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Ambiguity Attitudes and Financial Diversification:

Can Ambiguity Likelihood Insensitivity Help to Explain Under-Diversification?

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by

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1. Introduction

When people make decisions they are not only confronted with risk, but in most cases also with uncertainty that is associated with the outcome of future events. The distinction between risk and uncertainty goes back to Frank H. Knight. According to his definition, risk refers to situations where the probabilities of all possible outcomes are either known or can be accurately assessed. In contrast to risk, uncertainty refers to situations where the probabilities of all possible outcomes are unknown and cannot be accurately determined (Knight 1921).

Forty years after Knight published his book on risk and uncertainty, Daniel Ellsberg showed that there was another critical component in decision making: ambiguity (1961). Until then, most models of decision making under uncertainty relied on the notion of subjective probability or probabilistic sophistication (Abdellaoui, Baillon, Placido and Wakker 2011). Those models assumed that decision makers assign subjective probabilities to the events for which objective probabilities are unavailable and then decide according to expected utility (Savage 1954). In his famous thought experiment, Ellsberg demonstrated that there are situations in which the assumption of subjective probabilities leads to the violation of basic principles of probability and is therefore incapable of describing human decision making properly. Based on the choice of a hypothetical subject to bet on a gamble with a known over a similar gamble with an unknown probability of winning, he suggested that such preferences not only depend on the *"relative desirability of the possible pay-offs and relative likelihood of the events"* but also on the *"nature of [the] information concerning the relative likelihoods of events"* (Ellsberg 1961, p. 657; see also Keynes 1921). In other words, decisions under uncertainty not only depend on the potential pay-offs and the assigned subjective probability of those pay-offs, but also on the individual's confidence in his estimated probability distribution. Based on this notion, Ellsberg concluded that in situations where an individual has to decide to bet either on a risky or an ambiguous gamble, he usually chooses the risky one. This preference of risk over ambiguity is referred to as *"ambiguity aversion"*.

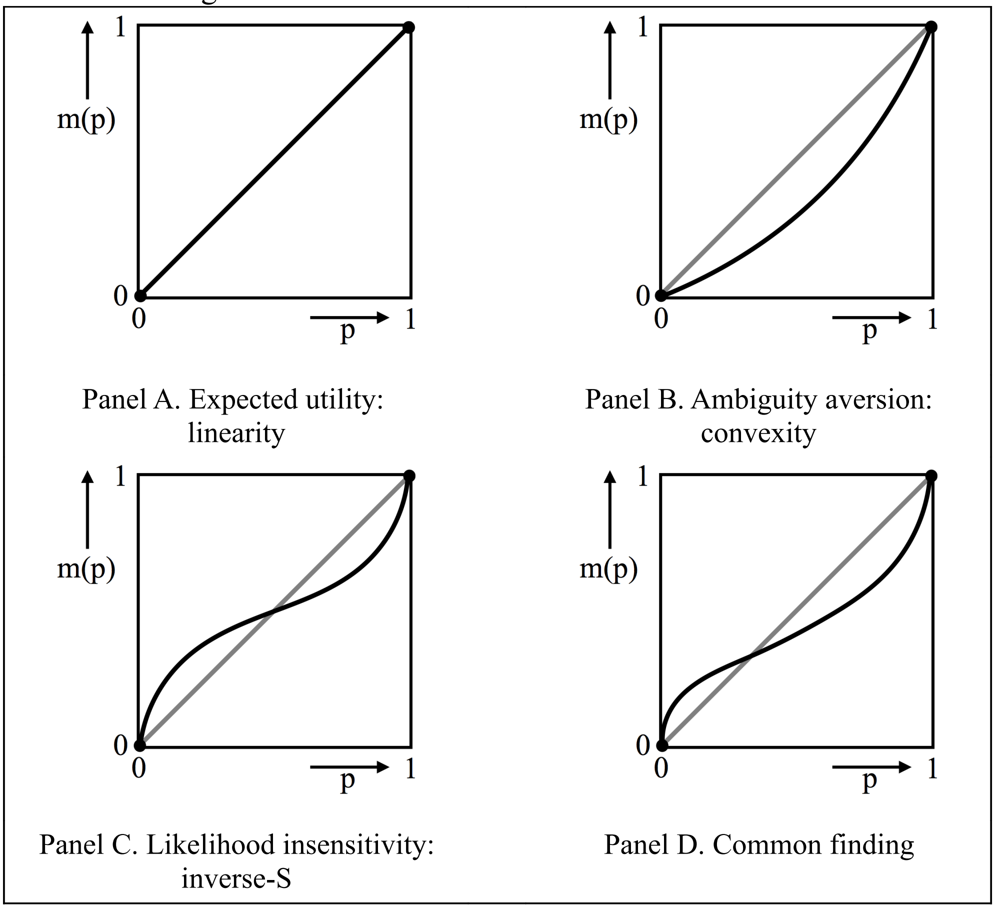
Since models based on subjective expected utility cannot accommodate the degree of confidence a decision maker has in his estimated probability distribution, Ellsberg's discovery lead to the development of new models incorporating attitudes towards ambiguity. Especially behavioral finance turned to ambiguity aversion to help to explain persistent empirical findings such as the *"home bias"*, *"equity premium puzzle"* or *"insufficient portfolio diversification"*, which stand in contrast to what normative models predict (French and Poterba 1991; Barberis and Thaler 2003).

Despite their contribution to the research of financial decision making, models incorporating ambiguity aversion only partially add to the explanation of these phenomenona (Maenhout 1999). Motivated by the notion that aversion towards ambiguity is only part of the explanation why people tend to insufficiently diversify their investments, this study turns to recent findings regarding decision making under ambiguity, aiming to improve the understanding of this phenomenon. More precisely, this study investigates whether ambiguity attitudes can help to explain portfolio diversification within an asset class (i.e. company stocks) and between asset classes (e.g. stocks, real estate and alternative investments).

In order to investigate the potential explanatory power of ambiguity attitudes on the tendency of individuals to insufficiently diversify their investments, this study begins by eliciting ambiguity attitudes using the source method developed by Abdellaoui et al. (2011). The authors introduced a tractable method for eliciting individual attitudes towards ambiguity through revealed preferences in Ellsberg style choice questions. In the subsequent application of their method, Abdellaoui et al. (2011) confirmed previous results reported by Einhorn and Hogarth (1985) and Tversky and Fox (1995) that attitudes towards ambiguity consist of two distinct components: ambiguity aversion and ambiguity generated likelihood insensitivity (a-insensitivity). One important advantage of the source method is that each attitude component is captured by an index, which can be combined into a single graph. This increases the usability of this method for empirical research and provides a clear interpretation.

Figure 1.1 illustrates the main characteristics of the source functions (Abdellaoui et al. 2011; Wakker 2010 § 7.1). All source function graphs in this study follow the same layout: ambiguity neutral probabilities *p* are depicted on the x-axis while the y-axis shows the matching probabilities *m(p)*. Matching probabilities are the probabilities which make a subject indifferent between betting on a gamble with known versus a gamble with unknown (ambiguous) probability of winning. Therefore, the matching probabilities are the weighted probabilities due to ambiguity and capture the individual's degree of confidence in the likelihood of the ambiguous events. Ambiguity neutral probabilities are the matching probabilities of an ambiguity neutral decision maker, who does not weight a risky gamble differently than an ambiguous one. **Panel A** depicts a source function of an ambiguity neutral decision maker. He does not deviate from (subjective) expected utility and his source function is linear. **Panel B** shows the source function of an ambiguity averse decision maker. He is generally pessimistic about the likelihood of ambiguous events and assigns lower weights to the outcomes. His deviation from expected utility is captured in the convex shape of his source function. **Panel C** illustrates the source function of an a-insensitive decision maker. Overweighting of low-likelihood and underweighting of high-likelihood ambiguous events result in an inverse S-shaped source function. Due to its shape, the function incorporates three distinctive characteristics. Concavity near p = 0 implies ambiguity seeking for small probabilities whereas convexity near p = 1 implies ambiguity aversion for large probabilities. The shallow region around p = 0.5 implies a lack of discriminatory power of intermediate probabilities. This insensitivity to changes in intermediate likelihood-levels results in the tendency of a-insensitive decision makers to treat these probabilities of ambiguous events as fifty-fifty (Wakker 2010 § 7; Abdellaoui et al. 2011). **Panel D** displays the common source function found in empirical studies (Wakker 2010 § 10.4.2; Trautmann and van der Kuilen 2013; Abdellaoui et al. 2011). It shows that the typical decision maker deviates from expected utility not only because he is ambiguity averse, but also because he is a-insensitive.

Figure 1.1. Characteristics of the Source Function.



The elicited ambiguity attitudes in this study confirm that the generally assumed aversion to ambiguity does not hold. Instead the results show that ambiguity attitudes for this sample range from ambiguity seeking to ambiguity aversion, depending on the individuals' perception of the relative likelihood of the ambiguous events. **Figure 1.2** illustrates the average source function obtained for the sample. The average source function is consistent with common empirical findings: participants are ambiguity seeking for low-likelihood events, insensitive to changes in likelihood-levels for intermediate probabilities and ambiguity averse for high-likelihood events.

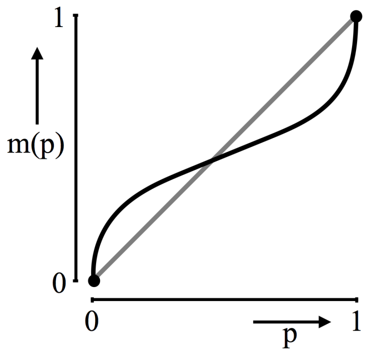


Figure 1.2. The average source function derived from the parameter capturing a-insensitivity and the anti-index of ambiguity aversion following the two-parameter function of Goldstein and Einhorn (1987, Wakker 2010 § 7.2).

After having obtained both ambiguity attitude components for each individual in the sample, the potential relationship between a-insensitivity as well as ambiguity aversion and financial diversification is investigated. In order to test if the attitude components can help to explain the commonly observed tendency of people to insufficiently diversify their investments, two measures capturing the individuals' degree of diversification are derived from the available data. Consistent with the hypotheses, the obtained test results suggest that subjects who are more a-insensitive hold more under-diversified stock portfolios and subjects who are more ambiguity averse hold less severely under-diversified portfolios of company stocks. In addition, the affect of both attitude components on a second measure of diversification is tested by looking at the number of different asset types a subject holds. The results indicate that ambiguity aversion decreases the probability of the participant to be maximally diversified across different asset classes whereas a-insensitivity increases the probability to be maximally diversified. Unfortunately, none of the results regarding ambiguity attitudes and diversification are significant and therefore do not provide strong empirical evidence in favor of the hypotheses. For a research paper (rather than a master's thesis as this text) it would be desirable to find larger data sets with more power, so that conclusions can be based on statistical significance.

Concluding this study, the relationship between different definitions and calculation methods of both ambiguity attitude components is examined. The results of this analysis show that there are disparities between the differently derived attitude measures in terms of aggregated ambiguity attitudes. Nonetheless, the attitude components calculated following different methods are highly correlated and lead to qualitatively similar results in empirical tests.

This study is structured as follows: the next section provides an overview of the existing literature regarding portfolio diversification, concluding with the currently prevailing explanation why people tend to hold insufficiently diversified portfolios. **Part 3** explains the methodology of this paper, including a detailed description not only of the elicitation process used to obtain the ambiguity attitudes, but also of the construction of both diversification measures. **Part 4** describes the theory this study is based on and concludes with a summary of the hypotheses. The statistical analyses as well as the obtained results are reported in **Part 5**. In **Part 6** the results and limitations of this study are discusses and the final part concludes.

2. Literature Review

With the introduction of the Capital Asset Pricing Model (CAPM), William F. Sharpe (1964) laid the foundation of modern portfolio theory. He showed that an investor could reduce the risk of holding few individual stocks by combining a large number of different stocks into well diversified portfolios. Based on this insight, normative investment theory postulates that a rational, risk averse individual should diversify his investment portfolio not only in terms of the number of different stocks he holds, but also in terms of what stocks he owns (i.e. companies operating in different industries and international markets). However, many empirical papers show that a large proportion of investors tend to make investment decisions which contradict these principles of diversification.

An early paper regarding individual investment decisions was published by Blume and Friend in 1975. The authors investigated real and self-reported investment decisions among the U.S. population by analyzing two large, independent data sets. In order to asses the degree of diversification of each subject in the sample regarding real investment decisions, two different measures were derived from data based on individual income tax reports filed with the U.S. tax authorities in 1971. The first measure is simply the number of different stocks the individual holds whereas the second captures the degree of diversification relative to the market portfolio (i.e. perfectly diversified portfolio). Regardless of the diversification measure used, the authors find that the majority of subjects hold highly under-diversified portfolios. Only approximately 11% of the individuals in their sample hold more than ten different stocks while approximately 60% own no more than two different company stocks. The second measure yields similar results, indicating that approximately 60% of the individuals hold only two different stocks in an equally weighted portfolio. Turning to the second sample regarding self-reported investment decisions, the authors derive thirteen different measures of individual portfolio diversification based on the 1962 Federal Reserve's Survey of the Financial Characteristics of Consumer (SFCC). Independent of the diversification measure used in the analyses, the results obtained are consistent with the findings reported for the real investment decision sample. Therefore, the authors conclude that the majority of people do not hold well-diversified portfolios as recommended by normative models based on the insights of the CAPM.

In order to test whether the tendency of people to hold insufficiently diversified portfolios has decreased over time, Morgan Kelly (1995) analyzed data from the Federal Reserve's 1983 SFCC, similar to Blume and Friend (1975). Based on the results reported in his paper, the author suggests that severe under-diversification among U.S. investors has not improved between 1962 - 1983 and is therefore a persistent phenomenon. Findings that under-diversification is not only a persistent phenomenon in the U.S. but also common among investors living in other countries are reported by Fuertes, Muradoglu, and Ozturkkal (2014). In their paper the authors show that, on average, the number of stocks owned by Finnish investors is approximately two, by German investors is approximately four and by Dutch investors approximately seven. Taking into consideration that, as a rule of thumb, a well-diversified stock portfolio should consist of 20-30 different, equally weighted stocks (Kelly 1995), it becomes apparent that under-diversification is not only common in the U.S. but also among international investors.

According to the CAPM, diversification not only refers to the number of different stocks an investors holds in his portfolio, but also what kind of stocks he owns. This second dimension captures the notion that the financial risk of a portfolio depends on the covariance between the stocks that make up the portfolio. Therefore, investors should ideally hold between 20-30 different stocks of companies operating in different industries and countries. In addition, the portfolio should further have no or only little correlation with the human capital of the investors, e.g. should not contain stocks of the employers company, since in case of bankruptcy the investor not only looses his investment but also his source of income.

Research regarding the second dimension of diversification reveals that investors not only exhibit severe under-diversification in terms of international stock holdings, but also tend to hold stocks of companies that are highly correlated with the investors' human capital, e.g. regional proximity and source of income. In their famous paper, French and Poterba (1991) report strong evidence that investors do not sufficiently diversify their portfolios by holding international stocks, instead they showed that not only U.S. but also Japanese, British, German and French investors mainly hold stocks from domestic companies. The tendency of investors to mainly invest in domestic stocks is referred to as the *"home bias"* (French and Poterba 1991). Evidence that people have a strong tendency to hold portfolios with a significant fraction allocated to stock from the employer's company is reported by Poterba (2003) and Benartzi (2001). Another preference pattern commonly observed in stock portfolios is the tendency to hold domestic stocks from companies operating in close proximity of the investor's residence. For example Huberman (2001) reports results suggesting that investors prefer to buy stocks of companies that are located in their area of residence by analyzing the shareholders of regional U.S. telephone companies. Evidence that such preferences are not only common among U.S. investors is documented by Grinblatt and Keloharju (2001). The authors show that Finnish investors tend to allocate a significant proportion of their portfolio to stocks from local companies that operate close to the area of residence, communicate in the same local dialect and language and is managed by a CEO with a similar cultural background as the investor.

Summarizing the extensive evidence, it is reasonable to conclude that many investors do not take full advantage of holding well-diversified portfolios as recommended by normative investment theory. Therefore, some authors refer to the tendency of investors to hold under-diversified portfolios as the *"diversification puzzle"* (Statman 2004).

Turning to the literature investigating possible explanations for the diversification puzzle, many papers report associations between individual characteristics of the investor and his propensity to hold an under-diversified portfolio. Goetzmann and Kumar (2004; 2008) report findings that age, income, level of education and financial sophistication have an effect on under-diversification among U.S. investors. Similar results are reported by Calvet, Campbell and Sodini (2009). In their study on investment mistakes among Swedish investors they find that, in addition to the investors' characteristics reported by Goetzmann and Kumar, financial wealth, total amount of household debt and household size affect the degree of portfolio under-diversification in their sample. Although these findings show that individual characteristics can help to identify investors who exhibit stronger tendencies to hold insufficient diversified portfolios, they do not explain why these investors tend to hold under-diversified portfolios. More precisely, it does not explain why people prefer exposure to unnecessary high levels of idiosyncratic risk by holding under-diversified portfolios when diversification can help to reduce idiosyncratic risk significantly.

So far, the explanation that appears to fit the observed pattern of under-diversification best entails that investors do not perceive their portfolio as a single entity with a certain level of risk which has to be managed, but rather focus on the characteristics of each stock contained in the portfolio (Statman 2004). This approach has the advantage that it allows the investor to have different attitudes towards the stocks he decides to hold. Since the future return and the risk associated with a particular stock are to a certain degree ambiguous, it becomes clear that the attitude of an investor towards ambiguity plays an important role in his investment decisions.

According to Barberis and Thaler (2003), ambiguity aversion offers an intuitive explanation why many investors hold under-diversified portfolios. For example an investor who is reluctant to hold foreign stocks may be more familiar with his national stock market and therefore perceive it as less ambiguous than stocks from other countries. Similarly, an investor perceives stocks from the company he works for or that operates in close proximity to where he lives as less ambiguous compared to stocks from other companies. Assuming that most people dislike ambiguity, it becomes clear that investors have a strong tendency to invest in stocks they are familiar with and therefore perceive as less ambiguous (Barberis and Thaler 2003). More generally, an investor's degree of confidence in the probability distribution of future returns for each stock are important determinants in his investment decisions. Following Barberis and Thaler's line of argument, investors' confidence in the probability distribution of future returns is higher for familiar than for ambiguous stocks.

Although the aforementioned explanation appears to describe the prevailing pattern of diversification well, it has one important disadvantage. It builds upon the assumption that investors are generally ambiguity averse. As mentioned in the introduction, recent findings suggest that general ambiguity aversion does not hold. Instead, individual attitudes towards ambiguity consist of two distinctive components which characterize the decision maker: ambiguity aversion and a-insensitivity.

The following part describes the methodology of this study. After a short description of the data set, the source method is described in detail followed by the derivation process of both ambiguity attitude indexes. The methodology part concludes with the explanation of both measures of diversification as well as the full set of control and demographic variables.

3. Methodology

3.1. The Data Set

The present study is based on data from the Longitudinal Internet Studies for the Social Sciences (LISS) survey conducted by CentERdata at Tilburg University in the Netherlands[1]. The LISS panel is well-suited for economic research due to the following characteristics:

- *Representative sample of the Dutch population*: To ensure representativeness of the sample, households are randomly chosen from a large number of addresses registered at the Dutch municipalities (Knoef and de Vos 2009).
- *Real-incentives*: Not only are participants compensated by CentERdata for each questionnaire they complete, but also participants can be paid extra incentives based on their actual choices in simple chance gambles.
- *Limited sample selection bias*: The LISS survey is conducted over the Internet and subjects complete each questionnaire at home. In order to avoid potential sample selection effects (Angrist and Pischke 2008 § 2.1), participants are provided with a computer and Internet access if necessary.

In addition to its economic relevance, the LISS panel is a valuable data source for this study, since it covers a great variety of relevant information, including the participants' economic situation (asset ownership, income, etc.), demographics (education, occupation, age, etc.) and the subjects' attitudes towards ambiguity. The particular dataset used in this study consists of four individual LISS panel modules. Module 1 contains the background variables, module 2 and 3 include information on the economic situation of the subjects, i.e. income and asset ownership, and module 4 consists of several measures of the participants' risk and ambiguity attitudes. The last module is an individually designed questionnaire included in the LISS panel in early 2010. It was developed by Dimmock, Kouwenberg and Wakker (2015) in order to investigate the relationship between ambiguity attitudes and real-life economic decisions.

3.2. Measuring Ambiguity Attitudes

In order to measure ambiguity attitudes, this study relies on a tractable method based on matching probabilities developed by Dimmock et al. (2015). This approach of eliciting the individual's attitude towards ambiguity is based on the source method established by Abdellaoui et al. (2011)

1 For additional information on the LISS panel see http://www.lissdata.nl/lissdata/About_the_Panel/.

and follows insights from Chew and Sagi (2008).

3.2.1. The Source Method

Following the classical Ellsberg paradox, Dimmock et al. (2015) propose an elicitation method that measures ambiguity attitudes relative to risk attitudes. In 1961, Daniel Ellsberg showed in his famous thought experiment that people are generally more willing to bet on prospects involving known probabilities than on prospects with unknown probabilities. A prospect is a list of outcomes with their associated probabilities. Consider, for example a simple gamble or a coin flip, where the participant has the chance to win 1 Euro with a probability of 50% and nothing otherwise. The notation for this example is: (0,5:1€;0,5:0€) or general (p_1:x_1;p_2:x_2). In his experiment, Ellsberg used two urns: the first urn contained in total 100 balls, exactly 50 black and 50 red balls. Hence, this urn is called the *"known urn"* or urn K. The second urn also contained in total 100 balls, but the proportion of red and black balls was unknown to the subject. Therefore this urn is called the *"unknown urn"* or urn U.

Based on this experimental setup, a hypothetical subject is asked to make a decision on the following paired gambles. First, he is asked to choose a winning color for both urns. The subject is told that if the chosen color is drawn from the urn, he wins a prize but gets nothing if the other color comes up. For each urn, he can choose to bet on either a red or a black ball as the winning color, or choose to be indifferent. Second, he is asked for each color, whether he prefers to bet on urn K or urn U from which a ball will be drawn to win.

The typical answer regarding the winning color is that most people are indifferent between red and black as the winning color in hypothetical choices. Turning to the second pair, the majority of people prefer to bet on a red ball to be drawn from urn K over a red ball to be drawn from urn U as well as a black ball to be drawn from urn K over a black ball to be drawn from urn U.

Taking a closer look at the second paired gamble decision, *"choosing urns"*, a preference of a red ball to be drawn from urn K over a red ball to be drawn from urn U, implies, following the basic Ramsey-Savage rule, that the subject seems to consider a red ball to be drawn from urn K as *"more probable"* than a red ball to be drawn from urn U (Ellsberg 1961). Simultaneously, the subject also prefers a black ball to be drawn from urn K over a black ball to be drawn from urn U in order to win. Given the composition of both urns, each containing only red and black balls, such a preference violates the basic notion of probability. Choosing urn K in this paired choice question, when red is the winning color, implies that the subject considers a red ball to be drawn from urn K as *"more probable"* but also considers a black ball to drawn from the same urn as *"more probable"* when black is the winning color.

Assuming that the hypothetical subject is probabilistic sophisticated in the sense that he assigns subjective probabilities to each color in the urn of which he only knows that it contains red and black balls without its proportions, then his preference for the known urn K, regardless of what the winning color is, can be simplified as follows: Although he knows that he does not know the precise composition of urn U, his preference for urn K implies that he believes that urn U contains less than 50% red balls as well as less than 50% black balls. In other words, the sum of the subjective probabilities of urn U, assigned by the decision maker, is less than 100%. This is clearly a violation of the addition rule for probability.

This tendency of people to prefer the known over the unknown urn, is referred to as ambiguity aversion or the Ellsberg paradox. Following this finding, the common conclusion was that decision models that are based on subjective probabilities cannot explain such observed preferences, i.e. probabilistic sophistication does not hold (Dimmock et al. 2015).

However, turning to the first paired gamble decisions *"choosing winning color"* it can be argued that people do make decisions in accordance with well-defined subjective probabilities. When the hypothetical subject is asked to bet on a color that will be drawn from the unknown urn U, the typical answer is that he is indifferent between betting on red or black as the winning color (Ellsberg 1961). In this case, being indifferent between the two colors implies that the subjects perceive the probability of winning to be identical for both colors or as *"equally probable"*. Based on the hypothetical preferences regarding both paired choice questions, it becomes clear that the violation of the general principles of probability arises in situations where the subjects are asked to compare two different urns – or more generally speaking, decisions that involve the comparison of two sources of risk and uncertainty.

The source method (Abdellaoui et al. 2011) is based on this distinction between different sources of uncertainty. Tversky and Fox (1995) established the term *"source of uncertainty"* to describe a set of events generated by the same underlying random process (e.g. the outcome of a coin flip or the daily returns of a stock index). Applying this insight into the choice questions involving two different urns, it becomes clear that urn K and urn U can be considered to be two different sources of uncertainty. Following this distinction, it is obvious that a decision maker may have different attitudes towards different sources of uncertainty.

Because the Ellsberg though experiment involves the direct comparison of a risky urn (known probabilities) to an ambiguous urn (unknown probabilities), such an experimental setup makes it possible not only to obtain the objective probability of urn K, but also the subjective probability of urn U. Although the hypothetical preferences show that probabilistic sophistication does not hold when two sources of uncertainty are compared, Chew and Sagi (2006, 2008) argue that subjective probabilities can still be properly defined within sources of uncertainty, if the preferences are consistent with their *"exchangeability condition"*.

Chew and Sagi (2008) define exchangeability as follows: *"Two events are [...] exchangeable if the decision maker is always indifferent to permuting their payoffs"* (p. 2 - 3). This means that two disjoint events can be defined as *"exchangeable"* if exchanging the payoffs under each event does not change the preference for the prospects (Abdellaoui et al. 2011).

According to the exchangeability condition by Chew and Sagi (2008), a rational decision maker should assign the same (subjective) probability of winning to urn U when directly compared with urn K. In other words, an ambiguity neutral decision maker will assign a subjective probability to the unknown urn that equals the objective probability of the known urn.

Therefore, under the exchangeability condition (Chew and Sagi 2008), the objective probability of urn K can be used as a benchmark. For example, if the subject weights the probability of winning differently for the ambiguous urn U than for the risky urn K, then it is possible to infer the individual's attitude towards ambiguity. In case the subject assigns less (more) weight to the probability of winning to urn U than to urn K, then he can be classified as ambiguity averse (seeking).

Returning to the Ellsberg experiment from the beginning, the common finding that most people prefer to gamble on the known to the unknown urn indicates that most people underweight the probability of winning for urn U. Following the insights of the source method, the subject can still be considered to be probabilistic sophisticated within each source, by allowing for different source dependent weighting function for urn K and urn U.

3.2.2. Measuring Ambiguity Attitudes through Matching Probabilities

As indicated before, this study relies on a questionnaire developed by Dimmock et al. (2015) implemented in the 2010 LISS panel survey. This survey module is based on the insights of the source method (Abdellaoui et al. 2011) using matching probabilities elicited through a series of chained questions to derive the individual's ambiguity attitudes.

In their questionnaire, the subjects are presented with three sets of choice questions similar to the Ellsberg experiment. For each set of questions the subject is asked to choose between gambling on an urn with known versus an urn with unknown composition of colored balls. As in the Ellsberg experiment, the subject wins a prize (15 Euro) if the winning color is drawn from the chosen urn. Prior to each set of questions, the participant had the option to choose the color of the winning ball. This question was added by the authors of the questionnaire in order to prevent suspicion among the subjects. For example Pulford (2009) suggests that subjects might behave more ambiguity averse when they perceive the unknown urn to be manipulated to their disadvantage. Less than 2% of the participants in the sample made use of this option, which is an indicator that subjects were not suspicious and perceived the gamble to be fair (Dimmock et al. 2015). The default setting for the winning color is purple for all questions. Using different colors for this experiment compared to the original Ellsberg urns was done in order to avoid problems with color blindness. Following the color selection question, the actual elicitation process started.

Each set of chained questions was used to elicit the subjectively perceived probability for one particular objective probability. Presented with an Ellsberg type choice question, the participant had three options to choose from, indicating his individual preference:

- Option K: This choice indicates that the subject prefers to gamble on the risky urn K versus the ambiguous urn U.
- Option U: The second option reveals the participant's preference of betting on the unknown urn U over the known urn K.
- Option *"Indifference"*: Selecting the third option does not indicates that the subject has no preference, but the he considers both urns to be equally attractive choices.

Given the primary goal to elicit the matching probability of urn K that makes the subject indifferent between betting on the risky versus the ambiguous urn, each question answered with either option K or option U was followed by a modified version of the previous question. This was achieved by using chained questions in which the composition of urn K was varied depending on to the previous answer while keeping urn U fixed. For example, if the subject preferred the risky urn over the ambiguous urn, then urn K's probability of winning was decreased in the follow-up question. Analogously, the probability of urn K was made more attractive in case the subject selected the ambiguous urn. Hence, the subject was presented with variations of the initial gamble until she selected the indifference option or answered at most six iterations without reaching indifference.

Based on this procedure, the authors define the matching probability as the objective probability of urn K for which the participant is indifferent between betting on the risky versus the ambiguous urn (Dimmock et al. 2015). In case indifference was not reached after the final iteration, the matching probability was obtained by taking the average of the minimum (lowest) and maximum (highest) probability of urn K (excluding the initial value of urn K).

In order to derive meaningful measures regarding the participants' overall attitude towards ambiguity, this method is used to obtain the matching probabilities for three different ambiguity neutral probabilities. Therefore, the survey module included three separate sets of gambles involving a low (10%), medium (50%) and high (90%) objective probability of winning for the risky urn K in the baseline condition.

The first set of gambles elicits the matching probability for moderate likelihood events: $m(p) = 0.5$. This condition involved two urns replicating the original Ellsberg experiment. The risky urn K contained in total 100 balls in two different colors, i.e. 50 yellow and 50 purple balls. The ambiguous urn also contained in total 100 balls, but the proportion of yellow to purple balls was unknown to the participant. Unlike the Ellsberg experiment, the authors decided to use the colors yellow and purple (instead of black and red) to prevent potential difficulties for colorblind participants to distinguish the different colors (Dimmock et al. 2015).

The second set of gambles elicits the matching probability for low likelihood events: $m(p) = 0.1$. In this condition, the subject is also presented with a choice task involving two urns. Again, both urns contain in total 100 balls, but unlike the previous experimental setup, each urn consists of ten different colors. Urn K contains ten balls of each color, making each color equally likely to be drawn, whereas urn U's exact proportion of colors is unknown to the subject. As in the gamble used to obtain subjective probabilities for $m(p) = 0.5$, the participant wins a prize if the winning color is drawn from the selected urn.

The third and final set of gambles is used to measure the matching probability for high likelihood events; m(p) = 0.9. In this experimental setup the initial composition of urn K is exactly the same as in the previous gamble, but unlike the gamble with low likelihood of winning, the subject wins a prize if any other color is drawn than the selected color. In other words, urn K initially contains 90 balls in nine different *"winning"* colors and only ten balls in the *"loosing"* color.

It is important to note that the experimental setup to elicit the matching probabilities for low and high likelihood events relies on two essential assumptions. The first assumption is that both the symmetry and the exchangeability condition (Chew and Sagi 2008) hold, not only for the gamble with two color urns, but also for urns with ten different colors. This assumption implies that an ambiguity neutral decision maker weights the probability of the winning color to be drawn from the unknown urn U not differently compared to urn K. Given the initial composition of urn K the matching probability should be 0.1 (or 0.9). In addition, this method further assumes that the source function of the ambiguous urn U with two different colors is the same as the source function of the ambiguous urn U when containing ten different colors. Considering that the unknown urns U share a similar underlying mechanism, this assumption appears to be legitimate (Dimmock, et al. 2015).

3.2.3. Advantages of Measuring Ambiguity Attitudes through Matching Probabilities

Using matching probabilities is an easy to implement, yet reliable method to measure ambiguity attitudes, requiring not more than three indifferences and approximately five minutes per participant. This method derives ambiguity attitudes based on the subjects' revealed preferences (i.e. participants' actual choices) and is therefore useful for analyzing the relationship between ambiguity attitudes and actual economic decisions. As the practical application of the source method (Abdellaoui et al. 2011), matching probabilities combine the theoretical foundation of modern decision models with empirical realism (Dimmock et al. 2015).

Another advantage lies in the elicitation process itself. Guiding the subject through a series of chained questions has the beneficial property that the individual answers converge gradually towards indifference. If the participant has not reached indifference after six iterations, the sequential elicitation process allows for close approximation of the respondents' indifference point. Using a sequential elicitation method versus a direct matching technique makes the elicitation process not only more convenient for the participants, but it also improves the reliability of the obtained measurements (Dimmock, Kouwenberg, Mitchell, Peijnenburg 2013). An example for direct matching is to ask the participant directly for the probability which would make him indifferent between the risky and ambiguous gamble.

Perhaps the most important feature of the matching probability method is that ambiguity attitudes are measured relative to risk attitudes. By eliciting the probability of urn K which makes the subject indifferent between risk and ambiguity, while keeping the prize unchanged, cancels out all other components of the decision process. Therefore, analyzing the *"within-subject"* differences between a risky and an ambiguous gamble makes this method convenient to use, because measuring individual utility features (i.e. risk aversion or probability weighting for risk and ambiguity) becomes unnecessary (Dimmock et al. 2013). The theoretical proof that matching probabilities capture individual ambiguity attitudes is provided in THEOREM 3.1 by Dimmock et al. (2015). Finally, it is worth pointing out that matching probabilities capture both ambiguity attitude components – ambiguity aversion and a-insensitivity – simultaneously.

3.2.4. Deriving Local and Global Ambiguity Indexes from Matching Probabilities

Following Dimmock et al. (2015) local or *"event-specific"* ambiguity indexes can be directly derived from the elicited matching probabilities. These local ambiguity indexes capture the individual deviation from ambiguity neutral probability for events with specific likelihoods. In this study, these events correspond to the sets of gambles with different likelihoods of winning. The local ambiguity indexes are defined as the difference between the ambiguity neutral probability and the matching probability and are obtained by subtracting the elicited matching probability from the objective probability:

Low likelihood events:	$AA_{10} = 0.1 - m(0.1)$
Medium likelihood events:	$AA_{50} = 0.5 - m(0.5)$
High likelihood events:	$AA_{90} = 0.9 - m(0.9)$

Since the local ambiguity attitude measures capture the deviation from ambiguity neutrality, the interpretation is straight forward:

Ambiguity averse:	$AA > 0$ or $m(p) < p$
Ambiguity neutral:	$AA = 0$ or $m(p) = p$
Ambiguity seeking:	$AA < 0$ or $m(p) > p$

For a given likelihood event, a subject can be considered to be ambiguity averse if the corresponding index (AA) has a positive value with matching probabilities smaller than ambiguity neutral probabilities. Further, a participant is considered to be ambiguity seeking with a negative local ambiguity index (AA) and matching probabilities above ambiguity neutral probabilities. An individual can be classified as ambiguity neutral with an event-specific ambiguity index equal to zero.

3.2.5. Global Ambiguity Attitude Indexes

Based on the three local ambiguity attitude indexes this study derives two measures each capturing a specific ambiguity attitude component: a-insensitivity and ambiguity aversion. Both measures capture the subjects' individual ambiguity attitudes over the entire range of likelihood events – in other words global measures of ambiguity attitude. As previously mentioned, this study follows in part the methodology proposed by Dimmock et al. (2015). For consistency, the present study adopts the *"local"* or *"event-specific"* and *"global"* ambiguity attitude indexes from their paper. Since ambiguity attitudes consist of two separate components, using two different indexes, one for ambiguity aversion and one for a-insensitivity, works well in empirical studies. In the literature, two different methods are used to obtain both ambiguity attitude measures. Both methods derive the global indexes from matching probabilities elicited by virtually the same process, but obtain their respective measures from very different underlying calculations. Although the main focus of this study lies on the more sophisticated method originally proposed by Abdellaoui et al. (2011), both calculation methods are applied. This helps to shed some light on the relationship between the two measurements and will provide some insights into how they perform empirically.

The first calculation method was introduced by Dimmock et al. (2013) and is a fairly simple and straight forward way to calculate both ambiguity attitude indexes. Based on the three elicited matching probabilities, or more precisely the local ambiguity aversion indexes (difference between the ambiguity neutral and the matching probability), the attitude measures are obtained as follows:

A- insensitivity index: $$a_{So} = AA_{10} - AA_{90} \qquad \text{(Eq. 3.1)}$$

Ambiguity aversion index: $$b_{So} = \frac{AA_{10} + 2 \times AA_{50} + AA_{90}}{4} \qquad \text{(Eq. 3.2)}$$

The second method was originally developed by Abdellaoui et al. (2011) and later applied in the study by Dimmock et al. (2015). Compared to the previously mentioned calculation, this is a more sophisticated method to derive the ambiguity attitude indexes from the elicited matching probabilities.

This method is based on neo-additive source functions with following characteristics (Wakker 2010 § 7.2):

$$m(0) = 0;\ m(1) = 1;\ 0 < p < 1 : m(p) = c + sp;\ s \geq 0,\ c \geq 0,\ s + c \leq 1 \qquad \text{(Eq. 3.3)}$$

Figure 3.1 below illustrates an example of a neo-additive source function consistent with the properties implied by **Equation 3.3**.

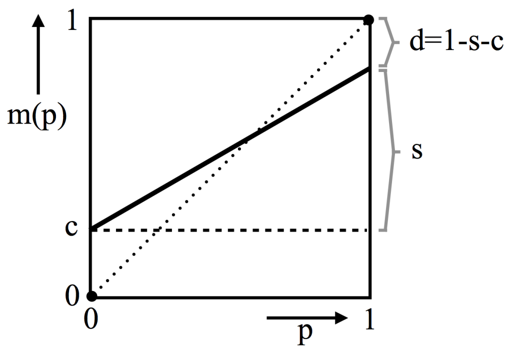


Figure 3.1. The neo-additive source function (Wakker 2010 § 7.2).

Using a neo-additive source function to derive both ambiguity attitude indexes is particularly useful, since the main deviations from ambiguity neutrality (depicted as the 45-degree dotted line in **Figure 3.1**) occur at both the upper (p = 1) and lower (p = 0) bound of the function. Applying the neo-additive source function has the benefit that the obtained indexes can be interpreted in a straight forward manner. It is important to note that the neo-additive source function does not necessarily fit the surveyed data best, but compared to other potential source functions, the obtained indexes are more convincing due to their clear interpretation (Wakker 2010).

The global ambiguity indexes are calculated in two steps. First, the best-fitting neo-additive source function is obtained through linear regression over the interval (0,1) and truncated at the endpoints 0 and 1. In other words, the best-fitting line is estimated between m(p) and p by minimizing the sum of the squared residuals while restricting the regression coefficients (Dimmock et al. 2015). In **Figure 3.1** this line is depicted as the bold line. Assuming that the regression line follows:

$$p \rightarrow c + sp \qquad \text{(Eq. 3.4)}$$

then, as shows in **Figure 3.1**, c is the intercept at p = 0 (d is the intercept at p = 1) and s is the slope. Based on the obtained regression coefficients c and s, the global ambiguity indexes are calculated as follows:

A-insensitivity index: $a_{So} = 1 - s$ or $a_{So} = c + d$ (Eq. 3.5)

Ambiguity aversion index: $b_{So} = 1 - s - 2c$ or $b_{So} = d - c$ (Eq. 3.6)

Index a_{So} is a measure of a-insensitivity since it captures the flatness of the source function, reflecting the individuals' lack of discriminatory power of intermediate likelihood levels. Index b_{So} captures the subjects' aversion towards ambiguity due to its inverse relationship with the average height of the source function (Dimmock et al. 2015).

Unfortunately, standardly available statistical software does not provide the option to impose interval restrictions on the regression coefficients as required by the calculation method proposed by Abdellaoui et al. (2011). Therefore this study applies a slightly different, more pragmatic calculation method, which, despite the technical issues, still follows the intuition of the described method.

First, the intercept c and the corresponding slope s is obtained by regressing the matching probabilities on the ambiguity neutral probabilities. Since no restrictions are imposed on the regression coefficients, some parameters violate the conditions implied by **Equation 3.3** More precisely, $s \geq 0$, $c \geq 0$, $s + c \leq 1$ does not hold for all subjects in the sample. Based on psychological insights, it is reasonable to manually adjust the parameters so that the conditions of **Equation 3.3** are satisfied (Wakker, personal communication, June 4, 2015). A detailed description of the manual adjustments of the estimated neo-additive source functions can be found in **Appendix A**.

Looking at the differences between the calculation method proposed by Dimmock et al. (2013) and Abdellaoui et al. (2011), it becomes clear that the former takes the elicited matching probabilities at face value. The method does not adjust implausible measures of ambiguity attitudes. As shown above, in the latter method such adjustments can be made, either by imposing interval restriction in the regression or, as in the case of this study, by adjusting the parameters manually after finding the best-fitting line between m(p) and p.

3.3. Measuring Portfolio Diversification

Most studies that analyze real investment behavior of people outside of experimental settings work with data sets that contain highly detailed information on individual stockholdings. Unfortunately, such data sets are only available for a small number of countries. Among those countries are Sweden and Denmark, where citizens are not only subject to income but also wealth tax. Therefore, highly detailed information on worldwide assets ownership and other financial holdings are available for every household through each country's national bureau of statistics (Calvet, Campbell and Sodini 2009; Andersen and Nielsen 2011).

The present study works with data on the Dutch population obtained from several modules of the LISS survey. Unfortunately, none of the LISS modules contain highly detailed information on individual asset ownership, e.g. specific stockholdings, the number of stocks or other financial investments. Nonetheless, the panel provides data on total wealth of the participants and the amount of money invested in different asset classes. This information is self-reported by the participants and is not mandatory for completion of the questionnaire. The following section provides an overview of the data on investment decisions (from the LISS panel), how portfolio diversification is assessed and the diversification proxy used in this study.

3.3.1. Data Provided by LISS: Economic Situation of Participants

As mentioned earlier, this study uses an assembled data set consisting of four different LISS panel modules. Observations regarding wealth and financial holdings of the subjects are obtained from the annually conducted LISS core studies. In particular, the variables of interest are based on questions regarding the possession of the following assets:

"On 31 December 2009, did you possess one or more of the following assets?":

- Liquid financial wealth: *"Banking account or giro (current accounts), savings accounts, term deposit accounts, savings bonds or savings certificates, bank savings schemes (banksparen)."*
- Insurance policies: *"Single-premium insurance policy, life annuity insurance, endowment insurance, etc."*
- Direct financial investments: *"Direct stock holdings, investments in shares or share funds."*
- Real estate: *"Real estate not used as one's own home, second home or holiday home."*
- Total financial investments: *"Investments (growth funds, share funds, bonds, debentures, stocks, options, warrants, and so on)."*
- Alternative investments: *"Any other assets not mentioned so far, e.g. musical instruments, art works, antiques, jewelry, collections etc."*

Conditional on the ownership of each asset, the participant was asked directly to provide the monetary value of the respective holding. If the participant did not know the particular amount invested, he was presented with a follow-up question asking to what category the holding belonged. The possible answers incrementally increased from *"less than € 50" to "€ 25.000 or more"*, yielding in total 15 different categories.

In order to obtain useable observations regarding the subjects' investment decisions, each answer from the follow-up questions was converted by taking the median value of the category. For example the range *"€ 7.500 to € 10.000"* was transformed to € 8.750 as the total amount invested in the asset class. If the subject indicated that his investment belonged either to the lowest or highest category, then the lower or upper bound was used. For example for the category *"less than € 50" ("€ 25.000 or more")* the value was set to be € 50 (€ 25.000).

In addition, the final data set also includes information that was obtained during other waves of the annual LISS core study on the economic situation of the subjects. Integrating information on asset ownership from different periods was done to obtain a richer data set and to reduce the number of missing observations. Based on the assumption that both the ambiguity attitudes and investment behavior is stable in the short and medium term, the time difference of one year between elicitation of ambiguity attitudes and financial holdings should not lead to a systematic bias in the data set.

The aim of the present study is two fold. At first, the relationship between stock portfolio diversification and the individuals' ambiguity attitudes is investigated. In addition, a second aspect of diversification is investigated: the relationship between the number of different asset types a subject holds and his ambiguity attitudes. The following section provides an overview of how diversification can be measured within and across assets. Additionally, a proxy for portfolio diversification is introduced due to data limitations.

3.3.2. Assessing Portfolio Diversification: Under-Diversification of Risky Assets

Following Calvet et al. (2009) this study assumes that assets are priced on worldwide markets and according to the global version of the Capital Asset Pricing Model (CAPM). In order to quantify to what degree a subject's portfolio deviates from a perfectly diversified (efficient) portfolio, each individual portfolio is compared to the overall stock market. Since there is no measure of the overall stock market, this study uses the MSCI World Index as a benchmark for a well-diversified portfolio (Calvet et al. 2009). Therefore, under-diversification of the subjects' risky portfolios is measured as the relative Sharpe ratio loss (S_{loss}):

$$S_{loss} = 1 - \frac{S_i}{S_m} \qquad \text{(Eq. 3.7)}$$

In **Equation 3.7**, S_i is the Sharpe ratio of the individual (i) and S_m is the Sharpe ratio of the broad stock index. The general formula of the Sharpe ratio is as follows (Sharpe 1994):

$$S = \frac{\bar{r}_p - r_f}{\sigma_P} \qquad \text{(Eq. 3.8)}$$

Where $\bar{r}$, r_f and σ_P respectively, denote the expected portfolio return, risk free rate and the portfolio standard deviation. As previously mentioned, the LISS panel does not contain detailed information on the individual stockholdings of the subjects, therefore a proxy is used for S_i. In the next section the used proxy is explained in detail. Regrading the used benchmark, this study uses the five year Sharpe ratio of the MSCI World Index, which is S_m= 1.00 (MSCI World Index Factsheet 2015). According to MSCI, the five year return of their World Index is 13.46% and the five year annualized standard deviation is 13.36%.

3.3.3. The Diversification Proxy

As mentioned in the introduction, most studies investigating diversification rely on data sets with detailed information on individual stock holdings. Since the LISS panel does not include such information, a diversification proxy is constructed following the methodology of Calvet et al. (2009). In their paper the authors construct and test several alternative measures of diversification. The test results reported show that a reasonable proxy for portfolio diversification is the share of funds held in the risky portfolio (*"risky share"*). This variable performed better than other measures of diversification, e.g. the total number of different risky assets (stocks) owned by the individual. Based on these findings, the proxy can be derived from the following variables based on liquid financial asset:

- Variable *"cash"* is the sum of the subjects' bank account balances and money market funds. Hence, this variable is analogous to the measure of *"liquid financial wealth"* obtained form the LISS panel.
- Variable *"direct financial investment"* is the amount invested directly in the stock market. In this study the terms *"direct financial investment"* and *"risky portfolio"* are used interchangeable.

- Variable *"total financial investment"* refers to the participants' total amount of money invested in risky assets and therefore captured by the second question used from the LISS panel.
- Variable *"total financial wealth"* is calculated for each subject by taking the sum of *"cash"* and *"total financial investment"*. For simplicity, and in accordance with Calvet et al. (2009), this study considers only the subjects' gross financial wealth and therefore does not include debt in any form.
- Variable *"risky share"* is defined for each participant as the fraction of total wealth invested directly in the stock market. Hence, this variable is obtained by dividing *"risky portfolio"* by *"total financial wealth"*.

Table 3.1 provides an overview and summary statistics for the described variables, including the diversification proxy *"risky share"*.

Table 3.1

Variable	Mean	Std. Dev.	Min.	Max.	Obs.
Cash	21136.31	37137.98	0	266295	357
Direct financial investments	2641.29	16732.01	0	200000	417
Total financial investments	8885.27	51401.41	0	700000	439
Total financial wealth	32390.56	75492.87	0	725000	354
Risky share	0.04	0.13	0	0.95	273

Calvet et al. (2009) tested the usability of the variable *"risky share"* as a proxy for diversification by analyzing its cross-sectional correlation with the actual Sharpe ratio of their participants. The results show that the correlation coefficient of the share of funds in the risky portfolio (*"risky share"*) and the actual Sharpe ratio is 0.49. Although the correlation between this variable and the actual Sharpe ratio is far from perfect, it is much higher than for the other alternative measures. Therefore the authors conclude that *"share of funds in risky portfolio"* is a suitable proxy for risky portfolio diversification in terms of Sharpe ratio. In order to be able to assess the degree of diversification, the individual Sharpe ratio proxy is compared to an optimally diversified portfolio. This is done by computing the relative Sharpe ratio loss.

The average Sharpe ratio loss of the entire sample can be computed by inserting the average value of *"risky share"* (S_i = 0.04) reported in **Table 3.1** and the Sharpe ratio of the MSCI World Index (S_m= 1.00) in **Equation 3.7**:

$$S_{loss} = 1 - \frac{0.04}{1.00} = 0.96 \qquad \text{(Eq. 3.8)}$$

3.4. Measuring Diversification Across Asset Classes

The second diversification measure is derived from the different asset classes each participant holds. This measure is referred to as *"asset diversification"*. Based on the LISS questionnaire regarding individual asset ownership, the total number of different asset classes held by the participant is computed. The asset classes are: 1.) banking and savings accounts, including saving bonds and bank saving schemes, 2.) insurance policies, including life annuity insurance and endowment insurance, 3.) investments, for example growth funds, bonds and share funds, 4.) real estate not used as one's own home, i.e. second or holiday homes, 5.) direct holdings of stocks and 6.) alternative investments, including art works, antiques, jewelry and other collectibles. Based on the total number of different asset a participant holds he is classified as *"minimally diversified"* if he holds none or one asset, as *"intermediary diversified"* if he holds two to four different assets and as *"maximally diversified"* if he holds up to six different asset types.

3.5. Demographic and Control Variables

This section provides an overview of the demographic and control variables used in this study. By including a wide set of control variables, this analysis follows a growing field of empirical literature that has documented a relationship between individual characteristics and real life investment decisions.

Most demographic variables are obtained from the basic LISS module covering the background information of each participant. All variables regarding the economic characteristics of the subjects, i.e. income, financial debt and wealth, are obtained from the LISS survey regarding the economic situation of the participants. The remaining variables including financial literacy and risk aversion are gathered from the specially designed questionnaire by Dimmock et al. (2015).

Age: Apart from being among the most basic demographic variables, age is an important explanatory variable for investment behavior. In the context of this study, age is especially interesting, since normative models of portfolio theory postulate that the proportion of wealth allocated to risky assets or stocks should be reduced with increasing age. In addition, empirical evidence shows that age has an positive effect on under-diversification, i.e. older participants tend to hold less severe under-diversified portfolios (Calvet et al. 2009). Therefore this analysis includes *"age"* and *"age^2"* as explanatory variables. Age is measured in years and at the time the participant answered the questions eliciting the ambiguity attitudes (January 2010).

Education: Most empirical papers that investigate the relationship between individual characteristics and economic behavior include some measure of education. For the present study, it is especially important to control for education, since a large body of literature suggests that risk and ambiguity attitudes are related to cognitive abilities and education. For example Petrova, van der Pligt, & Garcia- Retamero (2013) found that numeracy has an effect on the shape of the probability weighting function for decisions under risk, i.e. a higher degree of numeracy is associated with less pronounced inverse S-shaped weighting functions (less likelihood insensitivity). This is consistent with Baillon, Bleichrodt, Keskin, L'Haridon & Li (2013) who interpret likelihood insensitivity as a cognitive bias. Assuming a strong correlation between cognitive abilities and education, controlling for the latter helps to obtain more accurate estimates of the attitude components. In addition, Calvet et al. (2009) found that better educated households tend to make fewer mistakes in regard to investment decisions including under-diversification. The level of education is derived from the classification used by Statistic Netherlands. Based on these six categories, the following dummies are included as controls: *"low education"*, *"intermediate education"* and *"high education"*. A participant has a low level of education, if he only attended primary or intermediate secondary school (vmbo). He is assigned an intermediate level of education when he received either a higher secondary education (havo/vwo) or intermediate vocational education (mbo). Finally, the subject is classified as highly educated if he received higher vocational education (hbo) or attended university (wo).

Employment: Many studies find that employment status and economic decision making are related. Following Calvet et al. (2009) this study controls for employment status, since the authors report that both, self-employed (entrepreneurs) and unemployed subjects, hold more under-diversified portfolios, whereas retired participants and students tend to be less severe under-diversified. Based on information regarding the subject's primary occupation, this study derived five dummy variables capturing the employment status: *"employed"*, *"self-employed"*, *"unemployed"*, *"pensioner"* and *"student"*.

Financial literacy: Consistent with other empirical research on ambiguity attitudes, this study controls for financial literacy, since familiarity with a particular kind of uncertainty can have a profound effect on the subject's decision making. Barberis and Thaler (2003) report findings in favor of the *"competence hypothesis"*. The competence hypothesis (Heath and Tversky 1991) states that people who feel competent about specific uncertain decisions show behavior that is contrary to general ambiguity aversion - they show preference for ambiguous decisions they are more familiar with. In addition, Kilka and Weber (2001) found that familiarity with a particular source of uncertainty reduces the likelihood insensitivity of the decision maker. Hence, decisions under uncertainty do not only depend on the estimated likelihood of the particular event and the accuracy of this estimate, but also on the subject's knowledge or understanding of the decision context. Hence, it is very likely that subjects who feel more competent about financial markets show different behavior in investing their money compared to subjects who feel incompetent. It is important to note that this effect is independent of whether the subject has correct knowledge in financial matters or simply thinks he has the knowledge. Following van Rooij, Lusardi, and Alessie (2011), who showed that stock market participation is related to financial literacy, Dimmock et al. (2015) used two questions to capture the subjects' financial knowledge. As previously mentioned, it is important to differentiate between perceived, actual and insufficient competence. Based on this insight, a subject is classified as incompetent, if he indicates that he is either unable or unwilling to answer both question. If he answers the questions, it is reasonable to assume that he at least perceives himself as competent. Therefore, a score regarding the actual competence is computed based on whether the subject gave the correct answer or not. This method yields two control variables: a dummy regarding incompetence (unable to answer the questions) and a variable with the individual competence score. The maximum score on the financial literacy questions is two, if the subject answered both questions correctly. Hence, a score of 0 indicates that the subject has little financial knowledge, but perceives himself as somewhat competent in that matter.

Gender: Similarly to age, gender is among the most basic demographic variables, but in the context of financial behavior highly relevant. For example, Barber and Odean (2001) found evidence that men are more likely to trade in stocks than women, which is consistent with results reported by Dimmock et al. (2015) indicating that women are less likely to participate in the stock market. In addition, Borghans, Golsteyn, Heckman and Meijers (2009) find that men and women react differently to ambiguity. Finally, Fehr-Duda, de Gennaro & Schubert (2006) report evidence that women are more likelihood insensitive than men. Therefore this study controls for gender effects by including a dummy variable *"female"* with the value 0 for male participants and value 1 for female subjects.

Household size: Interestingly, some studies report that the household size has an effect on financial decision making. For examples larger families are less likely to make severe investment mistakes (Calvet et al. 2009), but are also less likely to participate in the stock market (Dimmock et al. 2015). Therefore it is interesting to investigate whether the subjects in this study hold less severe under-diversified portfolios conditional on stock market participation. *"Household size"* is measured in terms of the total number of family members.

Income: Several studies have empirically confirmed a relationship between income and financial behavior. Dimmock et al. (2015) show that income has an positive effect on stock market participation. Hence, it is reasonable to assume that there is also a relationship between income and portfolio diversification. Evidence for this assumption is provided by Calvet et al. (2009), who have reported that higher incomes are associated with less portfolio under-diversification. *"Income"* is measured as the net monthly household income in Euro.

Risk aversion: As previously mentioned, this study measures ambiguity attitudes applying a method developed by Dimmock et al. (2015). Although this method elicits ambiguity attitudes relative to risk attitudes, including a measure of risk aversion in the analyses is important for several reasons. First, controlling for risk aversion can help to ensure that both ambiguity attitude components capture distinct aspects of the subjects' preferences (Dimmock et al. 2013). Second, since it cannot be ruled out that risk and ambiguity attitudes are highly correlated, adding a risk aversion variable to the analyses can provide insights into the relationship between both preference components. Third, assuming that ambiguity and risk attitudes indeed capture distinct preference components, it is nonetheless possible that risk aversion has greater influence on the individuals' tendency to insufficiently diversify their investments given the link between risk and return of financial investments. The risk aversion measure is elicited through two sets of hypothetical choice questions. **Appendix B** provides a detail explanation of how risk attitudes are measured and how the risk aversion indexes are calculated.

Trust: When people make economic decisions, trust plays an important role. For example Guiso, Sapienza, and Zingales (2008) report results showing a positive relation between trust and stock market participation. Therefore, it is reasonable to assume that people who are generally less trusting have different preferences regarding investments. For example, a person who participates in the stock market but has a low level of trust in other people might only invest in a company he particularly trusts, limiting his possibilities to hold a diversified portfolio. Hence, people who are generally less trusting might be more likely to hold under-diversified portfolios. The used measure of trust is based on the question *"Generally speaking, would you say that most people can be trusted, or that you can't be too careful in dealing with people? Please indicate a score of 0 to 10."* obtained from the LISS panel module regarding the participants personality. Higher values on the trust scale are associated with a higher degree of trust in other people.

Total liabilities: Although this study excludes any form of debt in the construction of the used diversification proxy, liabilities can still have an effect on financial decision making. This is supported by findings reported by Calvet et al. (2009). The authors show that higher levels of total liability is associated with more severe under-diversification. Following their approach, this study includes the total amount of debt as a control variable. The participant is directly asked to provide the total amount of his liabilities. If he is not able to provide the precise number, he is asked to indicate to what category his total debt belongs. As with the other categorical questions, the value was obtained by taking the median value of the category. In order to obtain more observations, information from other waves (2007 and 2011) of the panel were integrated. *"Total liabilities"* are measured in Euro.

Total financial wealth: In the context of investment decisions, the total level of financial wealth plays an important role. For example Dimmock et al. (2015) report a positive effect of the total amount of financial assets on stock market participation. In addition, Calvet et al. (2009) show that richer households tend to make normatively better investment decisions. This includes that subjects with higher financial wealth hold less under-diversified portfolios. *"Total financial wealth"* is the sum of all liquid assets the subject holds and is measured in Euro.

4. Theory

Several empirical papers confirm that individual attitudes towards ambiguity consist of two distinctive components: ambiguity aversion and a-insensitivity. The following sections provide a detailed description of both attitude components, an explanation of how they relate to financial diversification and a summary of the hypotheses that this study tests.

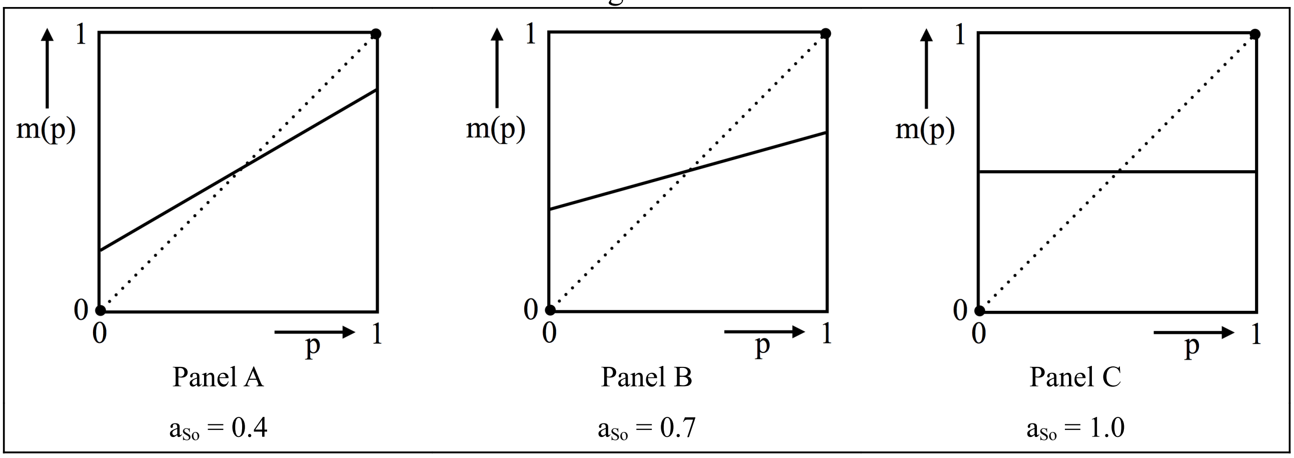
4.1. Ambiguity Attitude Components

The first component is the well-known and widely documented aversion to ambiguity. People who are ambiguity averse generally dislike ambiguous situations. In the context of prospects, this means that most people prefer to bet on risky prospects with known probabilities rather than on ambiguous prospects with unknown probabilities. Therefore, ambiguity aversion describes a comparative concept of pessimism, since a person who prefers a risky gamble over an ambiguous gamble evaluates ambiguity more pessimistically than risk. Based on Ellsberg's (1961) discovery, it has been widely accepted that ambiguity aversion holds in general. But recent papers show that, apart from aversion, the attitude towards uncertainty has a second dimension: a-insensitivity. As already discussed in the context of the local ambiguity attitude indexes, this study also finds, on average, an inverse S-shaped source function computed over the entire sample.

4.1.1. Ambiguity Likelihood Insensitivity

As described in the section regarding the global ambiguity attitude indexes, parameter a_{So} captures a-insensitivity. Thus, a_{So} captures a deviation from ambiguity neutrality (or rationality). A subject with $a_{So} = 0$ is not likelihood insensitive and hence is fully able to discriminate between different likelihood-levels when making decisions under uncertainty. Looking at the average values obtained for the main a_{So} index used in this study, it becomes clear that people in this sample are, on average, not ambiguity neutral. Following **Equation 3.5**, an a-insensitivity index $a_{So} > 0$ implies a slope of the estimated neo-additive source function with a value less than 1. This means that the decision maker is not able to fully discriminate between different intermediate likelihood-levels as he puts more weight on the extreme likelihood-levels. **Figure 4.1** illustrates the deviation from ambiguity neutrality (45-degree dotted line) for increasing values of a_{So} (when index $b_{So} = 0$).

Figure 4.1



The figure above shows that increasing values of a_{So} lead to less steep slopes of the neo-additive source function, which translates into less discriminatory ability of intermediate likelihoods and increasing focus on extreme events near $p = 0$ and $p = 1$. **Panel C** depicts an extreme case of likelihood insensitivity, where the decision maker only differentiates between three different events: *"certainly to happen"*, *"certainly not to happen"* and *"50-50 chance to happen"* for all events with non-extreme outcomes (Baillon et al. 2013; Wakker 2010 § 7). It follows that people with higher levels of a_{So} increasingly underweight high likelihood events and overweight low likelihood events.

Linking under- and overweighting to the decision makers' behavior, the underweighting of high likelihoods is consistent with ambiguity aversion, whereas overweighting of low likelihoods is associated with the opposite of aversion - ambiguity seeking. Hence, in the context of financial and economic decisions, a-insensitivity reinforces risk taking in situations that deliver large potential gains with low-likelihoods and at the same time increases risk aversion for situations that provide small gains with high-likelihoods.

Recent papers investigating a-insensitivity support the importance of this notion. Referring to Ellsberg (2001 p. 203), Dimmock et al. (2015) argue that insensitivity to probability enhances risk seeking behavior for small likelihoods of high gains. This effect is even more pronounced in situations where probabilities are unknown than with known probabilities. They conclude that for ambiguity *"people (over)value unlikely big gains"* (Dimmock et al. 2015 p.2). In addition, the authors write that due to a-insensitivity, people do not take preventive actions to reduce uncertainty. This is because people underweight the benefit of reducing ambiguity, while overweighting the benefit of its total elimination. Based on these insights, a-insensitivity can be seen as the *"cognitive dimension"* of the decision making process under uncertainty or simply as a *"cognitive bias"* due to the lack of discriminatory power between different levels of likelihood (Baillon et al. 2013).

4.1.2. Ambiguity Aversion

Ambiguity aversion is the second component of ambiguity attitudes. In this study, the degree of ambiguity aversion for each subject is captured by attitude index b_{So}. **Figure 4.2** shows the effect of increasing ambiguity aversion for a given degree of a-insensitivity (a_{So} = 0.6). As in **Figure 4.1** ambiguity neutrality is depicted by the 45-degree dotted line and the 30-degree dashed line is the neo-additive source function with a_{So} = 0.4 and b_{So} = 0. The parallel solid line reveals how the dashed line is shifted downwards for a_{So} = 0.4 and b_{So} = 0.25.

The downward shift of the neo-additive source function implies that the decision maker assigns less weight - m(p) - to the most favorable outcome and therefore enhances his focus on the most unfavorable outcome (Baillon et al. 2013). More generally, ambiguity aversion decreases the decision weights, which in turn increases pessimism and therefore increases the decision maker's dislike of ambiguity relative to risk. In addition, **Figure 4.2** shows that the interpretation of index b_{So} is straight forward. Higher values of b_{So} imply increased pessimism regarding ambiguity compared to risk. Negative values of b_{So} are associated with more optimism for ambiguity than for risk, i.e. ambiguity seeking (Abdellaoui et al. 2011).

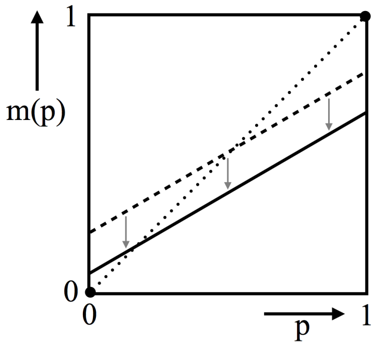


Figure 4.2 depicts the downward shift of the neo-additive source function for $a_{So} = 0.4$ and increasing values of b_{So}.

4.2. Ambiguity Attitudes and Diversification

Turning to financial decisions, a number of recent studies suggest the importance of ambiguity attitudes for analyzing investment behavior. These authors argue that ambiguity attitudes play an important role in the context of financial markets, since the future return on risky assets is to a certain degree ambiguous (Anderson, Ghysels, and Juergens 2009). The following section briefly explains the mechanism underlying stock portfolio diversification (diversification within an asset class) and discusses how it relates to ambiguity attitudes, especially focusing on a-insensitivity. In addition, the potential relationship between both ambiguity attitude components and a second measure of diversification is investigated by looking at the individuals' decision to diversify across asset classes.

4.2.1. Diversification Within and Across Asset Classes

Diversification is generally characterized by the trade-off between risk and return of the underlying assets that make up the portfolio (Welch 2009 § 8.2). Following standard financial practice, the expected rate of return of a risky asset is calculated as the average of all possible returns weighted by their particular probability of occurrence. The common measure of financial risk is the standard deviation of the asset's rate of return. Both measures are not only used to asses the expected profitability and the risk associated with individual assets, but are also applied to portfolios consisting of more than one risky asset, i.e. company stocks. It is important to note that most asset pricing models rely at least partially on information derived from historic performance of the particular asset. Since the past performance of an asset contains only a limited amount of relevant information regarding future performance, the financial measures of return and risk are to a certain degree ambiguous.

Based on the two measures of financial risk and return, portfolio theory states that the standard deviation of a portfolio can be reduced by combining different risky assets, as long as the returns of underlying assets are not perfectly correlated (Welch 2009 § 8.2). Under the assumption that a rational investor is generally risk averse, normative models of diversification postulate that he will hold a highly diversified portfolio. By holding a perfectly diversified portfolio, the investor can reduce the total risk of his investment to the systematic or undiversifiable risk underlying the entire market (market risk). Hence, an investor with access to well-diversified assets, i.e. mutual funds or index funds, will only accept a higher level of risk when he is compensated with a higher expected rate of return compared to the overall market. In terms of portfolio preference this means that he will only hold an under-diversified portfolio consisting of few individual stocks when he expects higher returns. Following the CAPM, a higher expected return implies greater risk (Mishkin 2004), which depends on the covariance of the underlying assets in the portfolio.

The second aspect of diversification, which involves the decision to hold several different types of assets, follows the intuition to not *"put all eggs in one basket"*. In the context of financial decision making this implies that individuals should not only diversify within a given class of assets, e.g. stocks, but also diversify across different asset classes.

The underlying mechanism follows the same logic as diversification within asset classes: reducing the covariance between investments. In other words, by holding different types of assets, the risk of total loss or loosing a significant proportion of the invested capital can be minimized by reducing the covariance among the assets. For example, individuals who solely invest in stocks, but do not hold any other assets expose themselves to the risk of loosing a significant proportion of their investment incase the global financial markets crash. On the other hand, if a person only invests in real estate, he faces high investment risks due to a potential housing bubble.

More generally, investors who do not diversify across asset classes face the risk of potentially loosing a significant proportion of their investment due to *"improbable, [but highly] consequential events"* (Taleb 2008, p. 18). Such events have to be considered as ambiguous, since they are nearly impossible to predict precisely. Therefore, ambiguity attitudes can potentially help to explain individual investment decisions regarding diversification across asset classes.

4.2.2. Ambiguity Attitudes and Diversification

Consistent with the tradeoff between financial risk and return, Polkovnichenko (2005) argues that an investor's preference to hold an under-diversified portfolio can be interpreted as a *"attempt to get ahead"*. This means that the investor's portfolio decision is driven by the attempt to earn large but highly unlikely gains, also referred to as return chasing (Frazzini and Lamont 2008). But since diversification will yield an expected return of the portfolio equal to the average return of the entire market, such abnormal returns are only possible by holding an under-diversified portfolio relative to well-diversified portfolio (Polkovnichenko 2005). If the decision to hold an under-diversified portfolio is in fact driven by the *"attempt to get ahead"*, then, conditional on stock market participation, under-diversification should be positively related to a-insensitivity. This effect is mainly driven by the increasing weight given to low likelihood events for large gains associated with a-insensitivity.

Theoretically, a-insensitivity not only leads to overweighting of large gains with low-likelihoods associated with increased willingness to take risks and uncertainties consistent with *"return chasing"* behavior, but also to overweighting of large losses with low-likelihoods (less willingness to take risk and uncertainties) inconsistent with *"return chasing"* behavior. Although it is well documented that potential *"losses loom larger than gains"* (Kahneman and Tversky 1979, p. 279), this study assumes that the decision to invest directly (or indirectly) in the stock market is primarily driven by the desire to make profits instead of retaining the purchasing power of the invested capital for future consumption, e.g. saving for retirement. Several papers report evidence supporting this assumption. For example Clark-Murphy, Gerrans and Speelman (2009) investigated the investment behavior of individuals in Australia and found that *"return chasing"* was an important driver of retirement savings decisions. In addition, Frazzini and Lamont (2008) report evidence showing that mutual fund investors also engage in *"return chasing"* behavior in order to attract private investors.

Apart from potentially enhancing return chasing behavior, a-insensitivity can also affect the decision to hold an under-diversified portfolio due to its association with the lack of taking preventive actions to reduce ambiguity (Dimmock et al. 2015). According to the authors, this behavior can be explained by the tendency of people to overestimate the benefit of eliminating ambiguity altogether while underestimating the benefit of reducing ambiguity without its elimination. As described above, diversification can reduce the financial risk of a portfolio significantly without eliminating it altogether. Even a perfectly diversified portfolio has a remaining risk based on the covariation of its underlying assets. Consistent with the argument that a-insensitivity leads to undervaluing diversification benefits, the a-insensitivity index a_{So} should be positively related to the first diversification measure, if the subject holds stocks directly.

Turning to the second measure of diversification, a-insensitivity also potentially affects the decision of individuals to diversify across different asset types. Following the argument that a-insensitivity *"implies extremity orientedness"* (Dimmock et al. 2015, p. 18), since individuals overweight the best and the worst outcomes, this study expects that the a-insensitivity index a_{So} is positively related to the number of different asset types an individual holds. The reason is that subjects with higher values of index a_{So} are more likely to invest in several different asset classes, because they overestimate the frequency of extreme negative events and therefore reduce their exposure to idiosyncratic risk through diversification. Hence, a-insensitivity increases the probability of an investor to be maximally diversified. For example, investors who diversify by holding not only stocks but also real estate and alternative investments overestimate the frequency of rare but consequential events for some asset classes, i.e. stock market crashes or housing bubbles.

In contrast to the assumption made regarding the motives underlying within asset class diversification, this study assumes that diversification across asset classes is not primarily driven by the attempt to maximize profits. Instead, this study assumes that an investor's decision to diversify his wealth by holding several different asset types is driven by the attempt to secure and retain the value of his wealth consistent with the notion that *"losses loom larger than gains"* (Kahneman and Tversky 1979, p. 279). For example, many people invest in real estate (including secondary or holiday homes) as a form of retirement provision or buy life annuity insurance as a supplement to the public pension system, in order to prevent declines in their living standards.

Regarding the second ambiguity attitude component, the effect of ambiguity aversion on portfolio diversification is somewhat more complex. Consistent with the distinction between optimism (increased ambiguity seeking relative to risk) and pessimism (increased ambiguity aversion relative to risk) previously described, a positive value of the ambiguity aversion index b_{So} generally reduces the decision weights for gains and therefore decreases ambiguity seeking for low-likelihood gains. Therefore, increasing ambiguity aversion should reduce return chasing behavior as well as the tendency to forgo diversification benefits. Conversely, the same should hold for increasing optimism (negative value of index b_{So}). Increasing decision weights enhance ambiguity seeking for low-likelihood gains and therefore reinforces return chasing behavior and underweighting of diversification benefits. Hence, increasing values of b_{So} reduce the tendency to hold a severely under-diversified portfolio, which implies lower values of S_{Loss}.

In addition, it is reasonable to assume that ambiguity aversion also effects the tendency of individuals to diversify across asset classes. In this context, Dimmock et al. (2015) report findings that ambiguity aversion reduces the tendency to directly hold stocks, since the distribution of future stock returns is ambiguous and less ambiguous alternative asset types are available, for example government bonds or guaranteed bank saving schemes. Applying the same logic to the decision of investing in multiple asset classes simultaneously, it can be expected that subjects who are more ambiguity averse will tend to hold a lower number of different asset types, since they refrain from investing in more ambiguous assets due to their preference for unambiguous alternatives. This prediction builds upon the following assumption. First, this study assumes that all investors have access to the same fixed number of different asset classes. Given the limited number of potential investment options, it becomes clear that a subject who is more ambiguity avers considers a smaller subset of asset types as a worthy investment compared to a less ambiguity avers subject. In other words, increasing ambiguity aversion decreases the number of asset types an investor is willing to hold and therefore increases his propensity to insufficiently diversify across asset classes. Taking into consideration that there are more ambiguous than unambiguous assets to invest in, increases the effect. Hence, this study expects to find a negative relationship between the ambiguity aversion index b_{So} and the number of different assets the subjects hold.

Comparing the potential relationship between both ambiguity attitude components and the individual tendency to hold an under-diversified portfolio, it is important to note that the effect of ambiguity aversion is much more difficult to determine. This difficulty is mainly due to the individual's perception of ambiguity associated with a particular risky asset. Although Dimmock et al. (2013) only investigate the effect of ambiguity aversion (without considering a-insensitivity), they point out that this effect depends on how the subject perceives the ambiguity of an individual stock relative to the entire stock market. When taken together with the notion of familiarity, it is reasonable to assume that a particular stock, e.g. a stock from the company the individual works for, is perceived as less ambiguous compared to other stocks. Hence, the number of stocks he is willing to invest in is very low. Given the limited detail of the data set used in this study, such relative ambiguity effects are impossible to test.

4.3. Hypotheses

Based on the discussion of how ambiguity attitudes relate to financial diversification decisions, this study test the following hypotheses:

1a. Conditional on stock market participation, subjects with higher levels of a-insensitivity hold more under-diversified portfolios (higher values of Sharpe ratio loss).

1b. Subjects with higher levels of a-insensitivity are more likely to be maximally diversified across asset classes.

2a. Conditional on stock market participation, subjects with higher levels of ambiguity aversion hold less severe under-diversified portfolios (lower values of Sharpe ratio loss).

2b. Subjects with higher levels of ambiguity aversion are less likely to be maximally diversified across asset classes.

Looking at the overview of the hypotheses and the preceding discussion, hypothesis 1a (2a) is qualitatively different from hypothesis 1b (2b), since the former investigates the tendency to diversify within a class of risky assets (stocks) whereas the latter looks at the tendency to diversify across asset classes. Hence, hypotheses 1a and 2a investigate the relationship between the two attitude indexes, a_{So} and b_{So}, and the first diversification measure, whereas hypotheses 1b and 2b tests the relationship between the ambiguity attitudes and the second diversification measure.

5. Analysis

5.1. Summary Statistics

The following **Table 5.1** provides the summary statistics for all variables used in this study. **Panel A** provides the statistics of the two dependent variables. **Panel B** and **Panel C** summarize the independent and control variables: in **Panel B** all continuous variables are summarized and **Panel C** provides the frequencies of the dummy variables. In addition, **Table C.1** in **Appendix C** provides a short overview of all variables and their definitions used in this study.

Table 5.1. Summary Statistics

Panel A - Dependent Variables

Variable	Mean	Std. Dev.	Min.	Max.	Obs.
Sharpe ratio loss	0.70	0.24	0.05	0.98	34
Asset diversification	1.38	0.52	1	3	454

Panel B - Continuous Variables

Variable	Mean	Std. Dev.	Min.	Max.	Obs.
Age	52.07	16.73	16	89	454
Financial literacy score	1.38	0.69	0	2	454
Household size	2.39	1.24	1	8	454
Income	2573.14	1379.44	0	13500	418
Index a_{So} (a-insensitivity)	0.40	0.34	0	1	454
Index b_{So} (ambiguity aversion)	0.12	0.36	- 0.76	0.88	454
Risk aversion	- 0.14	0.42	- 0.5	0.75	454
Trust	5.77	2.24	0	10	350
Total liabilities	7025.33	42892.62	0	800000	443
Total financial wealth	32390.56	75492.87	0	725000	354

Panel C - Dummy Variables

Variable	Frequency	Percent
Education		
Low education	191	42.07
Intermediate education	147	32.38
High education	116	25.55
Employment		
Employee	205	45.15
Self-employed	25	5.51
Unemployed	64	14.10
Pensioner	126	27.75
Student	34	7.49
Incompetence	129	28.41
Female	228	50.22
Stock market participation	81	17.84

The next sections describe and shortly discuss the main variables of interest. Beginning with an overview of the dependent, each section concludes with a discussion and statistical tests in case there are missing observations. In the interest of brevity, only the independent and control variables with missing observations are discussed. A detailed description of each variable is included in **Part 3.5** and **Tables 5.1 - 5.2**.

5.1.1. Dependent Variables

As mentioned in the methodology part, this study includes two different dependent variables capturing diversification: "*Sharpe ratio loss"* and *"asset diversification"*. Dependent variable number one captures a specific concept of diversification based on individual investments in the stock market whereas the second variable looks at the subjects' tendency towards diversification across different assets types.

The first dependent variable *"Sharpe ratio loss"* is calculated only for individuals who participate in the stock market. From the summary statistics it can be seen that approximately 18% of all 454 participants in this sample own stock directly. A paper by Giannetti and Koskinen (2010) states that the overall stock market participation rate for the Netherlands is 14%. Comparing both measures, it becomes clear that the participation rate in this study is somewhat higher, but taking into account the overall sample size of this study, a deviation of less than 4% is reasonable to maintain the assumption of representativeness of this subsample.

The average *"Sharpe ratio loss"* is 0.70, which indicates, on average, a relative high degree of under-diversification. But looking at the minimum and maximum of the first dependent variable, it can be seen that the values range from highly diversified (0.05) to severe under-diversification (0.98).

As previously mentioned, all information regarding asset ownership are self-reported by the participants. Unfortunately, not all participants who invest directly in stocks have reported the value of their respective holdings. Looking at the summary statistics reported in **Panel A** of **Table 5.1** it can be seen that there are some missing values for this measure. In total, there are 34 valid and 47 missing observation regarding the first dependent variable. The result of two Mann-Whitney U tests show that there is no, significant (5% level), difference regarding both ambiguity indexes (a_{So} and b_{So}) between subjects who did and did not report the value of their stock holding *(a_{So}: p-value = 0.88; b_{So}: p-values = 0.40)*.

The second dependent variable *"asset diversification"* is derived from the different asset classes each participant holds. *"Asset diversification"* is a categorical variable, ranging from 1 to 3. A value of 1 indicates that the participant is minimally diversified across asset types whereas a value of 3 indicates a high degree of diversification across asset types. **Table 5.2** shows the distribution of the number of different assets held by the participants of this study.

Table 5.2. Frequencies of the Variable *"Asset diversification"*.

Value	Frequency	Percent
1	289	63.66
2	157	34.58
3	8	1.76
Total	454	100.00

From **Table 5.2** it can be seen that approximately 64% of the participants hold either none or only one type of asset and that approximately 35% hold up to four different assets. In addition, one can see that only a minority of participants are highly diversified by holding up to six different assets. There are no missing observations for the variable *"asset diversification"*.

5.1.2. Independent and Control Variables

The summary statistics of the explanatory variables in **Panel B** of **Table 5.1** reveal that there are some missing observations for the variables: *"income"*, *"total liabilities"*, *"total financial wealth"* and *"trust"*. The three variables regarding the financial situation of the participants are self-reported and not mandatory to complete the survey. Given the sensitive nature of the questions, it is not surprising that some participants are reluctant to provide information of such kind. Turning to the variable *"trust"*, the reason why there are some missing observations is due to the fact that this variable was included in this data set from another LISS panel module. Since not every subject participates in each individual questionnaire conducted by CentERdata, the missing observations can be explained by a lack of overlap between the different modules. In order to ensure that there is no systematic difference regarding both dependent variables between the subjects with and without missing observations, a Mann-Whitney U test is conducted.

Looking at the sub-sample regarding the dependent variable *"Sharpe ratio loss"*, only the variable *"trust"* has four missing observations. The Mann-Whitney U test indicates that subjects with missing observation for trust have no significant (5% level) different median *"Sharpe ratio loss"* compared to subjects without missing observations *(p-value = 0.16)*. In addition, the potential difference between participants with and without missing observations of trust and both ambiguity attitude indexes was investigated. The results of the Mann-Whitney U tests indicates that there is only a marginally significant (10% level) difference between subjects with missing observations on trust and the second ambiguity attitude index capturing aversion (index b_{So}). Subjects with missing observation on trust have a significant (10% level) lower median ambiguity aversion index b_{So} *(p-value = 0.05)*.

Turning to the entire sample regarding the dependent variable *"asset diversification"* the results of the Mann-Whitney U tests for the four variables with missing observations are as follows:

- *"Income"*: Subjects with missing observation on income have a significant (1% level) different median regarding the number of different assets they hold compared to participants without missing observation *(p-value = 0.01)*.
- *"Total liabilities"*: Subjects with missing observation on total debt have no significant (10% level) different median regarding the number of different assets they hold compared to participants without missing observation *(p-value = 0.97)*.
- *"Total financial wealth"*: Subjects with missing observation on total financial wealth have a significant (1% level) different median regarding the number of different assets they hold compared to participants without missing observation *(p-value = 0.03)*.
- *"Trust"*: Subjects with missing observation on trust have no significant (10% level) different median regarding the number of different assets they hold compared to participants without missing observation *(p-value = 0.12)*.

In addition, the potential difference between participants with and without missing observations regarding both ambiguity attitude indexes was investigated. The results of the Mann-Whitney U tests do not indicate a significant (10% level) difference between subjects with and without missing observations in terms of both ambiguity attitude indexes.

Based on these results, the empirical test described in **Part 5.3** will take into account these differences based on the missing observations of the variables *"income"*, *"total financial wealth", "total liabilities"* and *"trust"*.

5.2. Ambiguity Attitudes in the Sample

The following section analyses and summarizes the ambiguity attitudes found in this study. **Table 5.3** summarizes the found attitudes towards ambiguity and their respective frequencies for each of the three different ambiguity neutral likelihood-levels used in the elicitation process.

Table 5.3

Ambiguity-neutral probability (p)	0.10	0.50	0.90
Ambiguity averse	34.14%	58.59%	46.48%
Ambiguity neutral	30.62%	22.91%	28.85%
Ambiguity seeking	35.24%	18.50%	24.67%

As described in the **Part 3.2.4**, a participant is considered to be ambiguity averse (seeking), if his individual matching probability is lower (higher) than the ambiguity neutral probability. In case the matching probability is equal to the ambiguity neutral probability, then the subject is classified as ambiguity neutral. Looking at the second column (ambiguity neutral probability = 0.10) of **Table 5.3**, it can be seen that approximately 35% of all participants preferred an ambiguous prospect with unknown probabilities over a risky prospect with a known winning probability of 10%. Therefore, a slight majority of subjects are classified as ambiguity seeking for low likelihood events. Continuing in the same column, the second prevalent attitude towards ambiguity is aversion with approximately 34%, followed by ambiguity neutrality with approximately 31%. In order to test whether ambiguity seeking is the dominating attitude for low likelihood ambiguous events in this sample a Chi squared test is conducted. The result shows that the matching probabilities elicited after six rounds of chained choice questions do not indicate that ambiguity seeking is the dominating attitude found for ambiguity neutral probability of 10% (*p-value* = 0.45). This finding stands in contrast to results reported by Dimmock et al. (2015), who found that for low likelihood events ambiguity seeking is the predominant attitude. Turning to column three and four in **Table 5.3** it can be seen that the majority of participants are ambiguity averse for both medium and high likelihood events. The results of two Chi squared tests indicate that in both cases, ambiguity aversion is the predominating attitude *(both p-values = 0.00)*.

Although this study does not confirm the finding of Dimmock et al. (2015) that ambiguity seeking is the predominant attitude for low likelihood events, **Table 5.3** shows that there is enough variation in the elicited attitudes towards ambiguity for prospects with three different levels of ambiguity neutral probability to conclude that general ambiguity aversion does not hold. Instead this study finds a great variety of different ambiguity attitudes. **Table 5.4** summarizes the frequencies of the aggregated ambiguity attitudes found in this sample. This table illustrates that only approximately 26% of all participants are strictly ambiguity averse. Apart from aversion, approximately 22% are ambiguity neutral and approximately 19% are even ambiguity seeking. The remaining participants either show inconsistent behavior in regard to ambiguity (approximately 20%) or behave consistent with a-insensitivity (approximately 13%).

Table 5.4

	Proportion of respondents
Ambiguity likelihood insensitive ($AA_{10} < 0$; $AA_{90} > 0$)	13.22%
Ambiguity neutral ($AA_{10} = 0$; $AA_{90} = 0$)	22.03%
Ambiguity seeking ($AA_{10} < 0$; $AA_{90} < 0$)	18.94%
Ambiguity aversion ($AA_{10} > 0$; $AA_{90} > 0$)	25.99%
Inconsistent ambiguity attitudes	19.82%

The finding that only 13.22% of all participants in this study have local ambiguity attitude indexes which reflect a-insensitivity stands in sharp contrast to the results reported by other studies. For example the study by Dimmock et al. (2013) that investigates attitudes towards ambiguity in a similar manner, report that 78% of American and 75% of Dutch participants in two independent studies exhibit a-insensitivity. It is important to note that the frequencies stated in **Table 5.4** are calculated directly from the elicited matching probabilities and are therefore not identical with the attitudes captured in the attitude indexes derived from the adjusted neo-additive source functions. Hence, the total number of subjects classified as a-insensitive is understated. **Appendix D** provides an overview of the ambiguity attitudes found in this sample based on the adjusted neo-additive source functions.

Turning to the elicited matching probabilities, **Table 5.5** provides the summary statistics for the three different matching probabilities as well as the local and global ambiguity attitudes.

Table 5.5

Variable	Mean	Median	Std. Dev.	Min.	Max.
m(0.1)	0.22	0.10	0.23	0.03	0.97
m(0.5)	0.40	0.34	0.23	0.03	0.94
m(0.9)	0.69	0.90	0.29	0.03	0.98
AA_{10}	- 0.12	0	0.23	- 0.87	0.08
AA_{50}	0.10	0.16	0.23	- 0.44	0.47
AA_{90}	0.21	0	0.29	- 0.08	0.87
Index a_{So} (A-insensitivity)	0.40	0.34	0.34	0	0.99
Index b_{So} (Ambiguity aversion)	0.12	0	0.36	- 0.76	0.88

Based on the reported statistics in **Table 5.5**, it can be seen that, on average, people are ambiguity seeking for low likelihood ambiguous prospects reflected in a negative local ambiguity attitude index $AA_{10} = -0.12$. The result of a two sided t-test indicates that the obtained mean of the local ambiguity attitude index for low likelihood levels (AA_{10}) is significantly (1% level) lower than 0 *(p-*

value = 0.00). Looking at the mean of the remaining matching probabilities, it can be seen that, on average, participants are ambiguity averse for medium and high likelihood prospects with positive local ambiguity attitude indexes AA_{50} and AA_{90}. As with low likelihood events, the results of two two sided t-tests indicate that both means are significantly (1% level) larger than 0 *(both p-values = 0.00)*.

This is a commonly found pattern and stands in contrast to the notion that people generally dislike ambiguity. Instead of obtaining a source function that is convex in shape, which implies general ambiguity aversion (all $AA > 0$), the results suggests an average inverse-S source function. The inverse S-shaped function reveals the two ambiguity attitude components, ambiguity aversion and a-insensitivity. Ambiguity aversion is reflected in positive AA index values with $m(p) < p$ whereas a-insensitivity is associated with negative AA indexes for low likelihood events ($p = 0.1$) and with positive AA indexes for high likelihood events ($p = 0.9$).

Turning to the global ambiguity indexes, the last two rows of **Table 5.5** show the average values of the a-insensitivity ($a_{So} = 0.40$) and the ambiguity aversion index ($b_{So} = 0.12$). Again the results of a two sided t-tests indicate that both means are significantly (1% level) larger than 0 *(both p-values = 0.00)*.

In order to investigate the relationship between both global ambiguity attitude indexes as well as between the global and the local indexes, a correlation matrix is obtained. **Table 5.6** shows the correlation coefficients for all combinations between the global and local indexes. All obtained correlation coefficients are significant (1% level). Consistent with Dimmock et al. (2015) this study finds a positive correlation between the two global ambiguity indexes a_{So} and b_{So} *(0.30; p-value = 0.00)*. This finding is not surprising since both indexes capture the deviation from rationality (i.e. expected utility), reflecting the individual's specific degree of irrationality (Dimmock et al. 2015). Although the correlation between a_{So} and b_{So} this study finds is higher than the reported correlation of 0.22 by Dimmock et al. (2015) and 0.09 Dimmock et al. (2013), it is still reasonably low to conclude that both indexes capture different attitude components towards uncertainty. There are two potential explanations why this study finds a higher degree of correlation between both ambiguity attitude indexes. First, the underlying sample size of 454 individuals in this study is smaller compared to 666 subjects in the study by Dimmock et al. (2015) and 3158 participants in the study by Dimmock et al. (2013). Second, the derivation method this study applies to obtain both global ambiguity attitude indexes differs from those applied by the previous studies (see **Part 3.2.5**).

Table 5.6

Variable	(1)	(2)	(3)	(4)	(5)
(1) Index a_{So}	1.00				
(2) Index b_{So}	0.30	1.00			
(3) AA_{10}	- 0.43	0.68	1.00		
(4) AA_{50}	0.13	0.69	0.37	1.00	
(5) AA_{90}	0.73	0.83	0.27	0.42	1.00

Having established that it is reasonable to assume that both ambiguity indexes capture different components of the individual's attitude towards ambiguity, it is also important to investigate the possibility that the ambiguity indexes are simply proxies for other individual characteristics of the participants. In order to examine this, the different ambiguity attitude indexes are regressed on the entire set of independent variables. **Table 5.7** contains the obtained regression coefficients.

Table 5.7

Variable	Index a_{So}	Index b_{So}	AA_{10}	AA_{50}	AA_{90}
Age	- 0.001	0.002	0.001	0.002	0.001
	[- 0.08]	[0.17]	[0.13]	[0.29]	[0.11]
Age^2	- 0.000	- 0.000	0.000	- 0.000	- 0.00
	[- 0.14]	[- 0.23]	[0.01]	[- 0.51]	[- 0.21]
Education					
Intermediate education	- 0.184***	- 0.056	0.042	0.012	- 0.122**
	[- 3.33]	[- 0.91]	[1.12]	[0.32]	[- 2.56]
High education	- 0.109*	- 0.058	- 0.003	0.035	- 0.096***
	[- 1.80]	[- 0.86]	[- 0.07]	[0.86]	[- 1.85]
Employment					
Employed	- 0.028	0.063	0.040	0.045	0.002
	[- 0.41]	[0.83]	[0.86]	[0.98]	[0.03]
Self-employed	- 0.218*	- 0.147	0.016	- 0.066	- 0.193
	[- 1.77]	[-1.08]	[0.19]	[- 079]	[- 1.82]
Pensioner	- 0.096	- 0.031	- 0.005	0.051	- 0.075
	[- 1.28]	[- 0.37]	[- 0.09]	[1.00]	[- 1.16]
Student	- 0.112	0.049	0.074	0.049	- 0.026
	[- 0.84]	[0.33]	[0.81]	[0.53]	[- 0.23]
Financial literacy					
Financial literacy score	- 0.038	- 0.027	- 0.003	- 0.001	- 0.038
	[- 1.02]	[- 0.64]	[- 0.14]	[- 0.00]	[- 1.21]
Incompetence	- 0.144**	- 0.041	0.029	- 0.008	- 0.099
	[- 2.04]	[- 0.52]	[0.60]	[- 0.18]	[- 1.62]
Female	- 0.059	0.003	0.026	0.036	- 0.040
	[- 1.27]	[0.05]	[0.84]	[1.11]	[- 0.97]

Table 5.7 *(continued)*

Variable	Index a_{So}	Index b_{So}	AA_{10}	AA_{50}	AA_{90}
Household size	- 0.023	0.012	0.021	0.006	- 0.002
	[- 1.08]	[0.50]	[1.41]	[0.38]	[- 0.09]
Income	0.000	0.000	- 0.000	0.000	0.000
	[0.39]	[0.03]	[-0.66]	[0.53]	[0.08]
Risk aversion	0.103*	0.003	- 0.047	0.022	0.039
	[1.96]	[0.05]	[- 1.30]	[0.60]	[0.88]
Total liabilities	- 0.000	- 0.000	0.000	- 0.000	- 0.000
	[- 1.26]	[- 0.20]	[0.71]	[- 0.46]	[- 0.78]
Total financial wealth	0.000	- 0.000	0.000	- 0.000	- 0.000
	[0.35]	[0.87]	[0.96]	[- 0.15]	[0.81]
Trust	- 0.03	0.002	0.003	0.001	- 0.002
	[- 0.30]	[0.15]	[0.41]	[0.18]	[- 0.32]
Adjusted R^2	0.05	- 0.03	- 0.03	- 0.03	0.02
Number of observations	261	261	261	261	261

Regarding **Table 5.7** as well as the remaining tables in this study, the asterisks (*, ** and ***) mark significant regression coefficients at the 10%, 5% and 1% levels. In addition, the constant of each regression is not included in the table. From the reported coefficients it can be seen that, overall, there is very little relation between economic and demographic variables and the ambiguity attitude measures. The only significant relationships found are between few demographic variables and index a_{So} as well as local ambiguity index AA_{90}. Variables capturing the economic and financial situation of the participants are not related to any measure capturing ambiguity attitudes.

Turning to the second and sixth column of **Table 5.7**, the obtained coefficients indicate a negative, significant relationship between both variables capturing *"education"* and index a_{So} as well as the local ambiguity index AA_{90}. This result is not surprising since a-insensitivity, captured by index a_{So}, is considered to be a *"cognitive bias"* (Baillon et al. 2013) which can be reduced through learning and education. Consistent with this notion, the negative, significant (5% level) relationship between *"financial incompetence"* and index a_{So} can be readily explained if one acknowledges that financial literacy is most commonly obtained through formal education. The negative significant effect of *"self-employed"* on index a_{So} is somewhat surprising, since the joint significance test indicates that together all variables regarding *"employment"* have no significant effect on index a_{So} *(p-value = 0.28)*. Although this study measures ambiguity attitudes relative to risk attitudes, the positive, significant (10% level) relationship with a-insensitivity can be explained by the notion that both measures are related to irrationality. But most importantly the adjusted R^2 values range from - 0.03 to 0.04, which implies that only a very low fraction of the variance of each ambiguity attitude index can be explained by the control and demographic variables. This is strong evidence that the variables capturing the attitudes towards uncertainty are not simply proxies for age, education, gender or the financial situation of the subjects. As a result, it is reasonable to assume that the attitude indexes capture new and independent information not contained in commonly used economic and demographic variables.

This section concludes by investigating if subject groups with specific characteristics have significant different median values in regard to both global ambiguity attitude indexes. Following groups of subjects were tested: male vs. female, low level of education vs. medium or high level of eduction and low or medium level of education vs. high level of education. The obtained Mann-Whitney U test results indicate that women do not have significant (10% level) different ambiguity attitude indexes in this sample. In addition, the results show that there is also no significant (10% level) difference in ambiguity attitude indexes for subjects with different levels of education.

5.3. Ambiguity Attitudes and Diversification

This part investigates the relationship between financial diversification and both ambiguity attitude components. The first section of this part tests if ambiguity attitudes can help to explain the phenomenon of portfolio under-diversification, for subjects that participate in the stock market. In the second section a different notion of diversification is tested by looking at the relationship between ambiguity attitudes and the number of different asset types each participant holds.

5.3.1. Ambiguity Attitudes and Portfolio Under-Diversification

This section investigates the relationship between the elicited ambiguity attitudes and the relative degree of portfolio under-diversification. As already mentioned, the dependent variable capturing the relative degree of stock portfolio under-diversification is the variable *"Sharpe ratio loss"*. Since the Sharpe ratio has only a meaningful interpretation in the context of stock portfolio decisions, this measure is only computed for subjects who participate in the stock market. Due to missing observations and the finding that subjects with missing observations on trust have significantly different values regarding their *"Sharpe ratio loss"*, the final sub-sample consists in total of 30 participants.

Following from the theory, this study hypothesizes a positive relation between the measure capturing a-insensitivity and the individual *"Sharpe ratio loss"*. In other words, subjects who are more a-insensitive hold more under-diversified stock portfolios, due to return chasing behavior.

Turning to the second ambiguity attitude component, ambiguity aversion, this study hypothesizes a negative relationship between index b_{So} and the relative measure of under-diversification. This effect is mainly driven by the notion that ambiguity aversion generally reduces the decision weights and therefore decreases ambiguity seeking for low-likelihood events. Therefore, subjects with higher values of b_{So} hold less severe under-diversified portfolios.

In order to test both hypotheses, the variable *"Sharpe ratio loss"* is regressed on both global ambiguity attitude index, a_{So} and b_{So}, as well as on the full set of demographic and control variables. The variable *"financial incompetence"* was excluded, since all subject were regarded as financially competent. Column (1) of **Table 5.8** shows the obtained coefficients from this regression.

Table 5.8

Variable	(1)	(2)
Index a_{So}	0.266	0.051
	[1.51]	[0.10]
Index b_{So}	- 0.093	- 0.589
	[- 0.62]	[- 1.28]
Age	- 0.013	- 0.002
	[- 0.48]	[- 0.02]
Age^2	0.000	0.000
	[0.70]	[0.24]
Education		
Intermediate education	0.066	0.619
	[0.47]	[1.46]
High education	0.180	1.083***
	[0.13]	[2.44]
Employment		
Employed	0.163	- 0.536
	[1.12]	[- 1.08]
Self-employed	- 0.131	- 0.610
	[- 0.04]	[- 0.68]
Pensioner	- 0.247	- 0.907
	[- 1.31]	[- 1.57]
Student	0.257	- 0.328
	[0.62]	[- 0.31]
Financial literacy		
Financial literacy score	- 0.015	0.603***
	[- 0.13]	[2.15]
Incompetence		0.131
		[0.23]
Female	- 0.035	- 0.431
	[- 0.21]	[- 1.24]

Table 5.8 *(continued)*

Variable	(1)	(2)
Household size	- 0.072	0.044
	[- 1.52]	[0.28]
Income	0.000	0.000
	[0.90]	[0.58]
Risk aversion	- 0.049	- 0.804***
	[- 0.41]	[- 2.00]
Total liabilities	- 0.000	0.000***
	[- 1.00]	[2.07]
Total financial wealth	- 0.000	0.000***
	[- 1.62]	[4.45]
Trust	- 0.030	0.150**
	[- 0.51]	[2.02]
Adjusted R^2 / Pseudo R^2	0.190	0.266
Number of observations	30	261

Looking at the results reported in **Table 5.8** it can be seen that the coefficient of index a_{So} is positive with a magnitude of approximately 0.266 and the coefficient of index b_{So} is negative with a magnitude of approximately − 0.093. Unfortunately, none of the obtained regression coefficients are significant at a 10% level. In addition, the overall adjusted R^2 value is relatively low with 0.19, which implies that only 19% of the variation of the relative Share ratio loss can be explained by the variables included in the regression. Although the results of this regression do not provide significant evidence in favor of the proposed hypotheses (1a and 2a), it is nonetheless worth pointing out that the direction of the effects of both ambiguity attitude components are consistent with the hypotheses.

5.3.2. Ambiguity Attitudes and the Number of Different Asset Classes

This section investigates if there is a relationship between the two ambiguity attitude indexes (a_{So} and b_{So}) and the number of different assets held by the participants. As previously described in the theoretical part of this study, it is hypothesized that a-insensitivity has a positive effect on the number of different assets owned, i.e. that subjects with a higher index a_{So} are more likely to be maximally diversified across different asset types. In addition, this study predicts a negative relationship between ambiguity aversion and the number of assets held by the participant: Subjects with a higher index b_{So} are less likely to be maximally diversified across asset classes. Both hypotheses, are tested by conducting an ordered logit regression with *"asset diversification"* as the dependent variable and including the full set of demographic and control variables. Based on the test results on the missing observations, subjects with incomplete data are excluded from the analysis. Therefore, the final sub-sample consists of 261 participants.

The results of the ordered logit regression are reported in column two (2) of **Table 5.8** above. As with the previous regression, the overall pseudo R^2 values is relatively low with 0.266, which implies that only 26.6% of the variation of the variable *"asset diversification"* can be explained by the variables included in the ordered logit regression. From the table it can also be seen that, again, both ambiguity attitude indexes are not significantly related to the number of different assets a subject holds. Therefore, this result does not provide evidence in favor of both hypotheses. Nonetheless, looking at the signs of both coefficients, it can be seen that the direction of the effects of a-insensitivity and ambiguity aversion is consistent with the prediction. The coefficient of index a_{So} is positive, which means that the probability of being maximally diversified across asset classes increases with increasing values of a-insensitivity, ceteris paribus. Turning to ambiguity aversion, index b_{So} has a negative coefficient, which implies that increasing ambiguity aversion decreases the probability of subjects to be maximally diversified across asset classes, ceteris paribus.

5.4. Relationship and Empirical Performance of the Different Global Ambiguity Attitude Indexes

Although the main focus of this study is to investigate whether ambiguity attitudes can help to explain under-diversification, it also examines how the two global ambiguity attitude indexes derived by different methods are related and perform empirically.

In total, three different sets of global ambiguity attitude indexes are calculated. Each set consists of two attitude indexes: the a-insensitivity index and the ambiguity aversion index. The first set of indexes is derived following the method introduced by Dimmock et al. (2013). This method derives both indexes directly from the local ambiguity indexes (AA) as previously described. Set number 2 and 3 are calculated based on a method developed by Abdellaoui et al. (2011) and later applied by Dimmock et al. (2015). This method relies on estimated neo-additive source functions to derive both indexes. Roughly one third of the estimated neo-additive source functions required manual adjustments, due to limitations of the estimation procedure (see **Appendix A**). In order to investigate how these adjustments affected the global ambiguity attitude measures, two sets of indexes are calculated. Set 2 is derived from the unadjusted neo-additive source functions whereas set 3 is calculated based on the adjusted parameters. **Table 5.9** provides the summary statistics for the three different sets of ambiguity attitude indexes.

Table 5.9. Summary Statistics: Global Ambiguity Attitude Indexes

Panel A

	Mean	Std. Dev.	Min.	Max.
Index a_{So1}	0.32	0.31	- 0.13	1.32
Index b_{So1}	0.07	0.19	- 0.40	0.43

Panel B - unadjusted

	Mean	Std. Dev.	Min.	Max.
Index a_{So2}	0.40	0.39	- 0.16	1.65
Index b_{So2}	0.13	0.37	- 0.77	0.88

Panel C - adjusted

	Mean	Std. Dev.	Min.	Max.
Index a_{So3}	0.40	0.34	0.00	1.00
Index b_{So3}	0.12	0.36	- 0.76	0.88

Panel A of **Table 5.9** shows the statistics following the method by Dimmock et al. 2013, **Panel B** shows the unadjusted, while **Panel C** contain the adjusted values of both indexes derived from neo-additive source functions. It can be seen that the calculation method proposed by Dimmock et al. (2103) yield lower ambiguity attitude indexes compared to the methods based on estimating neo-additive source functions.

Table 5.10. Correlation Matrix: Global Ambiguity Attitude Indexes

Panel A

Variable	a_{So1}	a_{So2}	a_{So3}
a_{So1}	1		
a_{So2}	1.00	1	
a_{So3}	0.97	0.97	1

Panel B

Variable	b_{So1}	b_{So2}	b_{So3}
b_{So1}	1		
b_{So2}	0.98	1	
b_{So3}	0.94	0.98	1

From the correlation matrices it can be seen that the overall correlation between the differently derived indexes is very high. Especially noteworthy is the correlation between the a_{So1} and a_{So2} and b_{So1} and b_{So2}. Although they are calculated following different methods, they are perfectly and almost perfectly correlated. Turning to the adjusted indexes a_{So3} and b_{So3}, one can see that, despite the manual adjustments, the correlation between the indexes following Dimmock et al. (2013) and the unadjusted indexes derived from the estimated neo-additive source functions is still very high. Regarding the relationship between the different global ambiguity indexes and the demographic as well as the control variables, the regression of both indexes on the full set of independent variables is repeated with the other two set of attitude indexes (see **Part 5.2** *"Ambiguity Attitudes in the*

Sample"). The obtained regression coefficients are shown in **Table 5.11**.

Table 5.11

Variable	Index a_{So1}	Index b_{So1}	Index a_{So2}	Index b_{So2}	Index a_{So3}	Index b_{So3}
Age	0.000 [0.01]	0.001 [0.25]	0.000 [0.01]	0.002 [0.22]	- 0.001 [- 0.08]	0.002 [0.17]
Age^2	- 0.000 [- 0.20]	- 0.000 [- 0.38]	- 0.000 [- 0.20]	- 0.000 [- 0.30]	- 0.000 [- 0.14]	- 0.000 [- 0.23]
Education						
Intermediate education	- 0.164*** [- 3.18]	- 0.014 [- 0.44]	- 0.205*** [- 3.18]	- 0.045 [- 0.71]	- 0.184*** [- 3.33]	- 0.056 [- 0.91]
High education	- 0.093* [- 1.66]	- 0.007 [- 0.20]	- 0.117* [- 1.66]	- 0.042 [- 0.61]	- 0.109* [- 1.80]	- 0.058 [- 0.86]
Employment						
Employed	- 0.038 [- 0.60]	0.033 [0.85]	- 0.047 [- 0.60]	0.058 [0.75]	- 0.028 [- 0.41]	0.063 [0.83]
Self-employed	- 0.209* [- 1.82]	- 0.077 [- 1.09]	- 0.261* [- 1.82]	- 0.161 [- 1.15]	- 0.218* [- 1.77]	- 0.147 [-1.08]
Pensioner	- 0.070 [- 1.00]	0.006 [0.13]	- 0.087 [- 1.00]	- 0.019 [- 0.22]	- 0.096 [- 1.28]	- 0.031 [- 0.37]
Student	- 0.100 [- 0.80]	0.036 [0.47]	- 0.126 [- 0.80]	0.064 [0.42]	- 0.112 [- 0.84]	0.049 [0.33]
Financial literacy						
Financial literacy score	- 0.036 [- 1.02]	- 0.011 [- 0.50]	- 0.046 [- 1.02]	- 0.029 [- 0.66]	- 0.038 [- 1.02]	- 0.027 [- 0.64]
Incompetence	- 0.127** [- 1.93]	- 0.022 [- 0.53]	- 0.159** [- 1.93]	- 0.052 [- 0.64]	- 0.144** [- 2.04]	- 0.041 [- 0.52]
Female	- 0.065 [- 1.51]	0.015 [0.55]	- 0.082 [- 1.51]	0.015 [0.29]	- 0.059 [- 1.27]	0.003 [0.05]
Household size	- 0.023 [- 1.12]	0.008 [0.62]	- 0.028 [- 1.12]	0.017 [0.67]	- 0.023 [- 1.08]	0.012 [0.50]
Income	0.000 [0.55]	0.000 [0.15]	0.000 [0.55]	- 0.000 [- 0.01]	0.000 [0.39]	0.000 [0.03]
Risk aversion	0.086* [1.76]	0.009 [0.30]	0.108* [1.76]	0.010 [0.16]	0.103* [1.96]	0.003 [0.05]
Total liabilities	- 0.000 [- 1.25]	- 0.000 [- 0.36]	- 0.000 [- 1.25]	- 0.000 [- 0.29]	- 0.000 [- 1.26]	- 0.000 [- 0.20]
Total financial wealth	0.000 [0.05]	0.000 [0.50]	0.000 [0.05]	0.000 [0.73]	0.000 [0.35]	- 0.000 [0.87]
Trust	- 0.005 [- 0.59]	0.001 [0.17]	- 0.007 [- 0.59]	0.001 [0.07]	- 0.03 [- 0.30]	0.002 [0.15]
Adjusted R^2	0.04	- 0.03	0.04	- 0.03	0.05	- 0.03
Observations	261	261	261	261	261	261

Given the high degree of correlation between the three different sets of ambiguity attitude indexes, it is not surprising to find that the results are qualitatively almost identical. Looking at the differences between the significant effects of *"education"*, *"self-employed"*, *"incompetence"* and *"risk aversion"* on the three different indexes a_{So}, it can be seen that coefficients only change slightly in terms of magnitude.

To conclude this section on the empirical performance the relationship between the different sets of ambiguity attitude indexes and both dependent variables is investigated. This is done by running the same regressions as in **Part 5.3** (*"Ambiguity Attitudes and Diversification"*) including each sets of indexes separately. Column 1 of **Table 5.12** shows the obtained coefficients from separately regressing the variables *"Sharpe ratio loss"* on the three different sets of global ambiguity attitude indexes as well as on the full set of demographic and control variables. Additionally, column two (2) of **Table 5.12** contains the results from the ordered logit regression of *"asset diversification"* on the different attitude indexes and the full set of explanatory variables. For brevity, the obtained coefficients of the demographic and control variables as well as the constant are not included in the table.

Table 5.12

	(1)	(2)
Index a_{So1}	0.309 [1.37]	- 0.135 [0.25]
Index b_{So1}	- 0.036 [- 0.10]	- 0.431 [-0.49]
Index a_{So2}	0.242 [1.99]	- 0.074 [- 0.17]
Index b_{So2}	- 0.045 [- 0.29]	- 0.371 [- 0.85]
Index a_{So3}	0.266 [1.51]	0.326 [0.81]
Index b_{So3}	- 0.093 [- 0.62]	- 0.406 [- 1.14]

The results obtained from the first regression shows that there is no qualitative difference between the obtained coefficients of the differently derived ambiguity attitude components. They vary in terms of magnitude, but the direction of the effect does not change and there is no difference in regard to statistical significance. Turning to the results from the second regression, one can see that the sign of the coefficient of index a_{So} changes, depending on the derivation method. The a-insensitivity index derived directly from the matching probabilities as well as from the unadjusted neo-additive source functions have negative coefficients whereas the coefficient of index a_{So} based on the adjusted neo-additive source functions is positive. This effect reversal of a-insensitivity on the participants' propensity to diversify across asset classes is somewhat surprising given the high degree of correlation between the adjusted index a_{So3} and both unadjusted indexes (a_{So1} and a_{So2}). Nonetheless, this finding can be explained by taking a closer look at the a-insensitivity index and how it is affected by the adjustment process. From **Equation 3.1** and **Equation 3.5** (see **Part 3.2.5** *"Global Ambiguity Attitude Indexes"*) it can be seen that the a-insensitivity index is closely related to the slope of the individual's source function. Therefore, it is reasonable to expect that the adjustments affecting the slope of the source functions, especially the cases with negative slopes (see **Appendix A.1** *"Violation 1 - Negative Slopes or Slopes Equal to 0 ($s \leq 0$)"*), underly this finding. Apart from this difference, the results are qualitative similar. In all three regressions, the coefficients from the variables *"high education"*, *"financial literacy score"*, *"total liabilities"*, *"total financial wealth"* and *"trust"* are positively related to the number of different assets the subject holds whereas *"risk aversion"* is negatively related.

6. Discussion

This part is structured as follows: First, the ambiguity attitudes found in the sample reported in **Part 5.2** are discussed followed by the results obtained from the statistical tests regarding both diversification measures. The final section discusses the empirical implications of the differently derived ambiguity measures for statistical analyses described in **Part 5.4**.

From the reported results regarding the prevailing ambiguity attitudes derived directly from the matching probabilities, one can see that there is enough variation to conclude that the assumption of general ambiguity aversion does not hold. In addition, comparing the prevailing attitude pattern derived directly from the matching probabilities to the attitude pattern derived from the adjusted neo-additive source function (**Appendix D**) reveals that the results differ depending on the method. Looking at the aggregated ambiguity attitudes over the entire range of likelihood events one can see that the dominant attitude directly derived from the matching probabilities is ambiguity aversion (25.99%), whereas the dominant attitude derived from the neo-additive source function is a-insensitivity (34.14%). This difference highlights one important limitation of this study that the calculation method matters. As mentioned in the **Part 3.2.5**, this study derived the ambiguity attitudes through estimated neo-additive source functions. Unfortunately, this study did not restrict the estimated regression coefficients and followed a more pragmatic approach by manually adjusting the parameters after the regression. Therefore, one recommendation for further research regarding the relationship between ambiguity attitudes and economic behaviors is to derive ambiguity attitudes through estimated neo-additive source functions with proper interval restrictions. This could be done by using a flexible programming language, for example R or Mathematica, to create an individual optimization program which allows to impose interval restrictions on the estimated parameters. Despite the limitation in the derivation method of both global ambiguity attitude indexes, this study confirms the finding of Dimmock et al. (2013; 2015) that each attitude index captures a different attitude component towards ambiguity. In addition, the regression of each attitude index on the full set of demographic and control variables shows that each index captures new information and are not simply proxies for other individual characteristics of the subjects.

Next, the results obtained from each statistical test regarding the relationship between both diversification measures and the attitude indexes are discussed. Overall, the results do not suggest that there is a significant relationship between both diversification measures and the ambiguity attitude indexes. This finding highlights another important limitation of this study. As previously mentioned, the information regarding financial holdings of each participant is self-reported and it is not mandatory to complete the survey in order to receive the participation fee. Therefore, it is not surprising that there are many missing observations because subjects are often reluctant to provide private information such as income, total wealth, financial investments etc. In addition, it is reasonable to expect that the self-reported information regarding financial decisions is inaccurate (Trusheim 1994). In order to avoid such inaccuracies, future research should be conducted using a data set based on observed, real financial decisions rather than self-reported survey information.

In order to test the first set of hypotheses, the dependent variable *"Sharpe ratio loss"* is regressed on the full set of demographic and control variables. None of the obtained coefficients are significant at a 10% level. There are three main explanations for this result. First, the number of subjects in the sub-sample is low with only 30 complete observations. Second, as already mentioned, the data set used in this study contains very little detail regarding individual stock holdings and therefore a proxy variable capturing portfolio diversification was constructed. Although other studies showed that this proxy variable is suitable for empirical research with limited data sets, it is still possible that in the context of this study it does not sufficiently capture the relative degree of diversification. This uncertainty regarding the empirical usability of the employed proxy is another limitation. Therefore, future research should be conducted with a data set that contains enough information allowing for precise calculation of the relative degree of under-diversification. In addition, the fact that none of the obtained coefficients are significant provides further evidence that the proxy variable does not sufficiently capture under-diversification. As previously mentioned, all control variables included in this study have been linked to investors' propensity to hold under-diversified portfolios. Third, the hypothesis that investors' preference for under-diversified portfolios is mainly driven by the *"attempt to get ahead"* or *"return chasing"* might be incorrect. Although it is possible that there are other reasons why investors tend to hold under-diversified portfolios, other studies have reported findings which suggest that *"return chasing"* plays an important role in the decision to invest in particular stocks as well as to hold under-diversified portfolios. For example Goetzmann and Kumar (2008) report that investors who hold under-diversified portfolios prefer to hold riskier stocks (higher volatility) and stocks with greater skewness of returns within their portfolios. Such preferences of *"positive skewness of returns offered by low probability and high variance"* (Golec and Tamarkin 1998, p. 2) are also commonly found among gamblers and can be interpreted as evidence in favor of the *"return chasing"* hypothesis.

Concluding the discussion of the obtained results from the first regression, the question whether such investment behavior can be considered to be *"rational"* is investigated. This question can be conveniently answered by looking at the returns delivered by holding an under-diversified portfolio. Unsurprisingly, the reported evidence on the performance of under-diversified portfolios suggests that they do not perform better than well diversified portfolios (Blume and Friend 1978; Goetzmann and Kumar 2008). Therefore, *"return chasing"* through holding an under-diversified portfolio has to be considered to be irrational investment behavior.

The second set of hypotheses is tested by running an ordered logit regression with *"asset diversification"* as the dependent variable and including the full set of demographic and control variables. Similar to the results obtained from the first regression, the effects of both ambiguity attitude indexes on the diversification measure are consistent with the hypotheses, but are not significant at a 10% level. The finding that the signs of both coefficients obtained for a_{So} and b_{So} are consistent with the hypotheses provides some evidence that diversification across asset classes does not follow the same logic as diversification within an asset class. Contrary to within asset class diversification, the evidence suggests that *"return chasing"* does not underly the decision to diversify across different asset classes. *"Return chasing"* would imply a negative (positive) relationship between a-insensitivity (ambiguity aversion) and the number of different assets owned.

Overall, the results of the ordered logit regression indicates that ambiguity attitudes do not play an important role regarding the individuals' tendency to diversify across asset classes. Instead, the results show that several individual characteristics are significantly related to the second diversification measure. In particular, the variables *"high education"*, *"financial literacy score"*, *"total liabilities"*, *"total financial wealth"* and *"trust"* are positively related to the number of different assets the subject holds whereas *"risk aversion"* is negatively related. It is not surprising that subjects with more financial wealth and more debt tend to hold more different assets than subjects with less financial wealth. Further, subjects with high education compared to subjects with low and intermediate education tend to be better diversified across different asset types as well as subjects who are more trusting and those with higher financial literacy scores. Somewhat more surprising is the finding that subjects who are more risk averse tend to be less diversified across different asset classes, due to the positive effect of diversification on the underlying investment risk. But, given that among the different asset classes there are also few assets that can be considered to be less risky than others, it becomes clear that people who are more risk averse than others have a tendency to only hold these few, less risky assets. Based on these results, it is reasonable to conclude that, contrary to within asset class diversification, other factors than ambiguity attitudes have a stronger influence on the individuals' tendency to invest in more different types of assets.

The final section of the analyses investigated the relationship as well as the empirical performance of the differently derived global ambiguity attitude indexes. Although the different derivation methods yield significantly different ambiguity attitude indexes, the results from empirical tests are qualitative similar. This is not surprising given their high degree of correlation. Only the sign of the coefficient obtained for the a-insensitivity index a_{So} differs depending on the calculation method, but it does not change in terms of statistical significance. Nonetheless, this result indicates that the derivation method matters. Based on the previously discussed advantages of the estimated neo-additive source functions, future research should focus on this method, due to its theoretical foundation and its clear interpretation of the obtained ambiguity attitude indexes.

7. Conclusion

The aim of this study was to investigate the potential relationship between individual attitudes towards ambiguity and under-diversification. Unfortunately, the statistical analysis did not yield significant results in favor of the hypotheses. Nonetheless, the obtained results indicate that ambiguity attitudes are potentially more relevant in regard to diversification within an asset class than for diversification across asset classes. Therefore further research should focus on the relationship between ambiguity attitudes and stock portfolio diversification. In addition, based on the previously discussed limitations of this study, further research should be conducted using a more detailed data set containing information on individual stock ownership that allows for precise assessment of the relative degree of under-diversification. Such data sets commonly exist for countries that impose wealth tax and therefore have access to individual stock ownership information. One problem that has to be solved when using existing data sets is how to match the stock ownership information with the measures capturing the individuals' attitudes towards ambiguity.

Appendix A. Manually Adjusting the Neo-Additive Source Function

The following sections describe in detail the manual adjustment process of the estimated neo-additive source functions' parameters. As previously mentioned, adjusting the estimated parameters is necessary, due to technical limitations of the statistical software used in this study. These adjustments are consistent with psychological insights and based on the characteristics of following equation (Wakker 2010 § 7.2):

$$m(0) = 0\,;\ m(1) = 1\,;\ 0 < p < 1 : m(p) = c + sp\,;\ s \geq 0,\ c \geq 0,\ s + c \leq 1 \qquad \text{(Eq. A.1)}$$

Figure A.1 gives an example of an estimated neo-additive source function, which satisfies the three conditions implied by **Equation A.1**: positive slope (s); positive intercept (c) and the sum of the slope (s) and the intercept (c) lower or equal to 1.

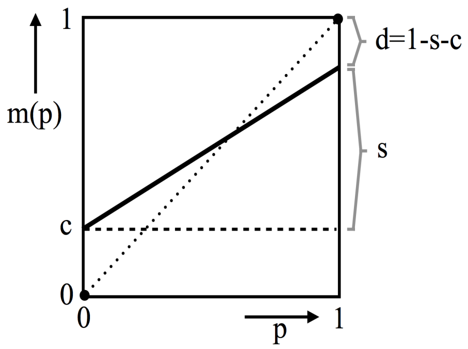


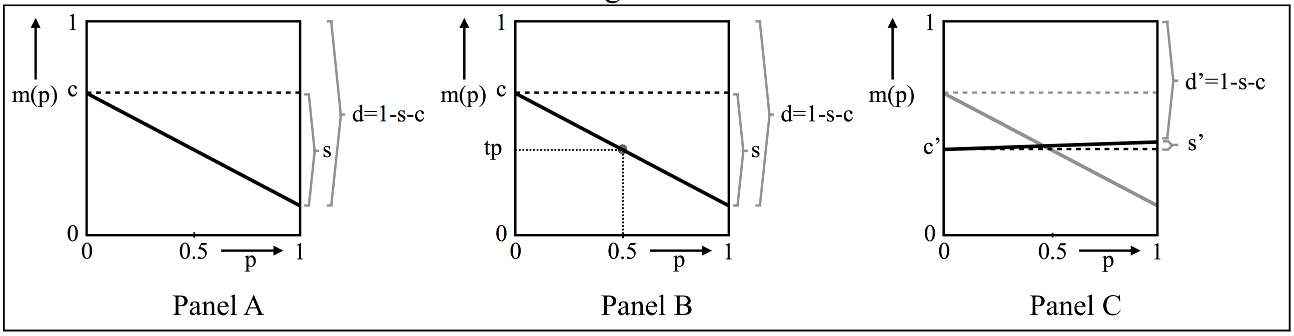
Figure A.1. The neo-additive source function.

The next sections provide an overview of five different violations of the conditions imposed by **Equation A.1** found in the sample. In addition, the manual adjustments are illustrated and described. Each section concludes with a table summarizing the modifications.

A.1. Violation 1 - Negative Slope or Slope Equal to 0 (s ≤ 0)

As described in the main text, the best-fitting neo-additive source function was estimated for each subject in the sample by regressing the elicited matching probabilities - m(p) - on the ambiguity neutral probabilities - p. Through this estimation process the slope (s) and intercept (c) are obtained. Since no interval restrictions were imposed on the regression coefficients, 27 out of 454 estimated neo-additive source functions had negative slopes (s), violating the condition s ≥ 0 implied by **Equation A.1**. In **Figure A.2** an estimated neo-additive source function with s < 0 is illustrated (**Panel A**).

Figure A.2



In order to correct for negative slopes, the adjusted neo-additive source function is fitted through the elicited matching probability at p = 0.5 with a slope s = 0.01. This manual adjustment process consists of two separate steps. The first step involves the calculation of a transition point (tp) through which the new source function will be fitted. This transition point is derived from the estimated parameters as follows:

$$tp = c + 0.5 \times s \qquad \text{(Eq. A.2)}$$

Panel B in **Figure A.2** illustrates the construction of the transition point. In the second step, the new source function is fitted through the transition point with a slightly positive slope (s') of 1/100. Based on the adjusted slope (s' = 0.01) and the transition point, a new intercept (c') is calculated as follows:

$$c' = tp - 0.5 \times s' \qquad \text{(Eq. A.3)}$$

Panel C in **Figure A.2** depicts the manually adjusted neo-additive source function with the altered parameters s' and c'. Adjusting not only for the slope but also the intercept is important, since the absence of coefficient restrictions on the regression line leads to upward biased parameter estimates when the best-fitting line has a negative slope. **Table A.1** gives an overview of the estimated and adjusted parameters for the 27 subjects with negative slopes.

Table A.1

Variable	Mean	Std. Dev.	Min.	Max.
Intercept c	0.57	0.23	0.07	0.95
Intercept d	0.70	0.17	0.30	0.95
Slope s	- 0.27	0.24	- 0.65	- 0.02
Intercept c' (adjusted)	0.43	0.17	0.06	0.76
Intercept d' (adjusted)	0.56	0.17	0.23	0.93
Slope s' (adjusted)	0.01	0.00	0.01	0.01

A.2. Violation 2 - Slope Exceeding 1 with Intercept (c) between 0 and 1 (s > 1; 0 < c < 1)

Another class of violations concerns estimated neo-additive source functions with slopes exceeding 1 but with an intercept at p = 0 between 0 and 1. Only nine out of 454 individual source functions exhibit those characteristics. **Figure A.3** depicts the manual adjustment process for these estimated source functions: the estimated intercept c is kept fixed while the regression line is shifted downwards.

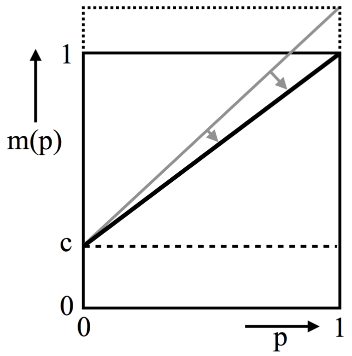


Figure A.3. Adjusting the neo-additive source function with s < 1 and 0 < c < 1.

The adjusted slope (s') is obtained as follows:

$$s\,' = \frac{(1-c)}{1} \qquad \text{(Eq. A.4)}$$

Table A.2 exhibits how the estimated slopes (s) and intercepts (c and d) change due to the manual adjustments.

Table A.2

Variable	Mean	Std. Dev.	Min.	Max.
Intercept c	0.07	0.03	0.02	0.12
Intercept d	- 0.16	0.03	- 0.20	- 0.11
Slope s	1.09	0.04	1.01	1.16
Intercept c' (adjusted)	0.07	0.03	0.02	0.12
Intercept d' (adjusted)	0.00	0.00	0.00	0.00
Slope s' (adjusted)	0.93	0.03	0.88	0.98

A.3. Violation 3 - Negative Intercept (c) and Slope Exceeding 1 (c < 0; s > 1)

The third group of estimated source functions that are manually adjusted have positive slopes with values greater than 1 and negative intercepts at p = 0. Approximately 7.7% (35 subjects) of the total sample have parameter estimates with these characteristics. **Figure A.4** depicts the estimated and the adjusted neo-additive source function as a gray and a black line respectively.

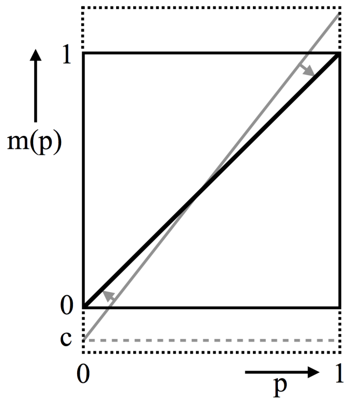


Figure A.4. Adjusting the neo-additive source function with $s > 1 \rightarrow s = 1$ and $c < 0 \rightarrow c = 0$.

Table A.3 shows the summary statistics of the estimated and the adjusted parameters for the 35 subjects with negative intercepts and slopes exceeding 1.

Table A.3

Variable	Mean	Std. Dev.	Min.	Max.
Intercept c	- 0.11	0.05	- 0.19	- 0.01
Intercept d	0.02	0.07	- 0.14	0.11
Slope s	1.09	0.04	1.03	1.16
Intercept c’ (adjusted)	0.00	0.00	0.00	0.00
Intercept d’ (adjusted)	0.00	0.00	0.00	0.00
Slope s’ (adjusted)	1.00	0.00	1.00	1.00

A.4. Violation 4 - Negative Intercept (c) with Slope (s) between 0 and 1 ($c < 0; 0 < s < 1$)

The fourth group of estimated neo-additive source functions that require manual adjustment exhibit negative intercepts at p = 0, but slopes with values that lie between 0 and 1. Among the total sample, 65 subjects have estimated source functions with parameters consistent with these characteristics. **Figure A.5** illustrates how the regression line is adjusted. The estimated slope is kept fixed, while the hole function is parallel shifted upwards, until the value of the intercept c becomes 0. **Table A.4** summarizes the adjustments of the parameters s, c and d.

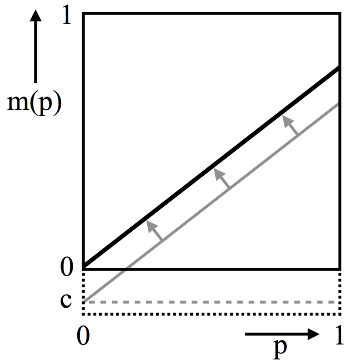


Figure A.5. Adjusting the neo-additive source function with $c < 0 \rightarrow c = 0$ and $0 < s < 1$.

Table A.4

Variable	Mean	Std. Dev.	Min.	Max.
Intercept c	- 0.05	0.04	- 0.16	- 0.01
Intercept d	0.30	0.20	0.01	0.81
Slope s	0.75	0.22	0.21	1.00
Intercept c’ (adjusted)	0.00	0.00	0.00	0.00
Intercept d’ (adjusted)	0.25	0.22	0.00	0.79
Slope s’ (adjusted)	0.75	0.22	0.21	1.00

A.5. Violation 5 - The Sum of Slope (s) and Intercept (c) is greater than 1 (s + c > 1)

The final group of violations concerns estimated neo-additive source functions where the sum of the values of the slope s and intercept c at $p = 0$ exceeds 1. In the overall sample, 23 source functions violate this condition. In order to ensure that each source function satisfies the condition $s + c \leq 1$, the regression line is parallel shifted downwards. This parallel shift is achieved by calculating a new intercept c while keeping the estimated slope fixed. The new intercept is calculated as follows: $c' = 1 - s$. **Figure A.6** illustrates this adjustment.

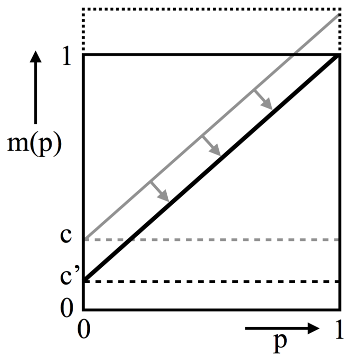


Figure A.6. Adjusting the neo-additive source function with $s + c < 1$.

Table A.5 gives an overview of the estimated and adjusted parameters for the 23 source functions that are adjusted in order to satisfy the condition $s + c \leq 1$ implied by **Equation A.1**.

Table A.5

Variable	Mean	Std. Dev.	Min.	Max.
Intercept c	0.21	0.17	0.04	0.76
Intercept d	- 0.05	0.05	- 0.13	- 0.01
Slope s	0.84	0.18	0.24	1.00
Intercept c' (adjusted)	0.16	0.18	0.00	0.76
Intercept d' (adjusted)	0.00	0.00	0.00	0.00
Slope s' (adjusted)	0.84	0.18	0.24	1.00

A.6. Summary of the Overall Adjustments

In total, approximately 34% of the estimated neo-additive source functions were manually adjusted according to the previously described processes. **Table A.6** shows how the manual adjustments have affected the average parameter values of the entire sample.

Table A.6

Variable	Mean	Std. Dev.	Min.	Max.
Intercept c	0.14	0.24	- 0.19	0.95
Intercept d	0.27	0.30	- 0.20	0.95
Slope s	0.59	0.39	- 0.65	1.16
Intercept c’ (adjusted)	0.14	0.21	0.00	0.76
Intercept d’ (adjusted)	0.26	0.28	0.00	0.94
Slope s’ (adjusted)	0.60	0.34	0.01	1.00

Appendix B. Derivation of Risk Aversion Index

This appendix provides a detailed account of the method used to derive the risk aversion index included as a control variable in this study. This method consist of two steps. First, two *local* risk aversion indexes are derived from choices made by the participants on two sets of hypothetical questions. Second, a *global* risk aversion index is derived by taking the average of the two local indexes.

Both local risk aversion indexes are computed using two different indifference points. Each indifference is elicited through a series of chained choice questions. The first set of questions is used to capture the subjects' attitude towards risk involving small, hypothetical prizes. In this condition, each participant is asked to choose between a sure gain and a risky gamble. Following the urn design used to elicit the ambiguity attitudes, each option was presented as a gamble involving a risky urn R and a sure urn S. Initially, the set up involved the choice between the following two prospects:

Urn S (1:500€) vs. Urn R (0.5:1000€; 0.5:0€)

The participant was asked to choose between three options: *"Urn S"*, *"Urn R"* or *"Indifferent"*.

Based on the individual choice, a modified follow up question was asked. If urn S was chosen, then the sure gain was made less attractive, i.e. urn S (1:250€). On the other hand, if urn R was preferred, then the sure gain was made more attractive, i.e. urn S (1:750€). This process was continued until the subject either reached indifference or was presented with three iterations of the initial choice question, in order to closely estimate his individual risk attitude. The second set of hypothetical choice questions is used to elicit the subjects' risk attitude for large prizes. In the initial setup the subjects were again asked to choose between two prospects:

Urn S (1:10,000€) vs. Urn R (0.5:18,000€; 0.5:0€).

As in the previous condition, the participant was presented with the same three answer options. The procedure for each answer was similar to the first set of chained questions. If the subject preferred the sure gain over the risky gamble, the sure gain was made less attractive and vice versa. Again, the process stopped if the subject indicated to be indifferent or in total six iterations were played. After the final iteration, the answers converged towards indifference and the individual risk attitude was estimated.

Based on the participants' indifference between a sure gain and the respective risky gamble, the risk aversion index can be derived by assuming that the subjects' utility function follows a CRRA (constant relative risk aversion) power function. Since both sets of lotteries do not involve losses ($\alpha > 0$), the utility function follows $U(\alpha) = \alpha^{\theta}$, only considering $\theta > 0$. Therefore $U(0)$ can be set equal to 0: $U(0) = 0$.

From the individual choices the certainty equivalent was either obtained directly or was closely estimated. Consistent with the definition of the certainty equivalent, the following condition is assumed to hold:

$$m \sim M_{0.5}0$$

where m is the elicited certainty equivalent of the prospect $M_{0.5}0$[2]. Given that expected utility can be applied, this can be rewritten as:

$$U(m) = 0.5(M) + 0.5(0) \qquad \text{(Eq. B.1)}$$

$$m^{\theta} = 0.5\mathrm{M}^{\theta} + 0.5 \times 0$$
$$m^{\theta} = 0.5\mathrm{M}^{\theta}$$
$$m^{\theta}/M^{\theta} = 0.5$$
$$(m/M)^{\theta} = 0.5$$
$$\ln((m/M)^{\theta}) = \ln(0.5)$$
$$\theta \ln(m/M) = \ln(0.5)$$

$$\theta = \frac{\ln(0.5)}{\ln(m/M)} \qquad \text{(Eq. B.2)}$$

Following **Equation B.2**, θ or the anti-index of concavity (Wakker 2010 § 3.5) is obtained for each participant based on the individual indifference points m_1 (*small gains*) and m_2 (*large gains*) as well as risky gains M_1 (*1,000€*) and M_2 (*18,000€*). The *local* risk aversion parameters (r_1 and r_2), i.e. coefficient of relative risk aversion, are obtained through:

$$r_n = 1 - \theta \qquad \text{(Eq. B.3)}$$

Consistent with Tanaka, Camerer and Nguyen (2010), θ is restricted to the range between 0 and 1.5, in order to simplify the interpretation of the relative risk aversion coefficient: $r_n = 0$ implies *"risk neutrality"*, $r_n = -0.5$ indicates *"risk seeking"* and $r_n = 1$ denotes the *"strongest level of risk aversion"* (Dimmock et al. 2013, p. 16). Finally, the *global* risk aversion parameter (r_3) is defined as

2 $M_{0.5}0$ is the efficient notation for the prospect (0.5:M; 0.5:0), i.e. (0.5:1000€; 0.5:0€) and (0.5:18.000€; 0.5:0€).

the average of the two *local* risk indexes. **Table B.1** shows the average values of the certainty equivalents m_1 and m_2, the coefficients of relative risk aversion θ_1 and θ_2, the *local* risk aversion indexes r_1 and r_2 as well as the *global* risk aversion index r_3.

Table B.1

Variable	Mean	Std. Dev.	Min.	Max.	Obs.
m_1	426.21	275.08	125	875	454
m_2	7990.09	5698.74	312.5	17750	454
θ_1	0.85	0.47	0.33	1.50	454
θ_2	0.87	0.50	0.17	1.50	454
r_1	0.14	0.47	- 0.50	0.67	454
r_2	0.13	0.50	- 0.50	0.83	454
r_3	0.14	0.42	- 0.50	0.75	454

The interpretation of the anti-index of concavity (θ) is as follows:

- An anti-index of concavity $\theta < 1$, implies risk aversion. Lower values of θ correspond to increasing risk aversion with $m < M$.
- An anti-index of concavity $\theta = 1$, implies risk neutrality with $m = M$.
- An anti-index of concavity $\theta > 1$, implies risk seeking. Higher values of θ correspond to increasing risk seeking with $m > M$.

As previously mentioned, this study restricted the anti-index of concavity (θ) to the range between 0 and 1.5 ($0 \leq \theta \leq 1.5$). Following **Equation B.3**, the *global* risk aversion index (r_3) can be interpreted as follows:

- A positive risk aversion index $r_3 > 0$, implies risk aversion with higher positive values of R correspond to increasing risk aversion (i.e. lower positive values imply less risk aversion).
- A risk aversion index $r_3 = 0$, implies risk neutrality.
- A negative risk aversion index $r_3 < 0$, implies risk seeking with higher negative values of R correspond to increasing risk seeking (i.e. lower negative values imply less risk risk seeking).
- Due to the interval restriction, the global risk attitudes range from -0.50 (strongly risk seeking) to 0.75 (strongly risk averse).

Appendix C. Summary and Definition of the Variables in this Study

Table C.1 provides an overview of all variables and their definitions used in this study: **Panel A** contains the two dependent variables and **Panel B** focuses on the independent and control variables.

Table C.1. Summary of the Variable and Definitions

Panel A: Dependent Variable	
Sharpe ratio loss	Relative measure of individual under-diversification. Conditional on stock market participation, this variable capture the deviation from a perfectly diversified portfolio. A value of 0 indicates severe under-diversification whereas values close to 1 indicate a high degree diversification.
Asset diversification	General measure of individual diversification. Unconditional on stock market participation, this variable indicates the number of different asset types each subject holds. Based on the total number of different asset a participant holds he is classified as *"minimally diversified"* if he hold zero or one asset, as *"intermediary diversified"* if he hold two to four different assets and as *"maximally diversified"* if he hold up to six different asset types. Hence, asset diversification is an ordinal variable ranging with values between 1 to 3. 1 indicates that the subject only holds 0 or 1 asset class whereas 3 indicates that the subject owns more than 5 different asset types.
Panel B: Independent / Control Variables	
Age	Age of the participant measure in years
A-insensitivity index	Index capturing the participants level of a-insensitivity. A low levels indicates low a-insensitivity and vice versa
Ambiguity aversion index	Index capturing the participants degree of ambiguity aversion or pessimism. A low levels indicates little ambiguity aversion or pessimism and vice versa
Education	
Low education	Indicator for participants who attended only primary or intermediate secondary school (vmbo)
Intermediate education	Indicator for participants who attended only higher secondary school (havo/vwo) or intermediate vocational school (mbo)
High education	Indicator if the participant attended higher vocational school (hbo) or university (wo)
Employment	
Employed	Indicator if the subject is employed
Self-employed	Indicator if the subject is self-employed
Unemployed	Indicator if the subject is unemployed
Pensioner	Indicator if the subject is retired
Student	Indicator if the subject is student

Panel B: Independent / Control Variables *(continued)*	
Financial literacy	
Financial literacy score	Ordinal variable ranging from 0 to 2, capturing the financial knowledge of the participant with higher values indicating higher financial sophistication
Incompetence	Indicator if the participant is financial incompetent or perceives himself as incompetent in financial matters
Female	Indicator for female participants
Household size	Total number of people living in the household
Income	Net monthly household income in Euro
Risk aversion	Individual risk aversion measure with $r > 0$ implying risk aversion, $r = 0$ implying risk neutrality and $r < 0$ implying risk seeking
Trust	Ordinal variable ranging from 0 to 10, capturing the participant's degree of trust in other people with low values corresponding to little trust in others whereas high values correspond to high degree of trust in other people
Total liabilities	The sum of the household's total debt measured in Euro
Total financial wealth	The sum of the household's total financial wealth measured in Euro

Appendix D. Ambiguity Attitudes Derived from the Estimated Source Functions

This appendix provides an overview of the ambiguity attitudes found in this sample derived from the estimated neo-additive source functions. **Figure D.1** shows how the matching probabilities are calculated based on the adjusted and unadjusted neo-additive source functions.

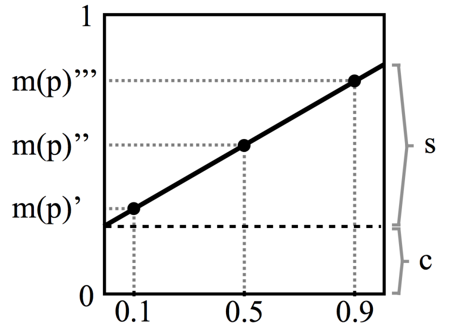


Figure D.1. Deriving the adjusted matching probabilities based on neo-additive source function.

The adjusted matching probabilities are calculated for every ambiguity neutral probability (p = 0.1; 0.5; 0.9) as follows:

$$m(p)' = c + (p \times s) \qquad \text{(Eq. D.1)}$$

Based on the adjusted matching probabilities, the attitudes towards ambiguity and their respective frequencies for each ambiguity neutral probability are calculated. The results are reported in **Table D.1**.

Table D.1

Ambiguity-neutral probability (p)	0.10	0.50	0.90
Ambiguity averse	24.45%	45.81%	58.81%
Ambiguity neutral	29.96%	29.74%	29.74%
Ambiguity seeking	45.59%	24.45%	11.45%

Comparing the frequencies of the ambiguity attitudes calculated directly from the elicited matching probabilities to the frequencies of the attitudes derived from the adjusted matching probabilities, it can be seen that the latter deliver much more pronounced results. In contrast to the results reported in **Part 5.2** (*"Ambiguity Attitudes in the Sample"*), ambiguity seeking is the predominant attitude for ambiguity neutral probability p = 0.10, confirmed by a Chi squared test *(p-value = 0.00)*.

Consistent with the results previously reported, the prevailing attitude for ambiguity neutral probabilities $p = 0.50$ and $p = 0.90$ is ambiguity aversion, also confirmed by two Chi squared tests *(both p-values = 0.00)*. These results are consistent with the notion of a-insensitivity: ambiguity seeking for low-likelihood events and ambiguity aversion for high-likelihood events.

Table D.2 summarizes the frequencies of the aggregated ambiguity attitudes based on the adjusted matching probabilities. In contrast to the results reported in the main text, it can be seen that the majority of participants are a-insensitive (approximately 34% vs. 13%), when the attitudes are derived from the estimated neo-additive source functions.

Table D.2

	Proportion of respondents
Ambiguity likelihood insensitive ($AA_{10} < 0$; $AA_{90} > 0$)	34.14%
Ambiguity neutral ($AA_{10} = 0$; $AA_{90} = 0$)	29.74%
Ambiguity seeking ($AA_{10} < 0$; $AA_{90} < 0$)	11.45%
Ambiguity aversion ($AA_{10} > 0$; $AA_{90} > 0$)	24.45%
Inconsistent ambiguity attitudes	0.22%

To conclude this section, **Table D.3** provides the summary statistics for the three different adjusted matching probabilities as well as the adjusted local ambiguity indexes AA_{10}, AA_{50} and AA_{90}.

Table D.3

Variable	Mean	Std. Dev.	Min.	Max.
m(0.1)	0.20	0.19	0.02	0.79
m(0.5)	0.44	0.18	0.06	0.88
m(0.9)	0.68	0.26	0.06	0.97
AA_{10}	- 0.10	0.19	- 0.69	0.08
AA_{50}	0.06	0.18	- 0.38	0.44
AA_{90}	0.22	0.26	- 0.08	0.84

This section confirms, that the ambiguity attitudes calculated directly from the elicited matching probabilities are somewhat different compared to the ambiguity attitudes derived from the adjusted and unadjusted neo-additive source functions. Especially, the number of subjects classified as a-insensitive is understated when the ambiguity attitudes are derived directly from the elicited matching probabilities.

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