity attitudes are 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), with correlations between repeated measures of ambiguity aversion 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, Marinacci and Mukerji 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 data also confirm insensitivity to the likelihood of ambiguous events as a second component of ambiguity attitudes, displayed by the large majority of investors.

Our paper also contributes to the literature on portfolio choice under ambiguity, by providing insight on how to model ambiguity attitudes.[22] Our findings support theoretical work that has modelled ambiguity attitudes with a single ambiguity preference parameter, but with different levels of perceived ambiguity depending on the investment source (e.g., Uppal and Wang, 2003; Boyle, Garlappi, Uppal, and Wang, 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 et al. (2016; Appendix D). 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.

[22] Dow and Werlang, 1992; Mukerji and Tallon, 2001; Cao et al., 2005; Easley and O'Hara, 2009; Bossaerts et al., 2010; Epstein and Schneider, 2010; Gollier, 2011.

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.

CHAPTER III
HOW FINANCIAL LITERACY IMPACTS RETIREMENT SAVINGS: THE ROLE OF PRESENT BIAS AND EXPONENTIAL GROWTH BIAS

3.1 Introduction

Saving for retirement is a matter of concern both for individuals and policy makers. In the United States, many employees do not plan for their retirement and end up accumulating an inadequate amount of savings (Lusardi and Mitchell, 2007a). In the Netherlands, only a small percentage of households (12.9%) admit that they have thought about retirement (Van Rooij, Lusardi, Alessie, 2011). This raises an important question about what kept them, during their younger age, from accumulating more wealth and preparing for their retirement adequately. Using a representative sample in the United States, Goda et al. (2019) show that present bias and exponential growth bias (EGB) have a negative relation with retirement savings. Present bias is a tendency to attach higher value to rewards that are closer to the present time (O'Donoghue and Rabin, 1999). It makes the decision maker strongly prefer consumption at present to consumption in the future, thus creating a tendency to spend more money on everyday consumption and accumulate less wealth for their future needs. EGB, on the other hand, prevents the decision maker from fully appreciating the benefits of compounding returns over a long horizon, thus making saving less attractive.

Given that present bias and EGB are common and widespread behavioral biases (Goda et al., 2019), changing people's saving behavior can be a challenging task. Policy makers cannot just ask people to be 'less present biased.' Therefore, our objective in this paper is to identify how the effects of present bias and EGB can be alleviated through better financial literacy. Lusardi and Mitchell (2007a, 2007b, 2011a, 2011b) show that financially literate people are more likely to successfully plan for their retirement. Similar findings are documented in the Netherlands (Alessie, Van Rooij, and Lusardi, 2011) and Italy (Fornero and Monticone, 2011). Moreover, planning for retirement can be a difficult task as it involves many factors such as consumption planning, understanding compound interest rates, and risk diversification. Therefore, without a proper level of financial literacy, a person might view the task as being too complex, underestimate its benefits, and end up taking no action. Stango and Zinman (2009) provide support for this argument by showing that individuals who cannot calculate interest rates correctly have a tendency to underestimate the compound interest rate in the long term, as well as the future value of investments. These households tend to borrow more and save less, ending up having a lower amount of wealth. Thus, financial literacy can be a good channel to alleviate biases and improve retirement savings because it not only allows individuals to see the benefits of saving, but also provides them an ability to do so.

Goda et al. (2019) demonstrate a strong link between present bias and retirement savings. That is, individuals who exhibit a higher degree of present bias accumulate relatively less wealth for their retirement. But does that also hold true for all individuals across different levels of financial literacy? Since financially literate individuals should be more aware of the bias and better able to avoid it, we hypothesize that financial literacy can reduce the effect of present bias on saving decisions. In other words, the influence of present bias on retirement savings is prevalent only among those who are financially illiterate. We look into the role of financial literacy as a moderator for the relationship between present bias and retirement savings. Despite having a preference for consumption at present time, financially literate individuals may be more aware of the importance of accumulating wealth for their retirement. Thus, they might try to alleviate the impact of present bias. Our findings show that the impact of present bias on retirement savings declines as a person’s financial literacy score increases. We are able to show that, among individuals who do best in the financial literacy questions, present bias has a very limited impact on their saving decisions. Thus, with a moderating effect of financial literacy on the relationship between present bias and retirement savings, improving financial literacy may be an effective approach to promote savings among individuals.

Then we further examine the effect of financial literacy on EGB. We expect that financial literacy can help reduce EGB because individuals with better financial knowledge are more likely to properly take compounding effects into account when calculating returns. Thus, financially literate people should have a more accurate perception about the exponential growth of their savings and be more willing to save. Our results show that financial literacy is negatively related to exponential growth bias (EGB) which has been identified as a major cause for lack of savings. Furthermore, we find that financially literate individuals are less affected by present bias.

We will present our theoretical framework and the relevant literature in the next section. Then, our research methodology will be explained in Section 3.2. In Section 3.3, we will report our findings and discuss their implications. Finally, we will conclude our study in Section 3.4.

3.2 Literature and Theoretical Framework

Previous studies have identified factors that partially explain the wide variation in retirement savings among households with similar incomes. One of the most common explanations is present bias. People with present bias tend to procrastinate and end up never starting to save for their retirement (O'Donoghue and Rabin, 1999, 2001). They often need to rely on illiquid assets as a way to commit in order to effectively save money (Laibson, 1997). This line of research mainly focuses on the time-inconsistent preferences arising when the decision maker has a hyperbolic discounting function. Liabson (1998) finds that hyperbolic models can explain phenomena such as lack of savings, consumption discontinuities at retirement, accumulation of illiquid assets, and declining national saving rates in developed countries. He argues that, according to the hyperbolic discounting model, early selves want to save more money in "the future" but then later selves who have control during "the future" period prefer to spend the money. Bernheim (1995) documents that baby boomers save only 5% of their income, in contrast to the saving target of 15%. This difference can be well explained by the hyperbolic discounting model.

Ainslie (1986) argues that people's discount function is of the hyperbolic form, which contradicts the traditional view that the discount factor is constant and choices across time are only different in the delay of consequences. With a greater discounting factor, when the time of an event is closer to the present, the benefits at present will be relatively more attractive. Economists refer to this phenomenon as time-inconsistent preferences, since a decision maker's preferences change over time. At each moment in time, the same decision maker has different preferences for the same reward or outcome. For example, a man who wants to lose weight plans to exercise on the coming weekend but when Friday comes, he does not feel like doing it and wants to postpone the exercise for another day. This example shows that his 'self' at time 0 uses a lower discount rate for the task on the weekend than his another 'self' on Friday, who applies a relatively higher discount rate to the task and thus wants to change the earlier decision.

Phelps and Pollak (1968) propose a quasi-hyperbolic discounting function in the consumption context as follows. Let X_t, y_t and c_t be cash on hand, income and consumption at time t, where t = 0, 1, 2, …, T. Then we can write X_t as,

$$X_t = (X_{t-1} - c_{t-1})\, R + y_t$$

Where, R is a real interest rate. If we assume that this person cannot borrow, then $c_t < X_t$ for any value of t. The utility for each "self" of this person at time t, U_t, can be written as

$$U_t(c_0, c_1, \ldots, c_T) = E_t[\; u(c_t) + \beta \sum_{i=1}^{T-t} \delta^i u(c_{t+i}) \;]$$

Where, $0 < \delta < 1$ is a long-run discount factor and $0 < 1 - \beta < 1$ is the degree of present bias. A greater value of β indicates a smaller degree of present bias.

Beside present bias, financial literacy and EGB are identified in the literature as determinants for the amount of retirement savings. Financially literate people are more likely to plan for their retirement (Lusardi and Mitchell, 2007a, 2007b, 2008, 2011a, 2011b). This might be because a lack of financial knowledge prevents many households from planning their finance effectively (Bernheim, 1998; Bernheim, Skinner and Weinberg, 2001). The lack of financial knowledge problem is closely related to EGB. People who fail to understand interest compounding tend to underestimate the future value of their savings in the long term (Stango and Zinman, 2009). Goda et al. (2012) document that once people correctly know the future values of their savings (through intervention), they increase their annual savings contributions.

As a measure of EGB, Levy and Tasoff (2015) propose a model where a person's perception of exponential growth is a function of the interest rate r, time horizon *T*, and individual's exponential growth perception parameter *α*. The perception at time $t < T$ can be expressed as,

$$P(r, t; \alpha) = \prod_{s=t}^{T-1}(1 + \alpha_i r_s) + \sum_{s=t}^{T-1}(1 - \alpha_i) r_s$$

The value of α varies between 0 and 1, ranging from linear growth (biased) to exponential growth (correct). An individual who completely ignores the compounding effect would have $\alpha = 0$. That is, he just sums up all the returns over the horizon and does not compound interest at all.

We propose that understanding of exponential growth can be improved by having better financial literacy. It is intuitive that a financially literate person would be more aware of the compounding effect and has better ability to calculate the exponential growth rate correctly. Therefore, we hypothesize that financial literacy can reduce the EGB.

3.3 Data and Methodology

3.3.1 Data

The dataset for this research is from the American Life Panel (ALP) survey fielded by Goda et al. (2019). The ALP is a national representative panel of members who are regularly interviewed for research purposes. It provides various aspects of household financial information including income, debt (secured and unsecured), and retirement savings, which is the main focus of this study. The sample consists of 1,743 observations after we handle missing data with listwise deletion.

3.3.2 Household Background Information

Table 3.1 shows the financial and demographic information of the households in the sample. On average, the respondents have saved \$129,210 (\$10,067 for median) for their retirement and have \$49,003 (\$3,000 for median) in their non-retirement accounts. They earn \$40,743 (\$32,000 for median) annually and up to \$63,750 (\$51,240 for median) when income from partners is included. About 43% of the respondents are male and the average age of this sample is fifty-two years. Over half of the respondents have at least an Associate degree and 45% have a Bachelor degree or higher. The survey also provides an elicitation of risk preferences and divides the respondents into risk categories based on their choices in hypothetical questions between prospect payoffs with different degrees of risk. Category 1 is for those who prefer a certain pay off (highest risk aversion) which consist of 37% of the sample, while another 21% are in Category 6 which is the lowest level of risk aversion.

In order to handle extreme values, following Goda et al. (2015), income variables are winsorized at 95% and retirement savings and non-retirement savings are winsorized at 99%.

Table 3.1 Financial and demographic information

Variables	**Mean**	**Median**	**Std.Dev**
Retirement saving amount	129,210	10,067	269,579
Non retirement saving amount	49,003	3,000	141,907
Incomes	40,743	32,000	36,221
Incomes (with spouse)	63,705	51,240	54,275
Male	0.426		0.495
Age	52.036	54	15.267
Education			
HS or Less	0.186		0.390
Some College	0.248		0.432
Assoc Degree	0.119		0.324
BA/BA Degree	0.268		0.443
Post BA/BA	0.178		0.383
Race			
White/Caucasian	0.769		0.421
Black/African American	0.116		0.320
American Indian or Alaskan Native	0.011		0.107
Asian or Pacific Islander	0.030		0.172
Other	0.072		0.259
Hispanic	0.159		0.366

Table 3.1 Financial and demographic information (cont.)

Variables	Mean	Median	Std.Dev
Risk category			
Category 1 (most risk-averse)	0.368		0.482
Category 2	0.156		0.363
Category 3	0.159		0.366
Category 4	0.067		0.250
Category 5	0.040		0.195
Category 6 (least risk-averse)	0.208		0.406
Marital Status			
Married or living with a partner	0.606		0.489
Separated	0.027		0.162
Divorced	0.131		0.337
Widowed	0.052		0.223
Never Married	0.184		0.387
Number of household member	1.024	0	1.472

3.3.3 Parameter Elicitation

This sub-section explains how the main variables for this study are measured. The measurements of present bias, and EGB, are explained in detail below.

3.3.3.1 Financial Literacy

To measure the respondents' understanding of basic financial concepts, the three questions designed by Lusardi and Mitchell (2011a) are used. This set of questions is generally accepted as an efficient way to capture financial literacy. The respondents were asked three questions about inflation and compound interest. Then, the number of the correct answers is summed up to create a financial literacy score from 0 to 3.

3.3.3.2 Present Bias

The time-preference staircase method of Goda et al. (2015) is used to elicit the parameters δ and β of the hyperbolic discounting model. The method consists of three questions asking the respondent to choose between receiving money at different points in time. The questions are stated as follows:

(1) Present-Future Staircase: Would you rather receive $100 today or $[X] in 12 months?

(2) Future-Future Staircase: Would you rather receive $120 in 12 months or $[Y] in 24 months?

(3) Prediction Staircase: Suppose that 12 months from now, you are going to be given the choice between the following: receiving a payment on that day (that is, 12 months from today) or a payment 12 months later (that is, 24 months from today) ...Do you think you would rather choose to receive $110 on that day or $[Z] 12 months later?

The amounts X, Y, and Z are always greater than the preceding value, that is, $100, $120, and $110, respectively. The amounts of X, Y, and Z will be adjusted based on the choice that the respondent makes. For each staircase, if the respondent prefers money sooner, the amounts of future money will increase, and vice versa in the following round. After a few rounds of the staircase, a narrow interval that contains the indifference point is obtained. The cutoff point for each of X, Y, and Z is the mid-point of the interval from the corresponding staircase. The values of δ and β can be elicited from the X_{Cutoff} and Y_{Cutoff}. The δ, which is the long-run discount factor, is calculated as 120/Y_{Cutoff}, and then β is identified as 100/($\delta\, X_{Cutoff}$).

The prediction staircase is also used to elicit the future time-preferences predicted by the respondent at the present time. According to O'Donoghue and Rabin (2001), people may overestimate the β of their future selves. Therefore, naïve individuals might have a value of $\hat{\beta}$ (predicted) greater than β, while sophisticated individuals, who are aware of their bias, have $\hat{\beta} = \beta$. From the prediction staircase data, $\hat{\beta}$ is obtained from 110/($\delta\, Z_{Cutoff}$).

3.3.3.3 Exponential Growth Bias

The exponential growth perception parameter (α), following Goda et al. (2015), is measured with the methodology of Levy and Tasoff (2015). First, the respondent will be asked a set of hypothetical questions involving compound interest. Examples of the questions are as follows:

(1) An asset has an initial value of \$100 and grows at an interest rate of 10% each period. What is the value of the asset after 20 periods?

(2) An asset has an initial value of \$100 and grows at an interest rate of -20% in odd periods (starting with the first), and at 25% in even periods. What is the value of the asset after 24 periods?

(3) Asset A has an initial value of \$100, and grows at an interest rate of 8% each period. Asset B has an initial value of \$X, and grows at an interest rate of 8% each period. Asset A grows for 10 periods, and Asset B grows for 24 periods. What value of X will cause the two assets to be of equal value?

The answer for question j by respondent i is denoted by y_{ij}. Let $\vec{a}(\alpha)$ be a vector of the answers for these questions based on the level of α. $\vec{a}(1)$ is the set of correct answers, when the exponential growth component is fully accounted for. The level of EGB of the respondent i is calculated by finding α_i such that the mean squared error between y_i and $\vec{a}(\alpha_i)$, normalized by the correct answer, is minimized. For a set of n hypothetical questions, the estimation can be written as,

$$\alpha_i = arg\min_{\alpha} \frac{1}{n} \sum_{j=1}^{n} \left(\frac{y_{ij} - a_j(\alpha)}{a_j(1)} \right)^2$$

Respondents who can answer all the questions correctly (have accurate exponential growth perception) would have $\alpha = 1$. On the other hand, having $\alpha = 0$ implies that the respondent has a linear view on the compound growth rate of money.

3.3.4 Financial Literacy and Preference Parameters

Table 3.2 displays the statistics for the financial literacy score and estimated preference parameters. The average financial literacy score is 2.56 out of 3, which indicates a good understanding about basic financial knowledge. As many as 1,180 respondents answered all of the financial literacy questions correctly, while only 22 people got a zero financial literacy score.

The discount factor (δ) and degree of present bias ($1 - \beta$) are calculated with the time-preference staircase method following Falk et al. (2014) and Goda et al. (2015). On average, the value of δ is 0.708 with a standard deviation of 0.173, while the average value of β is 1.025 with a standard deviation of 0.203. The average value of parameter β close to one indicates that, overall, the respondents in this sample have time-consistent preferences. However, the large standard deviation of β indicates a strong variation among the respondents.

EGB is identified by α which is calculated based on the methodology of Levy and Tasoff (2015). The respondents are asked to answer a set of hypothetical questions that involve compound interest. Then α is a degree of EGB that best fits with their answers to the questions. The value of α is allowed to exceed 1 and capped at 1.5 in order to allow the respondent to 'over-compound' or overestimate the effect of exponential growth. The average value of α is 0.571 with a standard deviation of 0.447. This indicates that respondents in this sample generally have a biased perception of the growth of their wealth, between being linear and exponential.

Table 3.2 Statistics for the estimated preference parameters and financial literacy score

Parameters	Mean	Median	Std.Dev	Min	Max
Financial Literacy	2.561	3.000	0.710	0.000	3.000
Beta (β)	1.025	1.000	0.203	0.468	2.136
Delta (δ)	0.708	0.709	0.173	0.461	0.985
Alpha (α)	0.571	0.680	0.447	0.000	1.500

3.4 Results

3.4.1 Retirement Savings

Table 3.3 displays the impact of the preference parameters on the amount of retirement savings. Following Goda et al. (2019), the retirement savings variable is winsorized at 99% in order to reduce the impact of outliers. And since there are many respondents who accumulate no wealth for their retirement at all, Tobit regression is used in this analysis (there are 328 left-censored observations at 0 retirement saving). We also include an extensive set of control variables. The demographic control variables are a male dummy, age, the number of household members, and dummies for five education categories, six ethnicity categories, and five marital status categories. Additional control variables include 14 income categories and 6 risk preference categories, following Goda et al. (2019). All of the specifications are reported with robust standard errors.

First, we explore the impacts of financial literacy on retirement savings. The financial literacy score is the only independent variable in Specification 1, then we add control variables in Specification 2. In Specification 1, the coefficient of financial literacy is significant with a value of 157,513. This implies that an increase of one standard deviation in financial literacy is associated with $111,912 more retirement saving. However, the coefficient becomes insignificant as control variables are added in Specification 2. Unreported coefficients show that male, older and higher educated individuals have accumulated more savings for their retirement.

Next, in Specification 3 to 5, we investigate the impact of EGB and present bias on retirement savings by regressing the retirement savings variable on α, $ln(\beta)$, $ln(\delta)$, α as well as financial literacy and a set of control variables. It is important to note that the same analysis is conducted in Goda et al. (2015) and we expect to find the same results. In Specification 5, the value of the coefficient of α is 47,352, which implies that the people without EGB ($\alpha = 1$) save $47,352 more for retirement than those who have linear growth perception ($\alpha = 0$). The results are consistent with the expectation that EGB is negatively related to the amount of retirement savings. The impact of $ln(\beta)$ and $ln(\delta)$ are also highly significant with coefficient values of 131,850 and 201,303, respectively. This indicates that smaller a degree of present bias (higher β) is associated with more retirement savings. One standard deviation increase in $ln(\beta)$ can be translated to \$23,381 more saving. Similarly, an increase of one standard deviation in the discount factor δ means \$50,778 more money in the retirement account on average. These results are consistent with findings in prior studies (O'Donoghue and Rabin, 1999; Diamond and Kőszegi, 2003; Zhang, 2013; Goda et al., 2015).

Table 3.3 Tobit regression of the amount of retirement savings on the parameters of present bias and exponential growth bias

Dependent variables **Retirement Savings**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Alpha				53845 ***	47352 ***
				[0.001]	*[0.004]*
ln(Beta)			131850 ***		131850 ***
			[0.003]		*[0.003]*
ln(Delta)			201303 ***		201303 ***
			[0.000]		*[0.000]*
Financial Literacy	157513 ***	11474	5600	9719	4177
	[0.000]	*[0.326]*	*[0.628]*	*[0.405]*	*[0.718]*
Demographic control variables	No	Yes	Yes	Yes	Yes
Number of obs	1743	1743	1743	1743	1743
Prob > F	0.0000	0.0000	0.0000	0.0000	0.0000
Pseudo R2	0.0043	0.0218	0.0229	0.0245	0.0231

P-value are shown in brackets and coefficients denoted by ***, **, and * are significant at 0.01, 0.05, and 0.1 respectively.

3.4.2 The Moderating Effect of Financial Literacy on Present Bias and Retirement Savings

In the previous section, present bias is identified as a determinant for the lack of retirement savings. Here, we further investigate whether the relationship also holds for all individuals with different levels of financial literacy. We expect that the amount of retirement savings among financial literate individuals is less affected by present bias because, despite exhibiting present bias, an individual with high financial literacy may still be inclined to accumulate wealth as he acknowledges the benefits and necessity of retirement savings. Thus, we hypothesize that the relationship between present bias (β) and the amount of retirement savings is moderated by financial literacy.

The moderating effect of financial literacy on the relationship between present bias and retirement savings is shown in Table 3.4. In Specification 1, where α and δ are excluded, the coefficient of $ln(\beta)$ is positive, consistent with the previous findings. Interestingly, the estimated value of the coefficient for the interaction term between $ln(\beta)$ and financial literacy is -102,339 with a p-value of 7.6%. This indicates that the impact of present bias is mitigated by financial literacy. Among financial illiterate respondents (financial literacy score = 0), those who exhibits present bias ($\beta = 0$) save $278,948 less than those without the bias ($\beta = 1$), but the gap in the saving amounts declines by $102,339 for every additional financial literacy score point the respondent has. Thus, for those who can answer all three financial literacy questions correctly, the impact of present bias is reduced to approximately zero. Figure 3.1 shows the relationships between $ln(\beta)$ and retirement saving amounts at different financial literacy scores. The line for zero financial literacy score has the steepest slope, indicating a strong negative relationship between present bias and retirement savings among financially illiterate individuals. On contrary, the line for those who can answer all the questions correctly is almost flat, suggesting an insignificant impact of present bias on their saving decisions. Specification 2, where all preference parameters are included, gives the same conclusion and is in line with our hypothesis that the relationship between the degree of present bias and the amount of retirement savings is moderated by financial literacy.

Table 3.4 Moderating effect of financial literacy on the relation between the amount of retirement savings and present bias

Dependent variable Retirement Savings	**(1)**	**(2)**
ln(Beta)	278947.7 *	397149.2 **
	[0.078]	*[0.012]*
ln(Beta) x Financial Literacy	-102338.9 *	-104963.5 *
	[0.076]	*[0.067]*
ln(Delta)		194251 ***
		[0.000]
Alpha		48269.63 ***
		[0.003]
Financial Literacy	12318.27	5137.94
	[0.285]	*[0.652]*
Demographic Control variables	Yes	Yes
Number of obs	1743	1743
Prob > F	0.0000	0.0000
Pseudo R2	0.0219	0.0232

P-value are shown in brackets and coefficients denoted by ***, **, and * are significant at 0.01, 0.05, and 0.1 respectively.

Although financial literacy does not have a direct impact on the amount of retirement savings in the presence of β and δ, it indirectly affects retirement saving decisions by altering the relationship between β and savings. Hence, even procrastinating people may still decide to accumulate wealth if they have better financial knowledge.

This finding has a significant implication for policy makers who want to promote retirement savings. Present bias has been identified as an important cause of inadequate retirement savings, but solving the problem can be a challenging task because changing people preferences can be hard. However, the moderation effect of financial literacy in our results suggest that the impact of present bias on savings is only pronounced among those with low financial knowledge. Thus, the detrimental effect of present bias may be avoided by improving financial literacy. Providing financial knowledge to the general public might be easier than changing their preferences.

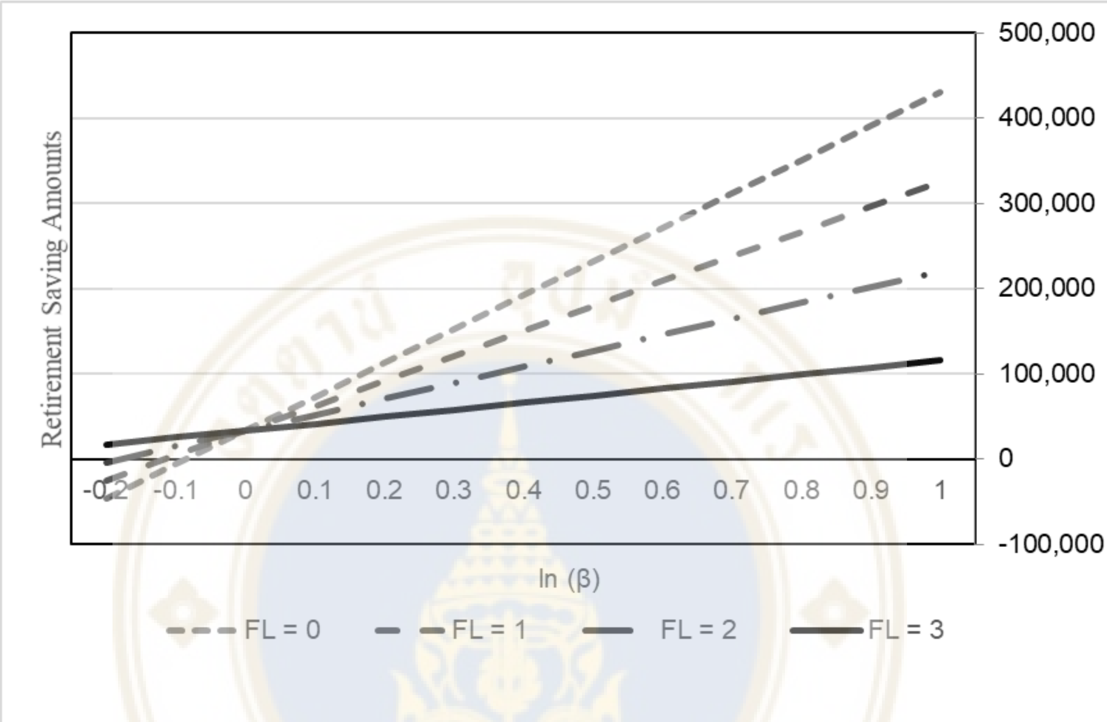

Figure 3.1 The relationship between present bias and the amount of retirement savings at different levels of financial literacy

3.4.3 Financial Literacy and Exponential Growth Bias

In Section 3.4.1, we have shown that EGB is associated with accumulating less wealth for retirement. However, financial literacy should be able to mitigate the bias by improving the accuracy of growth perception. Here, we investigate the impact of financial literacy on the parameter α. It is important to note that we cannot simply interpret that the greater value of α means the better exponential growth perception. An individual may over-compound, making the value of α go beyond than 1, which is also considered biased perception.[23] To handle this issue, a new variable 'exponential growth bias (α_e),' defined as the absolute difference between α and 1 (accurate perception of exponential growth), is used as the dependent variable instead of α.

[23] Our descriptive statistic shows that 242 out of 1743 respondents has α greater than 1.

Since the value of α_e is bounded by 0 and 1, the relationship is analyzed with a Tobit regression, with a lower-bound at 0 and an upper-bound at 1.

Table 3.5 Tobit regression of the exponential growth perception error on financial literacy

Dependent variable **Exponential growth perception error (α_e)**	**(1)**	**(2)**
Financial Literacy	-0.148 ***	-0.065 ***
	[0.000]	*[0.008]*
Demographic Control variables	No	Yes
Number of obs	1743	1743
Prob > F	0.0000	0.0000
Pseudo R2	0.0171	0.0525

Exponential growth perception error (α_e) is defined as the absolute difference between α and 1 (accurate perception of exponential growth). P-value are shown in brackets and coefficients denoted by ***, **, and * are significant at 0.01, 0.05, and 0.1 respectively.

Table 3.5 reports the impact of financial literacy on α_e. In Specification 1, without control variables, the coefficient of financial literacy is negative and significant. This means that people with better financial knowledge have a more accurate perception of exponential growth (less bias). With the estimated value of -0.148 for the financial literacy coefficient, the average EGB (α_e) of the respondents who can answer all of the three financial literacy questions correctly is 0.445 less than those who get a zero score on financial literacy. The size of the difference is economically significant since the average value of α_e is 0.468. Thus, this result is consistent with our expectation that financial literacy reduces EGB. When control variables are added in the Specification 2, the magnitude of the impact decreases, but the effect is still strongly statistically significant.

Our results show that financial knowledge is associated with a more accurate perception of exponential growth. Though we cannot claim a causal relationship, it is plausible that the lack of retirement savings problem can potentially be addressed through policy and education, such as a campaign to improve people's financial literacy. Not only do financially literate people possess better financial knowledge, they also have a more accurate perception of their wealth accumulation.

3.4.4 Limitations: Endogeneity and Reverse Causality Concerns

Although we would like to address potential concerns about endogeneity and reverse causality, we can only do so within the limits of our dataset, and the dataset lacks good instruments for our key variables which are present bias, EGB, and financial literacy. Thus, we can only claim that the reported relations between retirement saving and behavioral biases are associations. However, it is unlikely that saving more money would impact the respondent's hyperbolic discounting preferences and make them less biased. Further, if we assume that present bias and EGB indeed affect the amount of retirement savings, the size of the impact is also substantial and economically relevant.

Nonetheless, the main focus in this paper is to demonstrate that the detrimental effect of present bias and EGB can be mitigated by having better financial literacy. We are aware of the possibility that the correlation between financial literacy and present bias and EGB can be driven by some hidden factor like IQ, or cognitive ability. We handle this problem by including a large set of control variables, including education. While this may not completely solve the endogeneity problem, the results provide support to our hypotheses that financial literacy alleviates biases in decision making and indirectly improves savings.

3.5 Conclusion

The analyses in this study show the impacts of financial literacy on time-preferences, exponential growth perception and retirement savings. An extensive set of control variables is also included in the analysis in order to avoid omitted-variable bias as well as to isolate the effect of the variables of interest.

We first replicate the analysis from Goda et al. (2015) to confirm the effects of time-preferences and exponential growth perception parameters on retirement savings. The results are similar to earlier studies: individuals who exhibit a lower degree of present bias accumulate more wealth, while those who have a lower long-term discount factor also save more for tomorrow. Moreover, EGB can explain the variation in retirement savings in the United States population well, even after controlling for financial literacy. Individuals who can perceive exponential growth more accurately tend to save more money for their retirement.

Then, we test how financial literacy impacts EGB. Our results demonstrate that financial literacy reduces the bias. Financially literate individuals have more accurate perceptions of the future values of their wealth. Thus, by enabling savers to have a more accurate growth perception, financial literacy indirectly can improve the amount of retirement savings.

Further, we examine the moderating effect of financial literacy on the relationship between present bias and retirement savings. Our findings reveal that financial literacy can greatly reduce the impact of present bias on savings. Among the most financially literate individuals, present bias does not affect savings at all. We can say that although individuals may feel reluctant to save money for tomorrow due to procrastination, they still save anyhow if they have high financial knowledge.

This study also has implications for policy makers or agencies who seek to increase retirement savings. Since personal preferences such as present bias and discount factors may be difficult to change, the results in this paper suggest that policy can still alter households' saving behavior by providing better financial knowledge in order to alleviate the impacts of those biases and preferences. The effectiveness of such interventions can be an interesting and relevant topic for future research.

CHAPTER IV
FINANCIAL LITERACY AND OVERCONFIDENCE

4.1 Introduction

The objective of this research is to investigate the relation between financial literacy and the degree of overconfidence across individuals. Overconfidence is one of the most common types of behavioral biases and a plausible explanation for irrational investment decisions. An abundant amount of research in psychology documents that people are generally overconfident. Overconfidence can well explain high trading frequency and portfolio underperformance. Odean (1998) argues that overconfidence causes excessive trading. Barber and Odean (2001) use male gender as a proxy for overconfidence. They explain that male investors are relatively more overconfident. Statman, Thorley, Vorkink (2006) investigate the role of market-induced overconfidence as a key factor for increased trading activity. They argue that a period of good market returns makes investors become overconfident and the investors subsequently engage in higher trading activity and turnover. In line with their argument, they find a significant positive relationship between turnover and lagged market returns.

The effect of overconfidence on individual investors' frequency trading was first documented in the literature by Odean (1998) and Barber and Odean (2001). However, Glaser and Weber (2007) find no significant relationship between the miscalibration form of overconfidence and high turnover in their research. Barber and Odean (2013) argue that using five or 10 survey questions for measuring miscalibration can be noisy and that would lead to a low test power. The insignificant relationship could be a result of the reliability of the measurement. Nevertheless, there is a good amount of evidence that relates overconfidence with individual investors' high turnover (Barber and Odean, 2001; Grinblatt and Keloharju, 2009).

In this study, we investigate the relation between financial literacy and overconfidence. Though overconfidence is common among individual investors, it is reasonable to expect that its variation across individuals can be influenced by financial literacy. In one way, financial literacy is expected to reduce the degree of overconfidence because financially literate people have a better understanding of evaluation concepts in investment such as compounding, risk-adjusted returns, and using appropriate benchmarks. On the other hand, financially literate people might become more overconfident because, with their knowledge, they may believe that they are better informed and more skillful than other investors in the market.

In this paper, we use data from two representative surveys fielded in the Netherlands and directly measure overconfidence. This is an improvement over previous studies that rely on indirect proxies such as gender, of which the measurement validity is questionable. First, we compare the statistics of each aspect of overconfidence between men and women. Then, we perform factor analysis on these aspects and find that they are unrelated and different from each other. Next, we use financial literacy as a predictor to explain the variation of overconfidence between investors. Finally, we look into how overconfidence can explain the trading activities that deviate from what is expected based on rational portfolio choice model.

4.2 Theoretical Framework and Hypotheses

The degree of overconfidence varies across individuals. As Barber and Odean (2001) suggest in their study, demographic variables such as an investor's gender can be a proxy for overconfidence (i.e. men tend to be more overconfident). This study explores the role of financial literacy as a plausible factor influencing the degree of overconfidence.

Overconfidence comes in many forms. One of the forms is miscalibration of one's ability. Overconfident investors overestimate their ability to evaluate securities and wrongly believe that the private information they hold is very precise. A classic experiment about this form of overconfidence is reported by Alpert and Raiffa (1982). In the experiment, the researchers tell the subjects a series of questions that the subjects are not expected to know; for example, "What is the length of the Nile river?" Then, the subjects are asked to give an upper and lower bound of their estimated range that has a 90% probability to contain the correct answer. Alpert and Raiffa find that the subjects usually give too narrow intervals and the ranges contain much fewer correct answers than they would have expected. In the long run, 90 percent of the estimated interval should contain the correct answer, however, they find that only about one third of the intervals do. This clearly shows that people generally overestimate the precision of the information they have.

Self-assessed competence can be closely related to the miscalibration form of overconfidence. Investors who overestimate their own ability would also assess themselves too favorably. Graham, Harvey, and Huang (2009) investigate the effect of investors' competence on their trading frequency. In the study, they ask the respondents "How comfortable do you feel about your ability to understand investment products, alternatives, and opportunities?" and let them answer on a five-point scale. They find that investors who feel competent trade more often. They suggest that people are more willing to bet on their own judgments when they feel skillful or knowledgeable.

Overconfidence can also be in a form where people believe that they are better than other people. This is alternatively called the "better-than-average" thinking (or effect). Alicke and Govorun (2005) explain that better-than-average thinking is a type of social comparison where people compare and overestimate their characteristics against the norm. The better-than-average effect is considered a robust phenomenon (Sedikides and Gregg, 2003). In an experiment, Svenson (1981) asks 161 subjects about their driving skills in relation to the overall group of drivers. He finds that 88% of the American and 77% of the Swedish subjects think of themselves as safer drivers than the median. He concludes that the cause is either a purely cognitive mechanism, or partially the lack of information about others, that make people think of themselves as better than average. This argument is supported by the finding from Alicke, Klotz, Breitenbecher, Yurak, and Vredenburg (1995) that the effect is reduced when the subjects have personal contact with the comparison targets. Brown (2012) argues that better-than-average thinking is motivated by an aspiration to preserve and enhance self-worth feeling. Consistently, the findings from Pedregon, Farley, Davis, Wood, and Clark (2012) show that the effect of better-than-average thinking is stronger if the context is considered socially-desirable by the subjects.

This study focuses on the two forms of overconfidence; miscalibration and better-than-average thinking. The influence financial literacy has on overconfidence can be mixed and ambiguous because it may impact the two forms of overconfidence differently. Therefore, it is important to study the impact on each form separately in order to isolate the effect.

First, the miscalibration aspect, which suggests that investors overestimate their ability and become overconfident, can be reduced by better financial knowledge. Financial literacy helps improve investors' ability to assess their skill because they possess the essential knowledge required to do the tasks. For example, a financially literate investor can choose a more appropriate benchmark to evaluate his investment performance. When the investor's portfolio has a 5% return over an investment horizon while the market yields 10% return during the same period, he knows that he underperforms. By contrast, another investor who is financially illiterate might enjoy the 5% return over the same period because of his perceived belief that he is outperforming, based on using a counterfactual that he is better off with the investment than not investing. With the inappropriate benchmark, this financially illiterate investor mistakenly thinks that he performs well and becomes overconfident.

In the literature, financial literacy has been found to help improve many investment decisions. Shapira and Venezia (2001) document that institutional investors, who are regarded as more financially sophisticated than individual investors, exhibit a lower degree of the disposition effect. Households with low financial literacy are found to have higher tendency to choose actively managed mutual funds even though they charge higher fees and do not perform better than passive funds (Gruber, 1996; Goetzmann and Peles, 1997). Financially literate investors, on the other hand, are more likely to be aware of ETFs or index funds and choose to invest in mutual funds with lower expenses (Muller and Weber, 2010). Guiso and Jappelli (2008) find that investors with high financial literacy can recognize the benefit of diversification and, thus, are holding more diversified portfolios. Although the evidence that financial literacy improves investment decisions is abundant, studies about how it impacts overconfidence are scarce (if there are any). This study expects financial literacy to mitigate the degree of overconfidence by reducing miscalibration through better knowledge and ability to assess one's investment skills. Thus, the first hypothesis is, Hypothesis 1: Financial literacy is negatively related to overconfidence through miscalibration.

However, it is important to also consider another form of overconfidence; better-than-average thinking. Since people tend to believe that they are better than other people, it is plausible that, in the context of investment, an investor who thinks that he is better informed than other investors would become overconfident, trade more actively, and overweigh the pieces of information he has. Heath and Tversky (1991) find that when people feel that they are competent, they are more likely to base their decisions on what they know. Similarly, Graham, Harvey, and Huang (2009) argue that people are confident in their judgments when they feel knowledgeable. Therefore, in the better-than-average aspect, investors can become overconfident as they possess more knowledge. In sharp contrast from its effect on overconfidence through reducing miscalibration, financial literacy can also boost the degree of overconfidence if investors with more investment knowledge have a higher tendency to engage in better-than-average thinking. Therefore, the second hypothesis is,

Hypothesis 2: Financial literacy is positively related to overconfidence through better-than-average thinking.

It is important to mention another factor that potentially affects the degree of overconfidence; experience. Investors can learn to adjust their trading behaviors as they gain more experience from their trading. Seru, Shumway, and Stoffman (2010) find that investors become better at trading as they accumulate more experience. A substantial number of investors are able to realize (through losses) that their trading skills are poor and quit trading as a result. Therefore, for investors who have more experience, the impact of financial literacy, both on miscalibration and better-than-average thinking, will be mitigated since they may have learned from their actual experience. In order to obtain a clean impact of financial literacy on overconfidence, it is necessary to control the moderating effect of experience on the relationship.

4.3 Expected Contribution

An extensive stream of literature provides evidence for the impacts of financial literacy on individuals' investment behaviors. For example, Guiso and

Jappelli (2008) argue that financial literacy can explain the lack of diversification in individual investors' portfolios. Better diversification as well as many other financial behaviors are positively related to financial literacy, such as stock market participation (Rooji, Lusardi, and Alessie, 2007), saving for retirement (Lusardi and Mitchell, 2007a), and mutual fund selection (Gruber, 1996; Goetzmann and Peles, 1997; Muller and Weber, 2010). However, what appears to be a gap in these studies is the mechanism behind the relation between financial literacy and these financial behaviors. This proposed study intends to show that overconfidence is one factor, among others, that can be influenced by the financial literacy of investors, and, in turn, overconfidence plays an important role in their investment decisions. Unlike previous studies that mainly focus on the outcomes of overconfidence such as excessive trading (Odean, 1998; Barber and Odean, 2001; Statman, Thorley, Vorkink, 2006), in this paper, we emphasize how financial literacy impacts overconfidence through its underlying mechanisms; miscalibration and better-than-average thinking. We expect to show that financial literacy has a mixed effect on overconfidence. It can help reduce overconfidence by providing the investor proper tools to make more accurate financial assessments. On the other hand, it induces the investors to exhibit better-than-average thinking and become overconfident, which is expected to be partially mitigated by investment experience.

This research also uses a different approach to measure overconfidence. Many of the finance studies about overconfidence rely on crude proxies, such as gender (Barber and Odean, 2001) and portfolio turnover (Statman, Thorley, Vorkink, 2006), to represent overconfidence. Although these proxies help reduce measurement error problems, their validity is unclear since we cannot be sure that they actually measure overconfidence. For example, Barber and Odean (2001) identify whether an investor is overconfident by looking whether that investor is male. While men in general are relatively more overconfident than women, the effect of overconfidence, as identified by gender, on investment behavior can be confounded because being male can be correlated with other factors that also affect investor behavior. In this study, we use alternative proxies such as perceived relative skills and the difference between perceived and actual skills. These proxies, although they can be noisy, are directly measuring overconfidence.

Finally, overconfidence is usually viewed as an exogenous variable. The expected finding that overconfidence can be influenced by financial literacy does not only imply a relationship but it also means that the degree of one's overconfidence is not fixed and can be altered. This can be useful in practice if policy makers or financial advisors can improve individual investors' behaviors by providing them more financial knowledge.

4.4 Data and Methodology

4.4.1 Data

The data used in this research comes from two surveys. The first survey is from Cox, Kamolsareeratana, Kouwenberg (2019). This survey was fielded in 2017 in the Dutch National Bank Household Survey (DHS) by CentERdata at Tilburg University. It provides financial information for a representative sample of Dutch households, both investors and non-investors. A panel member is considered an investor if she held any financial assets as of 31 December 2016. That is, if a person is holding a mutual fund, that person is classified as an investor. A group of non-investors is also included as a reference group. A total of 274 investors and 345 non-investors completed the survey.

The survey from Cox et al. (2019) asks the investors about their general information which includes demographic variables such as gender, age, income, education, marital status, and occupation. It also contains a set of questions that measures the respondents' financial literacy, elicits their better-than-average thinking, and also asks about their trading behaviors. Unfortunately, the survey does not contain information necessary for a calculation of miscalibrating overconfidence.

The second survey is from Anantanasuwong, Kouwenberg, Mitchell, Peijnenberg (2019), which is also a DHS survey managed by CentERdata. This survey, fielded in 2018, consists of 571 respondents. The main focus of this dataset is on ambiguity and risk attitudes, which we will use to calculate for miscalibrating overconfidence. There were real incentives for the questions about ambiguity attitudes. The respondents were told that one of the questions would be randomly selected and real prize money would be rewarded to them based on their choice for the selected question. These two DHS datasets are merged into a single dataset that we will use throughout this research.

4.4.2 Summary Statistics

Our merged dataset consists of 571 respondents. Financial and demographic information about the respondents is presented in Table 4.1. On average, the respondents earned €3,049.08 monthly and own €96,641.60 worth of financial assets. There are more men (64%) than women (36%) with the average age of 57.04 years old, showing that the Dutch investors tend to be older men. About 30% of them are single and almost half of the respondents (46%) have at least a bachelor degree. Forty-four percent of the respondents are either invest independently or have their investment managed by professionals, while the remaining 56% do not invest.

Table 4.1 Financial and demographic information

Variables	Mean	Median	Std.Dev	Min	Max
Monthly Income (Euro)	3,049	2,850.00	1,569.26	0.00	11,975
Total Financial Assets (Euro)	96,642	35,574.00	227,571.20	0.00	3,245,889
Female	0.36		0.48		
Age	59.04	62	15.37	19	93
Education					
High School	0.29		0.46	0	1
Bachelor	0.27		0.45	0	1
Master	0.19		0.39	0	1
Occupation					
Regular Employee	0.77		0.42	0	1
Business Owner	0.12		0.32	0	1
Unemployed	0.16		0.37	0	1
Retired	0.37		0.48	0	1
Investor	0.44		0.50	0	1

Table 4.1 Financial and demographic information (cont.)

Variables	Mean	Median	Std.Dev	Min	Max
Risk Premium	0.07		0.59	-1	1

Note: Sample size is N = 571. Due to incomplete responses, the figures for Total Financial Asset and Risk Premium are calculated based on 554 and 552 observations respectively.

4.4.3 Measurements

There are four main variables in this study; financial literacy, miscalibration, better-than-average thinking, and overconfidence. The measurement methods for each of the variables will be discussed in detail below

4.4.3.1 Financial Literacy

Financial literacy is measured with a set of questions developed by Van Rooij, Lusardi, Alessie (2011). This set of questions is modified from Lusardi and Mitchell (2007a), and consists of 16 questions in total. The questions are divided into two modules; basic literacy, and advanced literacy. The basic literacy module consists of 5 questions about basic financial concepts such as numeracy, interest rate compounding, inflation, time value of money, and money illusion. The questions in this module are designed to assess the ability to make basic calculations and financial decisions in everyday life. The advanced financial literacy module is designed to measure more sophisticate financial knowledge such as investment and portfolio choice. There are total 11 questions in the advanced module, which cover financial knowledge on topics such as stocks, bonds, mutual funds, risk, and how the stock market works. In the survey of Cox et al. (2019), however, the number of questions in advanced module was reduced to seven due to time constraints. A complete list of financial literacy questions for both of the modules are listed in Appendix G.

4.4.3.2 Miscalibration (Form of Overconfidence)

The most commonly used method to measure miscalibration is the interval production task. In this interval production task, the respondents are given a set of questions to which the answers are unknown to them. Then, they are asked to provide intervals such that they are confident to the requested level that the true answers (unknown) fall between the lower and upper bounds of their intervals. One classic example of the interval production task is from Alpert and Raiffa (1982), asking about the length of the Nile River. Their subjects were asked to estimate the interval which they are 90% confident that the true length of the river lies within. With many interval estimations, for a person who is neither overconfident nor underconfident, the average number of the true answer that falls within the provided interval, or 'hit rate,' should be the same as the requested confidence level. However, a lower (higher) hit rate than the requested confidence level indicates overconfidence (underconfidence).

Neither DHB survey module, however, asks the respondent to provide any interval for the calculation of miscalibration. Therefore, it is impossible to estimate a value for this form of overconfidence using the traditional approach. Fortunately, the survey of Anantanasuwong et al. (2019) contains a set of questions that ask the respondents to provide probabilities for events that the return of a stock market index will fall into given intervals. In the first question, the respondents are asked to choose between Option A or Option B,

Option A: pays off €15 if the AEX index neither decreases by more than 4% nor increases by more than 4% in one month time compared to what the index value is today. ($-4\% < r < 4\%$)

Option B: pays off €15 with a *x%* chance

Then the second question asks the respondent to make a similar decision to question 1 for the complement of the event of the first question.

Option A: pays off €15 if the AEX index either decreases by more than 4% or increases by more than 4% in one month time compared to what the index value is today. ($r < -4\%$ or $r > 4\%$)

Option B: pays off €15 with a *x%* chance

The survey finds the matching probability, *x%* in Option B, which make the respondents indifferent between the two options. With this information, we can calculate a proxy for miscalibration based on the matching probabilities. The matching probability for ($-4\% < r < 4\%$) depends on the respondents' beliefs about the mean return, estimation of volatility, and ambiguity attitudes. Investors who are overconfident may greatly underestimate the magnitude of the volatility, and give a high matching probability for (-4% < *r* < 4%). At the same time, they will also give a low probability for the interval (*r* < -4% or 4% < *r*). Therefore, we use the difference between the matching probabilities of (-4% < *r* < 4%) and (*r* < -4% or *r* > 4%) as a measurement of the miscalibration (volatility) form of overconfidence. Taking the difference between two matching probabilities will also make the effect of beliefs and ambiguity attitudes cancel out to a large extent. In this paper, we will refer to overconfidence measured by this method with the term *overconfidence: volatility estimation*.

The Cox et al. (2019) survey asks the respondents to evaluate themselves on how they perform in the financial literacy module. The question is written as follows;

How many of the previous 9 knowledge questions do you think you have answered correctly?

The answer to this question provides an alternative way to measure miscalibration. We take the difference between perceived and actual number of correct answers as a proxy to identify whether the respondent is overconfident. A higher perceived number of correct answers indicates overconfidence, as the respondent rates his own skill higher than it actually is. We will use the term *overconfidence: self-evaluation* to refer to this measurement of overconfidence. However, it is important to note that this measurement has a weakness, as investors who answer all of the questions correctly cannot overrate their own financial knowledge.

In this paper, we use both "overconfidence: volatility estimation" and "overconfidence: self-evaluation" as measures for miscalibration in our analyses.

4.4.3.3 Better-than-average Thinking (Form of Overconfidence)

Another form of overconfidence that is studied in this research is better-than-average thinking. Better-than-average thinking is a type of social comparison where people have a tendency to overestimate their own good qualities and underestimate the bad ones (Alicke and Govorun, 2005). Svenson (1981) provides evidence for better-than-average thinking by showing that the majority of subjects think that they are safer drivers than the median. Nevertheless, Svenson's methodology is not appropriate for measuring a specific individual's better-than-average thinking (e.g. each investor) since it measures at the aggregate level (e.g. a group of people). According to Alicke and Govorun (2005), there are two ways that better-than-average thinking can be measured; directly and indirectly. For the direct measurement, the respondents are asked to make a self-comparison to an average peer on a single scale which has 'average' as a midpoint. In an indirect measurement, the respondents evaluate themselves and peers on two different scales, then the numbers from those two scales are subtracted in order to produce the better-than-average thinking measure.

The direct measurement is used in the survey from Cox et al. (2019), where the respondents are asked if they think they are better than other investors. The question is written as follows;

Do you think that you are a better investor than the average Investor?

The answer to this question is measured with a five-point scale ranging from "No, I perform much worse than the average" to "Yes, I perform much better than the average." This measure of better than average thinking will be referred as *overconfidence: better-than-average* later in this paper.

It is important to note that the answer to this question only tells how the respondents evaluate their own skill relative to other investors regardless of the fact whether they actually are better than the other investors. However, this is how better-than-average is commonly measured in the literature (Alicke et al., 1995; Alicke and Govorun, 2005; Deaves, Lüders, and Luo, 2008; Brown, 2012; Pedregon et al., 2012). For example, Alicke et al., (1995) uses the same question as in Cox et al. (2019) but with a nine-point scale. Deaves, Lüders, and Luo (2008) asked the subjects,

OF the 32 (yourself included) people doing this experiment (not just those in today's session), how many do you think will end up making more money from it than you?

The answer from this question is then subtracted by 15.5, which will place the value for neither better nor worse than average at zero.

One limitation of our study is the fact that the Cox et al (2019) survey only asked the better-than-average question to respondents who identified themselves as an investor during the screening questions. As a consequence, there are only 179 respondents who answered the question for *overconfidence: better-than-average*, which is significantly fewer than for the other overconfidence measurements.

4.5 Results

4.5.1 Financial Literacy and Overconfidence Summary

In Table 4.2, we report the descriptive statistics for our three measurements of overconfidence, as well as financial literacy. The first and second panels present the statistics based on the subsamples of men and women, and the last panel includes both of the subsamples. Men appear to be more overconfident than women on all of our three measurements for overconfidence, however, the differences are not statistically significant for two of the three measurements. The mean of *overconfidence: volatility estimation* is measured at -0.23 and -0.28 for men and women respectively, with p-value of 0.1325 for the null hypothesis that they are equal. The historical volatility of AEX returns is 13.38% (estimated based on VAEX from the year 2017 to 2018) which can be translated to a 70% chance that the return of AEX over one month will be between -4% and 4%. Therefore, for ease of interpretation, the mean for *overconfidence: volatility estimation* presented in this table is subtracted by 0.40 so that the zero value indicates an accurate estimation of volatility. The negative values for men and women suggest an overestimation of volatility, thus, underconfidence. The mean of *overconfidence: self-evaluation* is -0.27 for men and -0.57 for women. These negative numbers indicate that the subjects actually performed better in our financial literacy elicitation tasks than they give themselves the credit for. A greater magnitude among women suggests that they tend to be relatively modest in their self-evaluation. This gap is also significant with p-value of 0.026. The *overconfidence: better-than-average* measure for men is slightly higher than women although the difference is not statistically significant (p-value = 0.527). Overall, our findings suggest that our subjects are underconfident on all of our measurements.

Table 4.2 also shows that men are more financially literate than women as they perform better on both of the financial literacy modules. Out of the full score of 5 and 7 for the basic and advanced modules, on average, men score 4.42 and 5.77 respectively. Women perform relatively poorer with mean scores of 4.06 and 4.68 respectively. These differences are strongly significant. One possible explanation is the fact that men have more investment experience than women. The survey shows that men have an average of 9.9 years of investment experience, while the number of years for women is much less at 4.0 years.

Table 4.2 Overconfidence and financial literacy by gender

Variable	Obs	Mean	Median	Std. Dev.	Min	Max	p-value for Male = Female
Male							
Volatility Estimation	352	-0.23	0.03	0.35	0	1	
Miscalibration	331	-0.27	0.00	1.25	-3.38	9	
Better-than-Average	143	2.78	3.00	0.77	1	5	
Financial Literacy: Basic	363	4.42	5.00	0.82	0	5	
Financial Literacy: Advanced	365	5.77	6.00	1.72	0	7	
Year of Investment Experience	365	9.86	2.00	12.47	0	70	
Female							
Volatility Estimation	195	-0.28	0.00	0.33	0	1	0.133
Miscalibration	180	-0.57	-0.56	1.77	-6	9	0.026
Better-than-Average	36	2.69	3.00	0.67	1	4	0.527
Financial Literacy: Basic	205	4.06	4.00	1.20	0	5	0.000
Financial Literacy: Advanced	206	4.68	5.00	2.04	0	7	0.000
Year of Investment Experience	571	7.74	0.00	11.57	0	70	

4.5.2 The Relation between Measurements of Overconfidence

We use three measures of overconfidence in this paper; volatility estimation, self-evaluation, and better-than-average thinking. In this subsection, we will explore the relation between our three measures of overconfidence. Table 4.3 shows the correlations among volatility estimation, self-evaluation, and better-than-average thinking. Overall, the correlation coefficients are small and insignificant. This implies that the three proxies are capturing three different aspects of overconfidence.

Table 4.3 Correlations between types of overconfidence

Overconfidence	Volatility Estimation	Miscalibration	Better-than-average
Volatility Estimation	1.000		
Miscalibration	-0.027	1.000	
	[*0.5583*]		
Better-than-Average	0.126	0.098	1.000
	[*0.0992*]	[*0.1916*]	

Pairwise correlations. P-value are shown in brackets.

We confirm the fact that the three measures are different aspects of overconfidence with a factor analysis. According to Table 4.4, we find that the first component can explain only 37% of the variation. Moreover, the Cronbach's alpha is as low as 0.045. Thus, volatility estimation, self-evaluation, and better-than-average thinking are not related. An investor can be confident about his own prediction, but does not believe in his own skills, yet still thinking that he is a better investor than others.

Table 4.4 Factor analysis, inter-item covariance, and Cronbach's alpha

Components	Eigenvalue	% Variance Explained	Cumulative% Variance Explained
Component 1	1.195	0.398	0.398
Component 2	0.932	0.311	0.709

Table 4.4 Factor analysis, inter-item covariance, and Cronbach's alpha (cont.)

Components	Eigenvalue	% Variance Explained	Cumulative% Variance Explained
Component 3	0.874	0.291	1.000
Average inter-item covariance	0.016		
Cronbach's alpha	0.045		

4.5.3 Impacts of Financial Literacy on Overconfidence

According to our hypotheses, we expect that financially literate investors would be able to calibrate their own skills more accurately, and thus have less miscalibration overconfidence. Yet, with better financial knowledge, the investors might also exhibit more better-than-average thinking. Therefore, financial literacy is expected to reduce overconfidence that comes from miscalibration, which are self-evaluation and volatility estimation, while enhancing the *overconfidence: better-than-average*.

Table 4.5 presents the regression results with the three measures of overconfidence as dependent variables and the financial literacy scores from both modules as independent variables. We also add other factors that are found to influence overconfidence such as gender, age, investment experience, as well as a set of control variables which include marital status, number of children, income, financial assets, risk attitude, and dummies for occupation. Specification 1 and 2 are estimated with OLS models with the *overconfidence: volatility estimation* and *overconfidence: self-evaluation* as dependent variables, respectively, and basic and advanced financial knowledge as independent variables. However, since the measure for *overconfidence: better-than-average* is ordinal, we use ordered logistic regression in Specification 3.

Table 4.5 Overconfidence and financial literacy

Dependent Variables	Overconfidence: Volatility Estimation	Overconfidence: Self-Evaluation	Overconfidence: Better-than-average
FL: Basic	-0.015	-0.259 **	-0.125
	[0.389]	*[0.029]*	*[0.672]*
FL: Advanced	0.023 ***	-0.182 ***	0.096
	[0.008]	*[0.000]*	*[0.688]*
Female dummy	-0.003	-0.516 ***	0.018
	[0.924]	*[0.001]*	*[0.961]*
Age	-0.0019	-0.0028	-0.0117
	[0.172]	*[0.631]*	*[0.590]*
Investment experience	0.001	0.008	0.050 ***
	[0.652]	*[0.121]*	*[0.005]*
Additional control	Yes	Yes	Yes
Number of obs	542	494	166
Prob > F	0.0050	0.0005	0.2647
R-square	0.0506	0.1351	0.0468

Contrary to our expectation, in Specification 1, we find a positive and significant coefficient for advanced financial knowledge. For every score point in advanced financial literacy module, the investor *overconfidence: volatility estimation* measure increases by 0.0226. This is economically relevant since the mean of *overconfidence: volatility estimation* is -0.2346. However, the effect of basic financial knowledge is insignificant. A possible explanation can be that knowledgeable investors are more aware of the true volatility of returns and thus underestimate volatility to a lesser extent.

The results from Specification 2 are consistent with our expectation. Both coefficients for basic and advanced financial knowledge are negative and significant. This suggests that investors with better knowledge tend to be more modest. That is, for each point the investor earned in advanced module, his excess perceived over actual number of correct answers will decrease by 1.8, thus less overrating himself. Female investors are also significantly more modest than males.

Neither basic nor advanced financial literacy are significant in Specification 3, thus, financial knowledge and better-than-average thinking are not related. More financially literate investors do not think that they are better than other investors. The only variable of interest that is significant is investment experience. The more years investors spend investing, the more they start to think that they are better than average investors. However, we should be cautious when making any interpretation from the results of Specification 3, because the overall model is not significant based on the F-test.

4.5.4 Overconfidence and Trading Behaviors

In this section we examine how these three aspects of overconfidence affect trading behavior. First, we take a look at the impact on diversification. Based on Goetzmann and Kumar (2008) who argue that under-diversification can be attributed to overconfidence, we expect that our measurements of overconfidence can explain diversification. In this analysis, we use the number of individual stocks and a dummy variable for whether the investor is holding a portfolio that consists of only one stock as proxies for diversification. Then, we investigate the relationship between overconfidence and trading frequency as suggested by Barber and Odean (2001). Overconfident investors are expected trade more frequently and more likely to engage in day trading activity.

Table 4.6 reports the multiple regression results. In Specification 1, we use a negative binomial regression with the number of individual stocks as the dependent variable. We use logistic regression in Specification 2 since our dependent variable is a dummy variable for a portfolio that consists of only one stock. Contrary to our expectation, neither *overconfidence: volatility estimation* nor *overconfidence: self-evaluation* can explain the number of individual stocks in the investors' portfolios. *Overconfidence: better-than-average* is marginally significant at the 10% level.

Table 4.6 Regressions of investment behavior on forms of overconfidence and financial literacy

Dependent variables	Number of individual stocks	Single stock portfolio	Trade Frequency	Day Trader
OC: Volatility Estimation	-0.104	-0.014	1.058	3.232
	[.867]	*[.987]*	*[.125]*	*[.142]*
OC: Self-Evaluation	-0.145	0.202	0.238	-1.618
	[0.422]	*[0.356]*	*[0.397]*	*[0.229]*
OC: Better-than-average	0.527 *	-0.580	0.063	-1.691 *
	[0.056]	*[0.140]*	*[0.893]*	*[0.050]*
FL: Basic	0.050	0.189	-0.148	-1.355
	[0.900]	*[0.671]*	*[0.761]*	*[0.135]*
FL: Advanced	0.117	-0.025	0.694	-2.888 ***
	[0.383]	*[0.939]*	*[0.135]*	*[0.007]*
Female dummy	-1.195 **	-0.599	-0.567	6.954 **
	[0.027]	*[0.407]*	*[0.573]*	*[0.027]*
Age	-0.011	0.061 *	-0.041	-0.302 *
	[0.685]	*[0.074]*	*[0.132]*	*[0.081]*
Year in investment	0.016	-0.023	-0.039	0.008
	[0.511]	*[0.454]*	*[0.338]*	*[0.848]*
Additional control variable	Yes	Yes	Yes	Yes
Number of obs	140	135	80	78
Prob > F	0.1552	0.2299	0.2752	0.0347
R square	0.1907	0.1375	0.1178	0.5270

P-value are shown in brackets and coefficients denoted by ***, **, and * are significant at 0.01, 0.05, and 0.1 respectively.

In Specification 3, we have trading frequency as the dependent variable. This trading frequency variable is measured as a five-point scale where the values 1 and 5 indicate the least and most frequent trading respectively. However, none of the overconfidence variables is significant. This is consistent with the findings from

Glaser and Weber (2007), where overconfidence is measured directly, that overconfidence is not related to stock trading frequency. Specification 4 is a logistic regression model to predict whether the investor is a day trader. The coefficient for *overconfidence: better-than-average* is negative and marginally significant. Better-than-average thinking is associated with a lower tendency to engage in a day trading activity. We also find that investors with advanced financial knowledge are less likely to be a day trader.

Our overall results in this section are disappointing as most of our models yield insignificant coefficients. A possible reason for these poor results is that the sample sizes in our analyses are quite small because there are only a few direct investors in the DHS panel. In fact, the majority of our regressions in this subsection have less than one hundred observations.

4.5.5 Limitations

A major limitation of this research is the fact that it relies on secondary data from two surveys. Therefore, the questions for overconfidence were not specifically designed for a comprehensive overconfidence study, and most overconfidence questions did not provide real incentives for the respondents. For example, in Cox et al. (2019), overconfidence is only used as a control variable in their compulsive gambling study, thus, the variables were measured with a few simple questions and without real incentives. Moreover, merging two datasets makes the number of observations that have a complete value for all required variables small. This leads to low test power. This is especially true in the analysis on overconfidence and trading behaviors where the number of observations in each model specification are small and the results are insignificant.

4.6 Conclusion

This paper first examines overconfidence among the respondents in the DHS panel using three different measures. We use the matching probability for an event that the return of the AEX index would fall into a predefined interval to measure the respondent's estimation of volatility. We also use the difference between their perceived financial literacy scores and their actual scores as a proxy for miscalibration. Finally, we ask the respondents to judge their investment skill in relation to other investors and use the answers as a measure for better-than-average thinking.

Contrary to the previous findings, we do not find that men are significantly more overconfident than women. Overall investors in our sample are in fact underconfident. We also find that men are more financially literate and have more investment experience then women. We then explore the relationship between the three measures of overconfidence. We find that the correlation coefficients among these measures are low and insignificant. This implies that these measures are measuring different aspects of overconfidence. That is, exhibiting one aspect of overconfidence does not mean the investor will also display the other two. This is also confirmed by the fact that the first component from a factor analysis can explain only little variation, and Cronbach’s alpha is also close to zero.

Next, we investigate the impact of financial literacy on each measure of overconfidence. We find that financially literate investors tend to estimate volatility of the AEX returns more accurately whereas other investors underestimate it. Yet, these investors are likely to humbly evaluate themselves. We do not find evidence to support our hypothesis that financial literacy affects better-than-average thinking. Having more knowledge does not make the investors exhibit better-than-average thinking. But as they accumulate more trading experience, they start to think that they are better than the others. Lastly, we find no significant connection between our measures of overconfidence and trading behavior. Our results contradict the findings form previous studies that measure overconfidence via proxies (Barber and Odean, 2001; Goetzmann and Kumar, 2008), but are in line with Glaser and Weber (2007) who measure it directly.

CHAPTER V
CONCLUSIONS

In the previous chapters, I have showed that financial literacy is important and can improve the quality of decision making on various topics, including but not limited to finance. The findings of this dissertation demonstrate that financial literacy is associated with smaller degrees of behavioral biases. Moreover, financially literate people are less affected by the biases because of their more accurate perceptions.

The study in CHAPTER II is the first to measure ambiguity attitudes about real-world investment sources of uncertainty in the field, while controlling for subjective beliefs. The results suggest that ambiguity aversion towards different investments are constant within the same individual. This implies that it is driven by one single preference factor. Perceived ambiguity, on the other hand, varies across the investments, which indicates that it is source dependent. Ambiguity aversion is correlated with risk aversion while perceived ambiguity is linked to education and financial literacy. Thus, it can be inferred that ambiguity aversion is a preference and perceived ambiguity is a cognition. This study also confirms that when investors perceive higher ambiguity about a particular asset, they are less likely to invest in it.

CHAPTER III shows the impacts of financial literacy on exponential growth perception, time-preferences, and retirement savings. The study confirms the findings from earlier studies that present bias is strongly associated with more retirement savings. A lower long-term discount factor contributes to the tendency to save more for tomorrow. In addition, individuals who can perceive exponential growth more accurately accumulate more wealth. This study also demonstrates that financial literacy reduces EGB. Better financial knowledge leads to more accurate perceptions of future wealth. So, through a more accurate growth perception, financial literacy indirectly can improve retirement savings. Finally, financial literacy is found to mitigate the impact of present bias. For financially literate individuals, their decisions regarding retirement savings are less affected by the bias.

In CHAPTER IV, the study focuses on different forms of overconfidence among investors and how it is affected by financial literacy. The study divides overconfidence into three aspects and shows that these aspects are different and unrelated to each other. Overconfidence is elicited directly through survey questions. Contrary to previous studies that measured overconfidence indirectly via proxies, the findings show that men are not more overconfident than women. The study then examines the relationship between financial literacy and each aspect of overconfidence. Financial literacy is associated with a better estimation of volatility while it is negatively related to miscalibration. However, better-than-average thinking is not affected by financial literacy. Finally, this study finds no evidence that overconfidence leads to irrational behavior in the stock market.

These studies contribute greatly to both academics and practitioners, especially policy makers. The first study suggests that ambiguity aversion towards different investments is driven by one preference factor. This implies that there is no need to model ambiguity aversion separately for each investment. However, perceived ambiguity is source-dependent thus it is necessary to model it specifically for each different source of uncertainty. Our results also support the interpretation of a-index as perceived ambiguity in the α-MaxMin model with the prior probability set of Chateauneauf et al., (2007). Moreover, the findings suggest that, in order to stimulate market participation, policy makers can promote investment in some assets by reducing the perceived ambiguity about that particular asset. Since perceived ambiguity is a cognitive component, it can be done by providing more information about the asset or through financial advisory service.

The second study shows factors that can be causes for the lack of retirement savings which can potentially be a serious problem, especially in a soon-to-be ageing society such as Thailand. Though directly adjusting people’s biases such as present bias can be a difficult task, policy makers can instead focus on providing financial literacy which is much easier to intervene via compulsory education or supplementary courses. Then financial literacy could eventually alleviate the impact of these biases on savings. The results of the third study contradict findings from previous studies about overconfidence but are consistent with Glaser and Weber (2007) which use a direct measurement of overconfidence. This raises a question about the validity of measuring overconfidence indirectly via proxies such as gender or speeding tickets.

The studies in this dissertation rely on population surveys that were fielded in the Netherlands and the U.S., thus most of the subjects are people who live in rich western democratic nations. It will be interesting for future research to explore the generalizability of these results in a wider context, especially in developing countries and emerging markets with different socio-economic and cultural backgrounds. For example, in a cross-country study on people's attitudes toward ambiguity, Rieger and Wang (2012) show that ambiguity aversion is associated to uncertainty avoidance, one of Hofstede's cultural dimensions. This suggests that people with different cultural background might have different attitudes toward ambiguity. Therefore, better understanding the effect of cultural traits on behavioral biases is crucial. This is especially true when we want to implement a policy to improve financial decision in a group of people with different cultural background.

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APPENDICES

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.

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.

<u>Option A</u> You win €15 if the coin comes up heads and nothing otherwise	A	B	**<u>Option B</u>** 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 A1 First choice list for eliciting risk attitudes

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%

Figure A2 Ambiguity practice question

APPENDIX B
RISK AVERSION AND FINANCIAL LITERACY

Section B.1 defines the risk aversion measures that are used as control variables in the main text, and discusses alternative measures as a robustness check. 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 is shown 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, and Peijnenburg (2018). 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 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, but 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

Column (1) and (2) show estimation results for the regression model in Equation (6), 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 (7), 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	0.212	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	

Table B3 Analysis of heterogeneity in ambiguity attitudes and perceived ambiguity (cont.)

	(1) Index *b*	(2) Index *b*	(3) Index *a*	(4) Index *a*
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 taken 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

APPENDIX C
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:

(C1) $b = 1 - \overline{m}_c - \overline{m}_s$,

with $-1 \leq b \leq 1$. Here $\overline{m}_s = (m_1 + m_2 + m_3)/3$ denotes the average single-event matching probability, and $\overline{m}_c = (m_{12} + m_{13} + m_{23})/3$ 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 reported good measurement reliability for index *b* 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:

(C2) $b_1 = 1 - (m_1 + m_{23})$

(C3) $b_2 = 1 - (m_2 + m_{13})$

(C4) $b_3 = 1 - (m_3 + m_{12})$

Table C1 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 sample 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 C1 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 C2 below shows the correlations between the three measurements of index *b* for each source, and the between-source correlations as well. We note that especially the within-source correlations of the three *b*-indexes are 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 a similar econometric model as Equation (6) in the main text, but with an additional "time dimension" *j*, representing the three measurements of index *b* for each source *s*:

$$\text{(C5)} \quad b_{i,j,s} = \beta_1 + \sum_{s=2}^{4}(\beta_s + v_{i,s}^b)d_s + \sum_{k=1}^{K}\gamma_k^b X_{i,k} + u_i^b + \varepsilon_{i,j,s}^b,$$

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

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 C3 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 Model 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 C3 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, explaining 14% (=19.4% - 5.3%) of the variation. All variables together explain 19% of the variation in index *b* in Table C3 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 C1 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

Table C1 Summary Statistics of Single-Event *b*-indexes for Ambiguity Aversion (cont.)

	Mean	Median	St dev	Min	Max	*n* (obs.)
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 C2 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 measurements 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
b1_aex	**1.00**											
b2_aex	**0.67**	**1.00**										
b3_aex	**0.72**	**0.71**	**1.00**									
b1_stock	**0.58**	**0.60**	**0.67**	**1.00**								
b2_stock	**0.55**	**0.56**	**0.58**	**0.68**	**1.00**							
b3_stock	**0.59**	**0.59**	**0.64**	**0.73**	**0.70**	**1.00**						
b1_msci	**0.59**	**0.59**	**0.63**	**0.66**	**0.56**	**0.62**	**1.00**					
b2_msci	**0.57**	**0.64**	**0.62**	**0.60**	**0.61**	**0.56**	**0.77**	**1.00**				

Table C2 Correlations of Single-Event *b*-indexes for Ambiguity Aversion (cont.)

	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
b3_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 C3 Analysis of heterogeneity in single-event *b*-indexes for ambiguity aversion

The table shows estimation results for the regression model in Equation (C5) 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 Model 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

Table C3 Analysis of heterogeneity in single-event *b*-indexes for ambiguity aversion (cont.)

	Model 1 Index *b*	Model 2 Index *b*	Model 3 Index *b*	Model 4 Index *b*	Model 5 Index *b*
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%

Table C3 Analysis of heterogeneity in single-event *b*-indexes for ambiguity aversion (cont.)

	Model 1 Index *b*	Model 2 Index *b*	Model 3 Index *b*	Model 4 Index *b*	Model 5 Index *b*
%, 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%

APPENDIX D
ROBUSTNESS CHECKS

Section D.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 D.2 reports the main results after screening out investors who make several mistakes on the ambiguity questions. In Section D.3 control variables for risk attitudes, education, financial literacy and the amount of financial assets are included in the asset ownership regressions.

D.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 are shown in Table D1. 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 are shown in Table D2. 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 not having sufficient data to estimate the model. The ICC in Table D2 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 D2, 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 D2 after screening out violations of monotonicity are similar, with the main difference being a moderate increase in measurement reliability and the percentage of variation explained by observed variables. We conclude that violations of monotonicity have limited impact on the measurement of ambiguity aversion (index *b*). Rather, monotonicity violations more strongly affect a-insensitivity (index *a*) and perceived ambiguity, as shown in the main text, as index *a* is measured from differences in matching probabilities between composite and single events ($\bar{m}_c - \bar{m}_s$).

Table D1 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 D2 Econometric Models for *b*-index after Excluding Monotonicity Violations

The table shows estimation results for the panel regression model in Equation (6), with index *b* (ambiguity aversion) as the dependent variable, similar to Table 2 in the main text, after excluding monotonicity violations based on *a* > 1.

	Model 1	Model 2	Model 3	Model 4	Model 5
	Index *b*	Index *b*	Index *b*	Index *b*	Index *b*
Constant	0.177***	0.147***	0.148***	0.229	0.237
Dummy Familiar Stock		0.018	0.015	0.015	0.016

Dummy MSCI World		0.057**	0.055**	0.056**	0.058**
Dummy Bitcoin		0.045*	0.045*	0.045*	0.045*

Table D2 Econometric Models for *b*-index after Excluding Monotonicity Violations (cont.)

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
	Index *b*	**Index *b***	**Index *b***	**Index *b***	**Index *b***
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%

Table D2 Econometric Models for *b*-index after Excluding Monotonicity Violations (cont.)

	Model 1 Index *b*	Model 2 Index *b*	Model 3 Index *b*	Model 4 Index *b*	Model 5 Index *b*
%, Observed Variables	-	0.2%	0.2%	7.2%	27.7%

D.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 for 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 they are made repeatedly for the six related events. Panel A of Table D3 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 3 or more mistakes on the 6 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 D3 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, compared to 0.18 in the full sample. Investors making many errors on the ambiguity questions have higher matching probabilities and larger values of index *b*, driven by the error of preferring unambiguous Option B on every row of the choice list. The mean of index *b* therefore drops after excluding these most ambiguity averse choices. For perceived ambiguity, there is no significant difference between those making more or less mistakes: the mean of *a*-index in Table D3 is 0.69, versus 0.71 in the full sample, and the same results also holds for a-insensitivity.

Table D4 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 D5 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 D5, slightly higher than the 14% in the full sample.

Table D3 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 less 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 less 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 Less 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 Less Errors

	Mean	Median	St dev	Min	Max	*n* (obs.)
a_aex	0.71	0.80	0.30	0.00	1.00	162

Table D3 Descriptive Statistics for Ambiguity Measures – Restricted Sample (cont.)

	Mean	Median	St dev	Min	Max	n (obs.)
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 D4 Analysis of heterogeneity in ambiguity aversion, investors making two or less errors

The table shows estimation results for the panel regression model in Equation (6), 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 less errors on the six choice list for a particular investment.

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
	Index *b*	**Index *b***	**Index *b***	**Index *b***	**Index *b***
Constant	0.129***	0.109***	0.110***	0.277	0.352
Dummy Familiar Stock		0.004	0.003	0.003	0.002
Dummy MSCI World		0.052**	0.051**	0.052**	0.051**
Dummy Bitcoin		0.024	0.022	0.023	0.023
Education				-0.001	-0.008
Age				0.005**	0.003*
Female				0.037	0.050
Single				-0.103*	-0.080*
Employed				-0.011	-0.028
Number of Children (log)				0.007	0.017
Family Income (log)				-0.030*	-0.008
HH Fin. Wealth (log)				-0.019**	-0.013**
HH Wealth Imputed				-0.103	-0.024

Financial Literacy					-0.015
Risk Aversion					0.396***

Table D4 Analysis of heterogeneity in ambiguity aversion, investors making two or less errors (cont.)

	Model 1 Index *b*	Model 2 Index *b*	Model 3 Index *b*	Model 4 Index *b*	Model 5 Index *b*
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 D5 Analysis of heterogeneity in perceived ambiguity, investors making two or less errors

	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***

	Model 1	Model 2	Model 3	Model 4	Model 5
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***

Table D5 Analysis of heterogeneity in perceived ambiguity, investors making two or less errors (cont.)

	Model 1 Index ***a***	Model 2 Index ***a***	Model 3 Index ***a***	Model 4 Index ***a***	Model 5 Index ***a***
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%

Table D5 Analysis of heterogeneity in perceived ambiguity, investors making two or less errors (cont.)

	Model 1 Index *a*	**Model 2 Index *a***	**Model 3 Index *a***	**Model 4 Index *a***	**Model 5 Index *a***
%, 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%

The table shows estimation results for the panel regression model in Equation (7), 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 less 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.

D.3 Asset Ownership Regressions with Control Variables

Table 5 in the main text shows results for probit models 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*). The models in Table 5 did not include control variables for two reasons. First, we want to see the total relation between investments and ambiguity attitudes, without filtering out potential indirect effects through other variables. Second, including a full set of socio-demographic control variables is not feasible, because the number of investors owning MSCI World and crypto-currencies is small, giving rise to perfect separation of the binary dependent variable.

In this appendix, as a robustness check we include key control variables for financial wealth, education, financial literacy and risk attitudes, to see if some of the effects of ambiguity attitudes are subsumed by these variables. Table D6 shows the results. First, column (1a), (2a) and (3a) show the original results from Column (4)-(6) of Table 5, where 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. Then in column (1b), (2b) and (3b) of Table D6 we add controls for household financial wealth and education, two key socio-demographic variables that are relevant for investment. The results show that perceived ambiguity still has a significant negative relation with investing in MSCI World, and ambiguity aversion has a negative relation with investing in Bitcoin. Only the effects of perceived ambiguity on the familiar stock and Bitcoin are slightly weaker than before, perhaps due to some confounding effects of education.

Subsequently, in column (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 (all investors in MSCI World have a full score for financial literacy). The results show that perceived ambiguity and ambiguity aversion have negative relation with investing in Bitcoin, while perceived ambiguity has marginally significant relation with investing MSCI World. Overall, the results do not change materially after including control variable.

Table D6 Investment in the familiar stock, MSCI world and crypto-currencies, with controls

	Invests in Familiar Stock			Invests in MSCI World			Invests in Crypto-Currencies		
	(1a)	**(1b)**	**(1c)**	**(2a)**	**(2b)**	**(2c)**	**(3a)**	**(3b)**	**(3c)**
Perc. ambiguity (fitted)	-0.239*	-0.192	-0.214	-0.093**	-0.109***	-0.099*	-0.143**	-0.090*	-0.122**
Amb. aversion (fitted)	-0.004	0.002	-0.038	-0.002	-0.008	-0.008	-0.046**	-0.048**	-0.058**
Education		0.027			-0.008			0.026***	
HH Fin. Wealth (log)		0.006			0.000			-0.005*	
Risk Aversion			0.057			0.011			0.012
Likelihood Insensitivity			0.071			0.004			-0.029
Financial Literacy			0.047**			---			0.001
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	-112.405	-111.636	-108.597	-13.727	-12.681	-13.591	-23.840	-20.859	-23.276
Chi-Square	3.486	4.924	9.762	6.860	29.337	17.431	6.206	17.482	15.189
P-value	0.175	0.295	0.082	0.032	0.000	0.002	0.045	0.002	0.010
Pseudo R-square	0.015	0.021	0.048	0.123	0.190	0.132	0.120	0.230	0.141

This table reports estimation results for a probit model explaining asset ownership with perceived ambiguity (index *a*) and ambiguity aversion (index *b*), similar to Table 5 in the main text, but with control variables included. The numbers displayed are estimated marginal effects. 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 coefficients at the 10%, 5% and 1% level.

APPENDIX E
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 are shown in Table E1. 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%, 24% based on *b_avg*, which is not significantly different from the investor group (63%, 9%, 28%). Table E2 displays summary statistics of ambiguity attitudes in the non-investor group. The mean level of aversion is similar in the groups of non-investors and non-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 E3 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 towards the four sources. Hence, in the non-investor group, ambiguity aversion towards investments is driven by a single underlying factor, without distinction among 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 E4 reveal that in the non-investor group, perceived ambiguity towards 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 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 tend to make little distinction in perceived ambiguity among different investments.

Further, in the group of non-investors, education and financial literacy do not have a significant relation with perceived ambiguity in Table E4, different from the results for investors in Table 4. Overall, observable variables explain only 7.5% of the variation in perceived ambiguity in the non-investor group. This adds to the overall conclusion that among non-investors there is less variation in perceived ambiguity between investments and between respondents, probably driven by overall unfamiliarity with investments in this group.

Table E1 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

Table E1 Descriptive Statistics of the Non-Investor Sample (cont.)

	Mean	Median	St dev	Min	Max
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 E2 Descriptive statistics for ambiguity measures – non-investor sample

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

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 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. 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*.

Table E3 Analysis of heterogeneity in ambiguity aversion, non-investors

The table shows estimation results for the panel regression model in Equation (6), with index *b* (ambiguity aversion) as the dependent variable, similar to Table 2 in the main text, but for 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. Therefore no random slopes are included.

	Model 1	**Model 2**	**Model 3**	**Model 4**
	Index *b*	**Index *b***	**Index *b***	**Index *b***
Constant	0.195***	0.196***	0.139	0.152
Dummy Familiar Stock		0.028	0.028	0.028
Dummy MSCI World		-0.007	-0.007	-0.007
Dummy Bitcoin		-0.025	-0.025	-0.025
Education			-0.039*	-0.015

Table E3 Analysis of heterogeneity in ambiguity aversion, non-investors (cont.)

	Model 1 **Index *b***	**Model 2** **Index *b***	**Model 3** **Index *b***	**Model 4** **Index *b***
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
$Var[v_{i,4}^b]$, Slope Bitcoin	-	-	-	-
$Var[\beta' D + \gamma' X]$, 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 E4 Analysis of heterogeneity in perceived ambiguity, non-investors

The table shows estimation results for the panel regression model in Equation (7), with index *a* (perceived ambiguity) as the dependent variable, similar to Table 4 in the main text, but for 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

Table E4 Analysis of heterogeneity in perceived ambiguity, non-investors (cont.)

	Model 1 Index *a*	**Model 2 Index *a***	**Model 3 Index *a***	**Model 4 Index *a***	**Model 5 Index *a***
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%

APPENDIX F
MULTIPLE PRIOR MODEL FOR AMBIGUITY ATTITUDES

In the context of the α-MaxMin model, Dimmock et al. (2015) and Baillon et al. (2018a) show that index *b* and *a* can be interpreted, respectively, as *ambiguity aversion* and the *perceived level of ambiguity*. In this online appendix, we derive those results to provide intuition for the meaning of index *b* and *a*, and to demonstrate that subjective beliefs are controlled for.

Let x_E0 denote a two-outcome prospect that pays amount $x \geq 0$ if event E occurs, and 0 otherwise. The decision-maker has an increasing utility function $U(x): \mathbb{R}_+ \to \mathbb{R}_+$ over payoffs, rescaled such that $U(0) = 0$. Ambiguity occurs when the decision-maker does not know the exact probability of the event E. Multiple prior models assume that the decision-maker considers a convex set $\mathcal{C}$ of possible probability measures $P \in \mathcal{C}$. In the MaxMin model of Gilboa and Schmeidler (1989) the decision-maker uses the worst possible distribution in $\mathcal{C}$, when evaluating the expected utility of the prospect, implying strong ambiguity aversion. In our simple setup $\mathcal{C}$ is an interval I_E of possible probabilities for event E, and the MaxMin model evaluates the prospect x_E0 as: $min_{p \in I_E} \{pU(x)\}$.

The α-MaxMin model (Hurwicz, 1951; Ghirardato, Maccheroni, and Marinacci, 2004) provides more flexibility in modelling ambiguity preferences, including ambiguity seeking behavior, by evaluating the prospect x_E0 as follows:

(F1) $\alpha \, min_{p \in I_E} \{pU(x)\} + (1-\alpha) max_{p \in I_E} \{pU(x)\}$, with $\alpha \in [0,1]$

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:

(F2) $I_{E,\delta} = \{p: (1-\delta)\pi(E) \leq p \leq (1-\delta)\pi(E) + \delta\}$, 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:

(F3) $\alpha\ min_{p\in[(1-\delta)\pi_1,(1-\delta)\pi_1+\delta]}\ pU(15) + (1-\alpha)max_{p\in[(1-\delta)\pi_1,(1-\delta)\pi_1+\delta]}$ $pU(15)$

$= \big((1-\delta)\pi_1 + (1-\alpha)\delta\big)U(15),$

where $\pi_1 = \pi(E_1)$ is the respondent's reference probability for event 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:

(F4) $m_1 = (1-\delta)\pi_1 + (1-\alpha)\delta$

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, which is a major advantage of this approach. Our survey module also elicits a matching probability for the complement event E_{23}. 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 the two matching probabilities m_1 and m_{23} deviates from 1:

(F5) $b = 1 - (m_1 + m_{23}) = 1 - (1-\delta)(\pi_1 + \pi_{23}) - 2(1-\alpha)\delta =$ $2(\alpha - \frac{1}{2})\delta$

Note that π_1 and π_{23} have dropped out in (F5), 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 (F5) also shows that index *b* is a rescaled version of α, ranging from $-\delta$ to δ (Baillon et al., 2018b). 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 $a = 0$.

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

(F6) $a = 3 \times \left(\frac{1}{3} - (\overline{m}_c - \overline{m}_s)\right) = \big(1 - (1-\delta)(\pi_{23} + \pi_{13} + \pi_{12} - (\pi_1 + \pi_2 + \pi_3)\big)$
$= \big(1 - (1-\delta)((1-\pi_1) + (1-\pi_2) + (1-\pi_3) - 1)\big) = \big(1 - (1-\delta)\big) = \delta$

Hence, index *a* measures the perceived level of ambiguity (δ). As perceived ambiguity cannot be negative ($\delta \geq 0$) and is bounded above by 1 ($\delta \leq 1$), this interpretation requires index *a* to be between 0 and 1 ($0 \leq a \leq 1$).

Some readers may be concerned that the interpretation of index *a* as perceived ambiguity is dependent on the particular prior distribution set introduced by Chateauneuf et al. (2007). Dimmock et al. (2015) show that this prior set has strong empirical support in a large dataset on the ambiguity attitudes of the U.S. population, while different prior sets (e.g., pessimistic [0,1], or symmetric intervals around π) are clearly rejected by the data.

APPENDIX G
FINANCIAL LITERACY QUESTIONS FROM VAN ROOIJ ET AL. (2011)

Basic Financial Literacy Module

(1) Suppose you had €100 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? (i) More than €102; (ii) Exactly €102; (iii) Less than €102; (iv) Do not know; (v) Refusal.

(2) Suppose you had €100 in a savings account and the interest rate is 20% per year and you never withdraw money or interest payments. After 5 years, how much would you have on this account in total? (i) More than €200; (ii) Exactly €200; (iii) Less than €200; (iv) Do not know; (v) Refusal.

(3) Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, how much would you be able to buy with the money in this account? (i) More than today; (ii) Exactly the same; (iii) Less than today; (iv) Do not know; (v) Refusal.

(4) Assume a friend inherits €10,000 today and his sibling inherits €10,000 3 years from now. Who is richer because of the inheritance? (i) My friend; (ii) His sibling; (iii) They are equally rich; (iv) Do not know; (v) Refusal.

(5) Suppose that in the year 2010, your income has doubled and prices of all goods have doubled too. In 2010, how much will you be able to buy with your income? (i) More than today; (ii) The same; (iii) Less than today; (iv) Do not know;(v) Refusal.

Advanced Financial Literacy Module

(6) Which of the following statements describes the main function of the stock market? (i) The stock market helps to predict stock earnings; (ii)The stock market results in an increase in the price of stocks; (iii) The stock market brings people who want to buy stocks together with those who want to sell stocks; (iv) None of the above; (v) Do not know; (vi) Refusal.

(7) Which of the following statements is correct? If somebody buys the stock of firm B in the stock market: (i) He owns a part of firm B; (ii) He has lent money to firm B; (iii) He is liable for firm B's debts; (iv) None of the above; (v) Do not know; (vi) Refusal.

(8) Which of the following statements is correct? (i) Once one invests in a mutual fund, one cannot withdraw the money in the first year; (ii) Mutual funds can invest in several assets, for example invest in both stocks and bonds; (iii) Mutual funds pay a guaranteed rate of return which depends on their past performance; (iv) None of the above; (v) Do not know; (vi) Refusal.

(9) Which of the following statements is correct? If somebody buys a bond of firm B: (i) He owns a part of firm B; (ii) He has lent money to firm B; (iii) He is liable for firm B's debts; (iv) None of the above; (v) Do not know; (vi) Refusal.

(10) Considering a long time period (for example 10 or 20 years), which asset normally gives the highest return? (i) Savings accounts; (ii) Bonds; (iii) Stocks; (iv) Do not know; (vi) Refusal.

(11) Normally, which asset displays the highest fluctuations over time? (i) Savings accounts; (ii) Bonds; (iii) Stocks; (iv) Do not know; (v) Refusal.

(12) When an investor spreads his money among different assets, does the risk of losing money: (i) Increase; (ii) Decrease; (iii) Stay the same; (iv) Do not know; (v) Refusal.

(13) If you buy a 10-year bond, it means you cannot sell it after 5 years without incurring a major penalty. True or false? (i) True; (ii) False; (iii) Do not know; (iv) Refusal.

(14) Stocks are normally riskier than bonds. True or false? (i) True; (ii) False; (iii) Do not know; (iv) Refusal.

(15) Buying a company stock usually provides a safer return than a stock mutual fund. True or false? (i) True; (ii) False; (iii) Do not know; (iv) Refusal.

(16) If the interest rate falls, what should happen to bond prices? (i) Rise; (ii) Fall; (iii) Stay the same; (iv) None of the above; (v) Do not know; (vi) Refusal.