Master Thesis Economic and Business - Behavioural Economics

The impact of optimism on information avoidance: Does the perception of probabilities influence our information acquiring behavior?

Anastassiya Kochetkova 472669ak

Supervisor: Xiao Yu

Second assessor: Tong Wang

Date final version: 14th of October

Abstract

Research related to information avoidance emphasizes the importance of determining behavioral biases when acquiring information. This study aimed to analyze the relationship between information avoidant behavior in personal financial decision-making and the optimistic attitudes. It was hypothesized that optimism is associated positively to information avoidant behavior. An experiment was conducted to test the relationship between economic optimism and information avoidance using student sample. Information avoidance related to the foregone investment opportunities was tested using Information Avoidance Scale. The optimistic attitudes were estimated using parameters of the probability weighting function under risk using midweight method. Based on the results, it cannot be concluded that optimistic attitude is associated with information avoidant behavior in the financial setting. This research contributes to the literature in the information avoidance by quantitatively studying the relationship between information avoidant behavior and one of the definitions of optimism, although further analysis is needed to reach conclusion about the true association of optimism and information avoidance.

Key words: *information avoidance, financial decision-making, probability weighting function, rank-dependent decision models, optimism, information avoidance scale, midweight method*

Table of Contents

1. Introduction

Information avoidance is widely examined in literature in several fields, such as health (Taber et al., 2015) and finance (Karlsson, Loewenstein & Seppi, 2009). The reason why people tend to avoid information, even though acquiring it possibly leads to better decisions has sparked considerable interest from researchers active in economics and psychology (Sweeny, Melnyk, Miller, & Shepperd, 2010; Shah, Harris, Bird, Catmur, & Hahn, 2016; Golman, Hagmann, & Loewenstein, 2017). In economics, it is essential to establish the determinants of avoidant behavior, as current decisions to acquire information have an impact on future actions and decisions.

Sweeny et al. (2010) define information avoidance as deliberately refraining from acquiring some negative information. In behavioral economics, it has been established that people obtain utility based on emotions (Kahneman, Diener, & Schwarz, 1999). In connection with information avoidance, undesirable information causes a decrease in the current utility level due to the negative emotions people can experience towards the information (Brunnermeier & Parker, 2005). What makes information undesirable? Some researchers link the lack of desire to face negative information to the positive perspective on the future (Yang & Kahlor, 2012), which psychology literature defines as optimism (Scheier, Carver, & Bridges, 2001). In economics, on the other hand, optimistic views are defined by the perception of probabilities people have about risky or uncertain events (Abdellaoui, l'Haridon, & Zank, 2010; Fehr-Duda, Epper, Bruhin, & Schubert, 2011).

In financial decision-making, information avoidance has a crucial implication. When making financial decisions, complete information about the likelihood of gaining or losing money is essential. People face financial decisions on a daily basis. For instance, choosing a pension fund, allocating personal or pension investments can be a difficult process. However, avoidant behavior sometimes makes decisions less optimal. Understanding the traits that make us behave more avoidant regarding some information can increase efficiency between individuals and financial institutions by providing further insights. Hence, establishing the relationship between information avoidance and optimism has great relevance to the research in financial decision-making.

Previous research has indicated connections between information avoidance and optimism. For instance, some economic literature provides models of information acquiring behavior and optimism maintenance (Brunnermeier & Parker, 2005; Huck, Szech, & Wenner, 2017). In general, most studies in economics and psychology interpret optimism as a belief that negative events are less probable to happen (Brunnermeier & Parker, 2005; Shah et al., 2016). However, the quantified link between the information avoidant behavior and perception of probabilities has not been established. This study uses parameters of the probability weighting function, elicited at the individual level during the experiment, as a measure of optimism. Hence, the paper at hand contributes to the existing research by establishing the quantitative relationship between optimism, measured by the probability weighting function, and information avoidance in the domain of personal financial decisions. The current study aims to answer the following research question:

To what extent is optimistic attitude associated with information avoidance in the financial domain?

This thesis consists of eight main sections. Firstly, a literature review on both information avoidance and optimism, as well as hypothesis developments are presented in section 2. Section 3 and 4 explain the methods behind the measures used and the design of the experiment, respectively. The obtained data is presented in Section 5. Furthermore, the results are presented in Section 6. Section 7 includes general discussion and limitations, and section 8 concludes.

2. Literature Review

This section aims to provide an overview of the research concerning information avoidance and its connection to optimism. Firstly, the concept of information avoidance is introduced in section 2.1. Furthermore, literature that acknowledges information avoidance and optimism is discussed in section 2.2.

2.1 Information Avoidance

There are many aspects of life where information avoidance is pronounced, which is not always optimal for decision making. For instance, in financial decisions, there is a tendency to avoid monitoring investments when the market is bearish, also known as ostrich effect (Karlsson et al., 2009). Research also shows the important implications of information avoidance in medical decisions. Studies point out that when people are given an option to know their medical results for cancer, genetic diseases or HIV, large number of people in the studies avoid the information (Sullivan, Lansky, Drake, & HITS-2000 Investigators, 2004; Miles, Voorwinden, Chapman, & Wardle, 2008; Taber et al., 2015). However, in the standard economic view, it is perceived that agents acquire all available information, which benefits their decision-making, regardless if this information is favorable or not (Arrow, 1972; Huck et al., 2017). Knowing the test results or learning the state of the financial market is essential information to consider for future actions. Thus, studies in psychology and economics aim to establish possible behavioral biases that cause people to ignore unpleasant information.

Although according to finance theory, individuals incorporate all available information to reach the most efficient outcomes, there is ample research that finds evidence of information avoidant behavior regarding personal finances. For instance, based on the data obtained from the Federal Reserve's Survey of Consumer Finances from 2004 and 2007, on average respondents largely underestimated the rates they had on their credit cards (Frank, 2011). Similarly, research in behavioral finance provides evidence that individuals avoid information about personal financial risk. Galai and Sade (2006) show that individuals sometimes prefer to have less information about the risk and return on investments (Galai & Sade, 2006), thus resulting in higher uncertainty regarding the outcomes of the decisions. In addition, financial risk information avoidance is more pronounced if people anticipate getting a negative emotional response from acquiring the information (Blajer-Gołębiewska, Wach, & Kos, 2018).

It is crucial to point out that information avoidance has two distinct forms, which are passive and active avoidance. Active information avoidance is when people prefer to refrain from acquiring information even though they know that it is available, and it is costless to obtain it (Golman et al., 2017). On the contrary, the passive form of information avoidance does not require the knowledge of information availability. It can be seen when people fail to seek knowledge instead (Sweeny et al., 2010). There are many ways people avoid information such as forgetting, disagreeing, or not asking for it. However, only the active form of information avoidance is associated with deliberate avoidance. Hence, information avoidance is referred to as its active form in this study.

2.2 Link between Optimism and Information Avoidance

Several scholars point out the relation between the information avoidance, people's emotions and perception of likelihoods. In psychology, optimism is generally associated with people's expectations about life (Weinstein, 1980). The expectations people have towards future events directly show whether or not a person is an optimist or pessimist (Armor, & Taylor, 1998, Scheier et al., 2001). For instance, it is shown in the literature that when people are unrealistically optimistic, they think that positive events are more likely to happen to them, whereas negative events are less likely (Shah et al., 2016). Interestingly, Lench (2009) argues that when people believe that the unfavorable outcome is less likely to happen, it can be an indication of "cognitive avoidance," which is cognitively rejecting the chance of the negative outcome happening. When people perceive the likelihood of undesired events in a biased way, they disregard information about negative events, thus having a more optimistic perspective on personal risk (Shah et al., 2016). Also, psychology literature indicates that people's perceptions of issues have an impact on information avoidance (Kahlor, Dunwoody, Griffin & Neuwirth, 2006; Yang & Kahlor, 2012). For instance, Yang and Kahlor (2012) showed that people that have negative and pessimistic emotions towards risks tend to seek more information, but those who feel hopefulness are more likely to avoid information about the risks.

In economic literature, some studies look at how people optimistically update beliefs concerning the information. Golman et al (2017) argues that acquiring behavior is influenced by the feelings people have about the information. Optimism maintenance is one of the examples where emotions are incorporated into the decision-making process. In particular, Brunnermeier and Parker (2005) have modeled optimism maintenance and its connection to individuals' utility. The model shows that an increase in utility can be obtained by reducing the risk of disappointments in the future, which is associated with optimistic views. Hence, when individuals prefer to maintain optimistic views, they would be likely to avoid unpleasant information to keep their views and expectations high. Moreover, by staying optimistic people try keeping their utility at the desired level (Brunnermeier & Parker, 2005).

Empirical studies reach similar conclusions in regard to information avoidance and optimism maintenance. Based on the data obtained in the lab, Huck et al. (2017) analyzed the information preference for the compensation for the tasks that participants had to perform.[1] The results show that more than 30% of the participants were avoidant towards the information and that participants who were uncertain about their compensation plan performed better than participants who were given certain piece rate. Huck et al. (2017) suggest that people hold optimistic beliefs, avoid information, and perform better in the real-effort related tasks under uncertainty. Comparably, Oster, Shoulson, and Dorsey (2016) show that people who avoid information about the genetic test believe in having lower chances of getting a genetic disease than they would have had potentially. Hence, the results form Huck et al. (2017) and Shoulson, and Dorsey (2016) are consistent with the model of Brunnermeier and Parker (2005).

[1] Huck et al. (2017) had four treatments to analyze information acquiring behavior concerting the compensation based on the real-effort tasks. In the first three treatments, participants had full information about their piece rate, no information, and a choice to opt out from the information. The piece rate was determined randomly using equal probabilities for low and high piece rate. The forth treatment had a value of piece rate based on the Bayesian correct expected value for uncertain compensation.

The above-mentioned literature does not establish a quantified relationship between information avoidance and the perception of probabilities. However, this relationship is highly plausible. For instance, Brunnermeier and Parker (2005) link optimistic beliefs with individuals' perception of the likelihood of good and bad outcomes. Similar definition of optimism is used in economic literature that quantifies optimistic profile (Diecidue & Wakker, 2000; Abdellaoui, l'Haridon, & Zank,2010; Webb & Zank, 2011). These studies establish that it is possible to determine the optimistic profile by the probabilistic risk attitudes, which are estimated based on the parameters of probability weighting function. However, the model of Brunnermeier and Parker (2005) does not provide quantitative relationship between information avoidant behavior and optimism. Further empirical studies based on the model of Brunnermeier and Parker (2005) also focus on broad definition of optimism rather the attitudes towards probabilities. Furthermore, Budescu and Fischer (2001) argued that people prefer to have optimistic views by showing how people choose to reveal information of favorable and unfavorable outcomes. The study emphasizes that people, when presented with a choice in which order to reveal information about the outcomes of the lotteries, prefer to reveal the outcomes of low probabilities of gain last. The authors conclude that people prefer to maintain optimistic beliefs and choose to continue to be uncertain for the least favorable outcomes. Even though, the study links optimistic beliefs to the orders of the outcomes, the probabilistic attitude is not measured.

To summarize, both psychology and economic literature indicate possible association between information avoidant behavior and optimism. As noted in the psychology literature, emotions that people derive from events directly influence the desire to acquire information. Thus, people may avoid information that is negative or contradicts with their beliefs because they have optimistic views. It is evident that there is a connection between the way people prefer to acquire information and the way they think about the likelihood of events. Also, it is plausible that when people decide on personal investments, they attach subjective probabilities to the outcomes of the investments, which can lead people to be optimistic about portfolio returns and try to avoid unfavorable information. Hence, based on the findings of previous research on information avoidance and the concepts of optimism, this study hypothesizes:

Hypothesis: People who are more optimistic (show higher probabilistic risk seeking behavior) show more pronounced information avoidant behavior in the financial domain.

3. Methodology

This section aims to elaborate on the methods behind the measures used in this study. Section 3.1 includes the explanation of the methods used to measure information avoidant behavior. Section 3.2 explains the methods used to determine the probability weighting function and establish the optimistic profile. The control measures are presented in section 3.3.

3.1 Information Avoidance Measure

Information Avoidance Scale (IAS) developed by Howell and Shepperd (2016) is used to measure information avoidance. IAS allows customizing the domain of the information without changing the structure of the questions. Moreover, IAS is a valid way to measure information avoidance, because it uses differently framed statements allowing to incorporate all types of information into the measurement. The scale consists of eight statements, which are evaluated on the 7-point Likert-scale from "Strongly disagree" to "Strongly agree" (see Appendix A). Four out of eight statements are displayed in the reverse order to be able to check for the quality of responses.

In this study, information avoidance is measured for personal financial decisions. The financial scenario used is related to the foregone opportunities in pension fund investments from Information Preference Scale (IPS) developed by Ho, Hagmann, and Loewenstein (2018).

3.2 Determining Optimism

The optimistic profile of participants depends on the curvature of the probability weighting function. Figure 1 shows the graphical representation of the probability weighting function with examples of optimism, pessimism, and neutral attitudes. More specifically, an individual is considered to be optimistic when he attaches higher subjective probabilities for favorable outcomes, thus decision weight increases and the function takes a concave form (Diecidue and Wakker, 2000).[2] Furthermore, the concave capacity of the probability weighting function can be used as a measure of optimistic attitude (Lewandowski, 2017). For instance, the higher the concavity of the function, the more optimistic the person is.

---

[2] Rank-dependent models, such as rank-dependent utility (RDU) and the cumulative prospect theory (CPT) allow the transformation of probabilities to capture the probability weighting function (Abdellaoui, 2000). More detailed explanation of rank-dependent models can be found in Appendix B

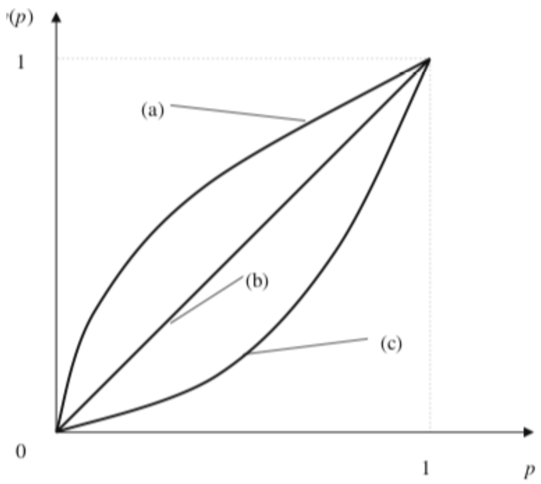


Figure 1. Examples of curvature of the probability weighting function with (a) having optimistic, (b) neutral, and (c) pessimistic attitudes. Reprinted from ‘Separating curvature and elevation: A parametric probability weighting function,’ by M. Abdellaoui, O. l’Haridon, and H. Zank, 2010, *Journal of Risk and Uncertainty, 41*(1), p. 46. Copyright by Springer Science+Business Media, LLC 2010.

The first step in the measurement of optimism is the elicitation of the probability weighting function. In this study, the midweight elicitation method of Van De Kuilen and Wakker (2011) is used to elicit probability weighting functions in a non-parametric way. The advantage of using a non-parametric method is that the elicited probability weighting function is not influenced by the choice of the parametric functional form and it is possible to elicit the data at the individual level (Abdellaoui, 2000; Bleichrodt & Pinto, 2000, Van De Kuilen & Wakker, 2011). A specific type of non-parametric elicitation method is the midweight method, which elicits probability weighting function of rank-dependent models by obtaining the midpoint on the probability weighting function (Van De Kuilen & Wakker, 2011).

The midweight method is a reliable and feasible way to elicit the probability weighting function. As a first step, Van De Kuilen and Wakker (2011) elicit the midpoints on the utility function, x_2 and x_0. The elicited utility midpoints are used in the elicitation of the probability weighting function, therefore the reliability of the measurement of the probability weighting function depends on the quality of the data obtained during the elicitation of utility function. Several scholars show that eliciting midpoints on the utility based on the subject’s preferences produces reliable outcomes (Vind,1991; Ghirardato, Maccheroni, Marinacci & Siniscalchi, 2003). Hence, this study uses the midweight elicitation method for gains under risk, as it is possible to obtain reliable results while having fewer questions in the survey (Van De Kuilen & Wakker, 2011).

To obtain midpoints on the probability weighting and utility functions, this study uses the tradeoff method. The tradeoff method requires participants to make a choice between prospects, which reveals the preferences of the participants (technical details about the tradeoff method can be seen in Appendix C). The advantage of tradeoff compared to other methods is that this method provides reliable results under rank-dependent models (Bleichrodt & Pinto, 2000).[3] For instance, when the utility function is elicited, the tradeoff method does not assume linearity of the probability weighting function. Moreover, due to the fact that all prospects in the utility elicitation have the same probabilities, any deviations from linearity are eliminated (Wakker & Deneffe, 1996). Therefore, under this method, the utility function can be elicited even if individuals distort probabilities or lack the understanding of the concept of probabilities (Wakker & Deneffe, 1996).

Firstly, the utility midpoints are obtained by asking participants their preferred choice between two prospects. In particular, participants are asked five subsequent questions to elicit each midpoint, x_1 and x_2. By making a choice between the prospects, it is possible to determine whether the true x_1 value for each participant is higher or lower than the x_1 value in the presented prospects. The first indifference interval is obtained when participants choose a preferred prospect. The average of the indifference interval is used as a value of x_1 in the prospect in the subsequent question. The indifference interval narrows down with each choice. After the fifth question, the average value of the indifference interval is used as a value of x_1. The same procedure is used to determine the value of x_2. The technical details of the elicitation process can be seen in Appendix D.

After utility elicitation, the probability weighting function elicitation is done by obtaining participants' choice between the prospects. The prospects are designed in such a way that the probabilities of one of the prospects vary. The values that are used in these prospects contain the obtained outcomes of the elicited utility midpoints, x_1 and x_2, for each individual. The following probabilities are elicited $w^{-1}(1/8)$, $w^{-1}(2/8)$, $w^{-1}(4/8)$, $w^{-1}(6/8)$, $w^{-1}(7/8)$, where $w^{-1}(p_i)$ is referred to as inverse-w probabilities, and $w(p_i)$ is the probability weighting function for gains (Van De Kuilen & Wakker, 2011). Each subjective probability is elicited using five

[3] The other methods are certainty equivalent (CE) and probability equivalent (PE) that are widely used as elicitation techniques in the literature. CE method elicits the certainty equivalent of the individual by varying a certain amount to reach indifference between the lottery and a certain amount, while probabilities are fixed (Ruggeri & Coretti, 2015). Likewise, the PE method elicits the probabilities, which makes an individual indifferent between the certain amount and a lottery, by fixing the certain amount and varying the probabilities (Hershey & Schoemaker, 1985).

questions. By making a choice between the prospects, the indifference interval narrows down. The average of the fifth indifference interval is used as a value of each elicited probability. Furthermore, the elicitation process starts by obtaining $w^{-1}(4/8)$ value. When $w^{-1}(4/8)$ is elicited it is used in the prospects for elicitation of w^{-1} (2/8) and $w^{-1}(6/8)$. Figure 2 shows that the midweight elicitation model distinguishes between elicitation of probabilities with low and high probabilities.

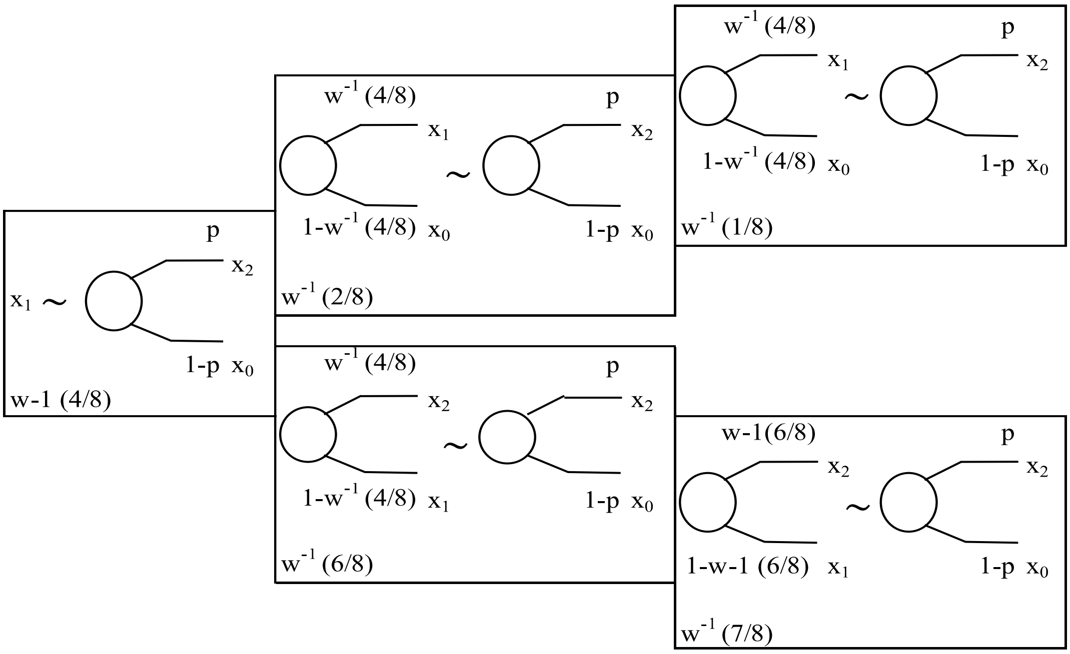


Figure 2. Elicitation of high and low probabilities on the probability weighting function. Adopted from 'The midweight method to measure attitudes toward risk and ambiguity,' by G.Van De Kuilen and P.P. Wakker, 2011, *Management Science, 57*(3), p. 586. Copyright by 2011 INFORMS.

Following the elicitation of the probability weighting function, it is possible to analyze the curvature of the function and to establish optimistic profile based on its parameters. Although, the non-parametric elicitation method is needed to obtain the data in the most reliable way, further parametric analysis allows to quantitatively establish optimism. By using parametric analysis, it is possible to determine the concave (convex) capacity of the probability weighting function. In this study, Prelec (1998) two-parameter specification form of probability weighting function is used, because it includes a parameter that defines optimism. Prelec (1998) probability weighting function takes following form

$$w(p) = \exp\{-\beta(-\ln p)^{\alpha}\}, \tag{1}$$

where β is an index of convexity, and α is an index of subproportionality. The lower the subproportionality, the more pronounced the probability distortions are (Fehr-Duda & Epper, 2012). For example, when α takes a value between 0 and 1, the weighting function has an inverse-S shape, whereas when α>1 the weighting function has an S-shape, which means that the individual is more sensitive to large probabilities than to small probabilities (Åstebro, Mata & Santos-Pinto, 2014).

The index of convexity can be used as a measure of optimism. Increase in β leads to an increase in convexity of the probability weighting function (Fehr-Duda & Epper, 2012). At the same time, change in β does not affect subproportionality (Prelec, 1998). Thus, β captures the degree of optimism or pessimism. For instance, when β takes a value between 0 and 1, an individual can be considered optimistic, whereas when β>1 the probability weighting function is convex, which refers to pessimism (Åstebro et al., 2014).

Using a nonlinear regression model, it is possible to estimate the parameters of the probability weighting function for each subject by minimizing the sum of squared residuals. The following formula is used for the minimization process

$$\sum_{i=1}^{5}(w_i - \widehat{w}_i)^2, \qquad (2)$$

where w_i is the sequence of actual probabilities for which $w^{-1}(p_i)$ is elicited and $\widehat{w}_i$ is the value that the probability weighting function gets with each elicited probability. For instance, when w_1 takes a value of 1/8 (12.5%), the corresponding elicited probability $w^{-1}(p_1)$ is used to determine parameters of the probability weighting function. The difference between these values shows the distance between the sequence of probabilities and the probability weighting function.

3.3 Control Measures

3.3.1 Demographics and Time Preferences

There are several studies that find a connection between avoidant behavior and demographic characteristics. Previous papers show that females tend to avoid or postpone acquiring information about their attractiveness or illnesses (Caplan, 1995; Meechan, Collins, & Petrie, 2002; Sweeny et al., 2010). Other studies point out that women are more prone to avoiding financial information than men, especially when they are young (McCloud, Jung, Gray, & Viswanath, 2013). Acknowledging results from these studies, both gender and age have a relation with information avoidance. Furthermore, association between educational level and information avoidance is noted in the literature (Taber et al., 2015). Additionally, it is observed that avoidance behavior varies between the countries (Elliot, Chirkov, Kim, & Sheldon, 2001; Schreier et al., 2010; Jang, Shen, Allen, & Zhang, 2017). Schreier et al. (2010, p. 1128) state that 'people in collectivistic countries have higher social anxiety and socially avoidant behavior than people in individualistic countries.' Participants' nationalities were categorized into either collectivistic or individualistic culture based on classification from Hofstede (2001).

It is also important to examine the time preferences of individuals when studying information avoidance. It is shown that people who avoid information can discount the value of the information with time (Ho et al., 2018). Furthermore, inconsistency in time preferences may cause leaning information with strategic ignorance (Carrillo & Mariotti, 2000), which is also pronounced in financial decision making (Karlsson et al., 2009; Sicherman, Loewenstein, Seppi, & Utkus, 2015). Hence, acknowledging previous literature, time preferences are used in the analysis as a control measure. Time preferences are elicited with the question: "How willing are you to give up something that is beneficial for you today, in order to benefit more from that in the future?" (Armin, Becker, Dohmen, Huffman, & Sunde, 2016), which is evaluated on the 5-point Likert scale with 1 being extremely unlikely and 5 being extremely likely.

3.3.2 Subjective Scenario Uncertainty Measure

To quantify the association between optimism and information avoidance, the uncertainty that people perceive from the financial scenario needs to be controlled for. Due to the fact that the scenario from IPS scale is used to measure information avoidance in the financial domain, participants can have different levels of uncertainty about the scenario. Golman and Loewenstein (2016) developed a theoretical framework for the role of risk and ambiguity aversion on the decision of obtaining information. The theory predicts that in uncertain situations, people might try to avoid information to the greater extent.

One of the indications of how uncertain participants are in financial situations can be the spread of the answers they give about the returns of the portfolios. In previous literature in behavioral finance, volatility has been used to measure the degree of overconfidence (Davidson & Cooper, 1976; Ben-David, Graham, & Harvey, 2013). The confidence intervals of each subject about the future returns of S&P 500 index were used to construct the individual volatility measure (Ben-David et al, 2013). In the current study, a similar approach is used. Participants are presented with the historical returns of a hypothetical investment fund B and are asked to estimate the highest and the lowest annual average percentage return on fund B in the investment period of the following 10 years (see Appendix E). Akter and Bennett (2013) used the spread between the answers to determine the variance of the uncertainty interval. For instance, The higher the variance of the distribution of the outcomes of the events, the higher the perceived uncertainty from the hypothetical scenario (Akter & Bennett, 2013). Hence, in this study, the variance of the distribution (σ) is calculated using the following equation

$$\sigma^2 = \frac{\Sigma(X-\mu)^2}{N}, \tag{3}$$

where μ is the mean of the outcomes and X is the highest and lowest subjective estimate of the outcomes.

4. Experimental Design and Data Collection

This section provides a detailed overview of the experiment that was conducted to establish the relationship between information avoidance and optimism. Information about participants is presented in section 4.1. Section 4.2 includes details about incentives. Section 4.3 present the software used and the experimental instructions and explains how the measurements used in this study. Section 4.4 discusses the randomization procedure and Section 4.5 elaborates on the design of the experiment and variables.

4.1 Participants

The data were collected by recruiting participants from Erasmus University Rotterdam. A total of 47 individuals were interviewed. The recruiting process took place at various locations on the University campus. Beforehand, during the trial study, three other students were interviewed. Interviewing participants in the trial study was needed to ensure that there were no mistakes in the elicitation method. On average, the duration of the interviews was 20 minutes, with a minimum of 9 and a maximum of 47 minutes.

4.2 Incentives

The survey included several measurements, which would require participants to understand the prospects and stay focused. Therefore, participants were given monetary incentives to complete the survey.[4] At the same time, all questions were framed as hypothetical questions, and participants were not paid based on the outcomes of the prospects. Arguably,

[4] Participants had a chance to participate in the lottery at the end of the interview. Three random email addresses were chosen for payment after the data were collected. Three participants were paid 25 euros, 10 euros, and 5 euros, respectively.

real incentives are essential for the internal validity of the experiments in economics (Holt & Laury, 2002). However, we can also observe from the experimental data that the outcomes of the hypothetical questions do not vary significantly to the ones that are incentivized (Camerer, 1989; Tversky & Kahneman, 1992, Beattie & Loomes, 1997).

4.3 Materials

4.3.1 Software

During the interview, participants were given a survey designed using Qualtrics software. The probability weighting function elicitation model was designed using Microsoft Excel. The minimization the sum of squared was done using R software.

4.3.2 Experimental Instructions

Each participant received experimental instructions at the beginning of the interview. During the survey, participants were also presented with experimental instructions for probability weighting function elicitation. As some questions in the survey were based on the understanding of the concept of probabilities, one practice question and two ten-sided dice were given to the participants to be able to visualize probabilities (see Appendix F).[5]

4.3.3 Eliciting Information Avoidance

IAS was combined with one of the hypothetical scenarios from IPS scale. After getting acquainted with the hypothetical situation presented in Figure 3, participants were asked to evaluate statements using IAS scale. The modified statements from IAS scale can be seen in Table 1.

> Imagine that 10 years ago, you had the opportunity to invest in two retirement funds: **Fund A** and **Fund B**. For the past 10 years, you have invested all your retirement savings in Fund A. Would you want to know the balance you would have if you had invested in Fund B instead?

Figure 3. Foregone investment opportunity scenario from IPS scale. Reprinted from 'Measuring Information Preferences,' by E. Ho, D. Hagmann and G. Loewenstein, 2018, *SSRN Electronic Journal*.

[5] The same procedure to ensure understanding of probabilities was implemented by Van De Kuilen and Wakker (2011).

Table 1. Scenario adjusted items for Information Avoidance Scale

Item number	Item
1	I would rather not know my balance if I would have invested in Fund B.
2	I would avoid learning about possible balance with Fund B.
3	Even if it will upset me, I want to know potential balance with Fund B.
4	When it comes to knowing about the balance invested in alternative investment, ignorance is bliss.
5	I want to know the balance I would have had, if I had invested in Fund B instead.
6	I can think of situations in which I would rather not know the balance of the alternative investment.
7	It is important to know the balance I could have had, if I had invested in Fund B instead.
8	I want to know the balance I would have had with Fund B immediately.

Note. Items were adopted to the scenario from IPS scale.

Information avoidance was measured using multiple item scale, which allows to form information avoidance score for each participant individually and also analyze the scale on the item level. On the participant level, the obtained scores were optimized by taking the average of the response for each item per participant. For the optimized item scale, the average response from each participant per item is computed. For both optimized scales, items are weighted equally. Moreover, it is assumed that the distance between the responses for each question on the Likert scale is equal. Using the optimized IAS score for the hypothetical scenario, participants could get a minimum of 1 and a maximum of 7 points, with any value possible between these intervals. The maximum score of 7 means that a person is extremely information avoidant, whereas a score of 1 defines participant as a person who does not avoid information.

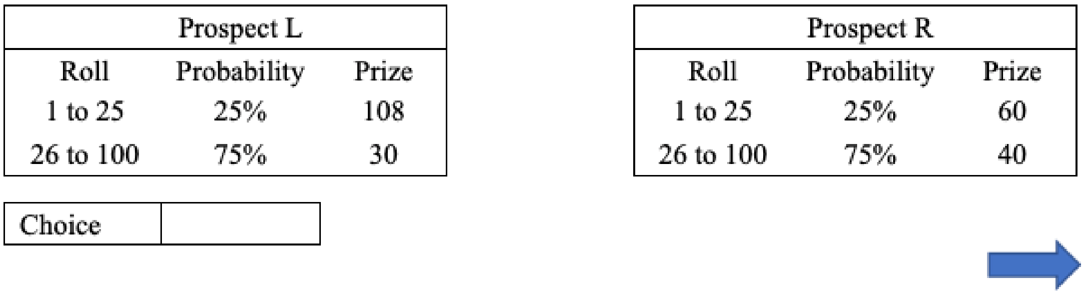
4.3.4 Eliciting Utility and Probability Midpoints under Risk

The tradeoff method was used to elicit utility midpoints and probability weighting function on the individual level. In this study, following method of Van De Kuilen and Wakker (2011), x_0 was set to 60, R = 30 and p = 0.25 and r = 40. All the values were presented in euro amount. Further, two points on the utility function, x_1 and x_2, were elicited using the following indifferences:

$$L = (\mathbf{x_1}{:}25\%, 30{:}75\%) \sim R\ (60{:}25\%, 40{:}75\%),$$

$$L = (\mathbf{x_2}{:}25\%, 30{:}75\%) \sim R\ (x_1{:}25\%, 40{:}75\%).$$

Figure 4 shows how the prospects were presented to the participants. Participants were asked to make a choice between Prospect L and Prospect R throughout the elicitation process. Further, the indifference interval was calculated based on the choice sequence of five questions.



Prospect L		
Roll	Probability	Prize
1 to 25	25%	108
26 to 100	75%	30

Prospect R		
Roll	Probability	Prize
1 to 25	25%	60
26 to 100	75%	40

Choice	

Figure 4. Example of the first x_1 elicitation question.

Table 2 shows an example of x_1 elicitation that is based on the median answers obtained during the survey.[6] For x_1 elicitation, the first interval was taken as [60, 156], which would consist of the true x_1 value for the participant. After participants answered the fifth question in one sequence, the average between the last interval [81, 84] was used as a value of x_1 for the given participant. The value of x_1 was rounded to the nearest whole number and used in further the elicitation of x_2. It is important to point out that in this study, x_1 and x_2 were elicited only once and directly used in the probability weighting function elicitation.

Table 2. Elicitation of x_1

Questions	Prospect L	Prospect R	Choice	Interval
1	**108**: 25%, 30: 75%	60: 25%, 40: 75%	L	60 - 156
2	**84**: 25%, 30: 75%	60: 25%, 40: 75%	L	60 - 108
3	**72**: 25%, 30: 75%	60: 25%, 40: 75%	R	60 - 84
4	**78**: 25%, 30: 75%	60: 25%, 40: 75%	R	72 - 84
5	**81**: 25%, 30: 75%	60: 25%, 40: 75%	R	78 - 84
				81 - 84
			x_1	83

Note. X_1 value is rounded to a whole number.

Table 3 shows an example of $w^{-1}(4/8)$ elicitation, which is based on the median answers of x_1, x_2, $w^{-1}(4/8)$ obtained during the survey. The average of the last interval [60, 63] was used as a value of $w^{-1}(4/8)$, which was rounded to the nearest whole number.

Table 3. Elicitation of $w^{-1}(4/8)$

Questions	Prospect L	Prospect R	Choice	Interval
1	83: 100%	107: **50%**, 60: **50%**	L	0% - 100%
2	83: 100%	107: **75%**, 60: **25%**	R	50% - 100%
3	83: 100%	107: **63%**, 60: **37%**	R	50% - 75%
4	83: 100%	107: **57%**, 60: **43%**	L	50% - 63%

[6] Median values are based on the reduced sample n=40 excluding heuristics and biased observations.

Questions	Prospect L	Prospect R	Choice	Interval
5	83: 100%	107: **60%**, 60: **40%**	L	57% - 63%
				60% - 63%
			$w^{-1}(4/8)$	62%

Note. $W^{-1}(4/8)$ value is rounded to a whole number.

4.3.5 Strategy Check Questions

Two strategy questions were asked at the end of the elicitation method to correctly elicit the utility midpoints and the subjective probabilities. Although, it is hard for people to understand the concept of the chained questions (Van De Kuilen & Wakker, 2011), it is still possible that some people would realize the structure of the questions and try to exploit it. Hence, participants were presented with the following questions, which were previously used in the study of Van De Kuilen and Wakker (2011): “Can you state briefly which method you used to determine your choice?” and “Was there any special reason for you to specially choose left more often, or specially choose right more often?” Participants were free to write their answers in any form. When the data were collected, the answers to the strategy check questions were evaluated by checking the key words.

4.4 Randomization

Randomization was used in this study to ensure that there are no order effects. Table 4 shows that the questions in the survey were divided into three different blocks. Within the information avoidance block, participants were always presented with the foregone investment opportunity scenario first. After that the order in which participants received IAS scale and subjective scenario uncertainty questions was randomized. For instance, after reading the scenario, 18 (29) participants were first asked to complete the IAS scale (scenario uncertainty questions) and then scenario uncertainty questions (IAS scale). Furthermore, two probability weighting function elicitation models were designed. Participants received either first or the second elicitation model with a random order. The first version of the model elicited probabilities $w^{-1}(4/8)$, w^{-1} (2/8), $w^{-1}(1/8)$, $w^{-1}(6/8)$, and $w^{-1}(7/8)$. In particular, 21 participants completed the first version of the elicitation model. The second version of the model elicited probabilities $w^{-1}(4/8)$, $w^{-1}(6/8)$, $w^{-1}(7/8)$, w^{-1} (2/8), and $w^{-1}(1/8)$. The second version was completed by 26 participants. Questions within the control questions block were not randomized. Further, the order in which information avoidance block and probability weighting function elicitation block was presented to the participants was randomized. For instance, 28 (19) participants first received questions from information avoidance block (probability weighting function elicitation block) and then answered questions from probability weighting function elicitation block (information avoidance block).

Table 4. Questions within randomization blocks

Block name	Questions included
Information avoidance block	Foregone investment opportunity scenario, IAS scale, and subjective scenario uncertainty
Probability weighting block	Two elicitation models
Control questions block	Demographic and time preferences questions

4.5 Design

Information avoidance level and probabilistic risk attitude were elicited using within-subject design. The data were obtained during one-to-one interviews. A personal interview was needed to reduce errors in the responses when the utility and probability weighting functions are elicited (Abdellaoui, 2000; Van De Kuilen & Wakker, 2011).

Data obtained through the interviews included dependent variable *IAS score*, independent variable β, and control variables α, *variance*, *time preference*, *gender*, *age*, *educational level*, *individualistic country*, *economic student*. Variables x_1, x_2, $w^{-1}(1/8)$, $w^{-1}(2/8)$, $w^{-1}(4/8)$, $w^{-1}(6/8)$, $w^{-1}(7/8)$ were used to determine α and β values. *Gender* and *individualistic country* are dummy variables which take a value of 1 when the participant is a male and from an individualistic county, and 0 otherwise, respectively. The optimized *IAS score* is a quasi-continuous variable, which forms a score for each participant and can be treated as an interval scale variable. Further, β, α and *variance* are continuous variables. Educational level is a categorical variable which takes a value of 1 when the student is enrolled in the Bachelor program, 2 in the Master program, 3 is a Ph.D. student. Likewise, time preference is a categorical variable which takes a value of 1 when participant future discounting is extremely high, 2 when it is high, 3 when the discounting neither high or low, 4 when the discounting is low, and 5 when it is extremely low. The variable *economic student* is a dummy variable which takes a value of 1 when the participant is enrolled in the study program from the School of Economic and 0 otherwise.

5. Data Sample

After the initial examination of the data, several biased answers were identified, and seven participants were excluded from the original sample due to the heuristic answers. Firstly, heuristics answers were identified if the elicited probabilities of the participants had the following values: $w^{-1}(p_{4/8}) > 0.98$, $w^{-1}(p_{4/8}) < 0.02$, $w^{-1}(p_{6/8}) > 0.98$, $w^{-1}(p_{6/8}) < 0.02$ (Van De Kuilen & Wakker, 2011). If these choices were observed, it could mean that participants either did not understand the prospects or made a mistake in one of the questions. It is important to remove participants from the sample with heuristic answers, because when the subjective probability for the first sequence of questions, $w^{-1}(p_{4/8})$, is above 0.98 (below 0.02), further elicitation questions would not be able to elicit further values, as the elicited value is already at the highest (lowest) point. After reviewing the answers, six participants answered questions for elicitation of probabilities $w^{-1}(p_{4/8})$ and/or $w^{-1}(p_{6/8})$ by always choosing Prospect L, resulting in subjective probabilities being 0.98. Thus, with these answers, further elicitation questions for measuring $w^{-1}(p_{7/8})$ should not be made. Biases in these answers were also observed during the interview, as these participants verbally indicated that the last questions were redundant. Moreover, among these participants, one of them answered $w^{-1}(p_{2/8})$, $w^{-1}(p_{4/8})$, $w^{-1}(p_{6/8})$ and $w^{-1}(p_{7/8})$ elicitation questions by always choosing Prospect L, resulting in a highly pessimistic profile (β of 99). Besides that, one participant answered questions for $w^{-1}(p_{4/8})$ elicitation by always choosing Prospect R, resulting in elicited subjective probability being 0.2. At the same time, none of the participants answered IAS scale questions with heuristics, having the same choices on the scale for original and reverse coded questions. Thus, the final number of observations after removing participants with heuristic answers is 40.

Table 5 presents the summary statistics for the experimental variables used in this study based on 40 observations. The median and mean β score is 1.266 and 1.797 points, respectively, whereas the median and mean α score is 1.006 and 1.142, respectively. The average avoidance score is 2.962 points with a standard deviation of 1.112. Moreover, 60% of the participants are male and 40% are female in the sample, with age between 19 and 33 years. This study uses a student sample out of which 65% are students in Economics. Furthermore, 70% of the participants are Master students, 27.5% are Bachelor students and 2.5% are Ph.D. students. Nationalities of the participants are varied. Individuals from 22 different countries were interviewed, with 27.5% having Dutch, 10% Italian and 10% Greek nationalities. The rest of the nationalities occur in the sample less than 10% each.[7] In the data, 57.5% of the subjects have nationality from countries which are considered to be individualistic, and 42.5% come from collectivistic countries.

---

[7] Other nationalities are Hungarian, Bulgarian, Egyptian, Syrian, Finnish, Uruguayan, Mexican, German, Brazilian, Surinamer, Indonesian, Spanish, Indian, Armenian, Russian, Moldovan, Slovakian, and Icelander.

Table 5. Descriptive statistics of experimental variables

Variables	Observations	Mean	Median	Frequency	SD	Min	Max
β	40	1.797	1.266	-	1.517	0.122	6.909
α	40	1.142	1.006	-	0.559	0.453	2.842
IAS score	40	2.962	2.687	-	1.112	1.25	7
Male	40	-	-	60%	-	0	1
Age	40	23.725	24	-	2.97	19	33
Educational level	40						
-Bachelor		-	-	27.5%	-	1	3
-Master		-	-	70%	-	1	3
-PhD		-	-	2.5%	-	1	3
Economics student	40	-	-	0.65	-	0	1
Individualistic	40	-	-	0.575	-	0	1
Time-preference	40						
-Extremely low		-	-	12.5%	-	2	5
-Low		-	-	80%	-	2	5
-Neither low or high		-	-	2.5%	-	2	5
-Hight		-	-	5%	-	2	5

Note. For binary and categorical variables frequencies are shown.

6. Results

In this section, the main results are presented. Section 6.1 includes the results of the tests measuring order effects, the internal consistency of the IAS scores, and strategy check. Afterwards, the results concerning the IAS scale, optimism, and the main hypothesis are presented in section 6.2. Further, the additional results are shown in Section 6.3.

6.1 Reliability

Before pulling the data together, the results of the several measures were tested for order effects, because it is plausible that the order in which the questions were given to the subject affected their answers. Firstly, neither of the measures, IAS scores, β, and α, were affected by the order in which the questions were given to the subjects (t-test: p_{IAS}=0.5222, p_{β}=0.1162, p_{α}=0.5129; Mann-Whitney U: p_{IAS}=0.7110, p_{β}=0.2340, p_{α}=0.3452). Furthermore, the order in which IAS scale and question to measure the subjective scenario uncertainty did not have a significant effect on the information avoidance measure (t-test: p=0.4342, Mann-Whitney U: p=0.1701). Thirdly, there are no order effects found in the data from probability weighting function elicitation (t-test: $p_{w^{-1}(\frac{1}{8})}$=0.9408, $p_{w^{-1}(\frac{2}{8})=}$=0.7953, $p_{w^{-1}(\frac{4}{8})}$=0.7063, p $p_{w^{-1}(\frac{6}{8})}$=0.9612, $p_{w^{-1}(\frac{7}{8})}$=0.9174, p_{β}=0.7477, p_{α}=0.9922; Mann-Whitney U: $p_{w^{-1}(\frac{1}{8})}$=0.6803, $p_{w^{-1}(\frac{2}{8})}$=0.9344, $p_{w^{-1}(\frac{4}{8})}$=0.5461, $p_{w^{-1}(\frac{6}{8})}$=1, $p_{w^{-1}(\frac{7}{8})}$=0.8235; p_{β}=0.9891, p_{α}=0.5564).

The strategy check questions did not show that subjects realized the chained nature of the questions or tried to exploit it. The majority of the responses for the first strategy check question (see section 4.3.5) included key words such as “computing the weighted average”, “expected average”, “expected return”, or “expected payoff.” Answers to the second strategy question were mostly "no." A few participants pointed out that the left option in probability weighting function prospects was more appealing to them, as it was "safer" than the right option.[8] All in all, the data should not be a subject to exploitation by the participants if the collected responses are truthful.

Cronbach’s alpha was used to establish the magnitude of internal consistency of the IAS scale. Cronbach’s alpha can range between 0 and 1, where a score of 0.7 and 0.8 is considered that the scale has an acceptable internal consistency (Gliem & Gliem, 2003). In this study, Cronbach’s alpha is 0.84 for IAS scale, which indicates that results of the scale have high internal consistency. Other studies that used IAS scale showed similar internal consistency (Howell & Schepperd, 2016; Losee, Shepperd, & Webster, 2018). Further, Cronbach’s alpha score can be influenced by the sample size. After determining minimum sample size for the scale used the relatively small sample size used in the analysis should not have any impact on the results of Cronbach’s alpha. [9]

6.2 Information Avoidance and Optimism

Information avoidance was analyzed at the participant and the item levels. On the participant level, the mean information avoidance is 2.96, which can be considered as somewhat not avoidant behavior. Figure 5 graphically shows mean avoidance scale on the interval between 1 and 7.

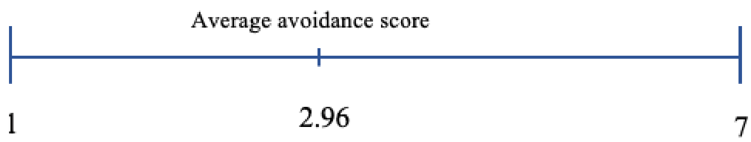


Figure 5. Optimized IAS score interval between 1 and 7.

[8] Three participants from the original sample with an indication that they preferred safer options, were excluded from the sample because their answers were heuristics, which is explained section 5; others with similar response had a high β estimate.

[9] To determine the minimum acceptable sample size for the reliable Cronbach’s alpha, calculation form the study by Bujang, Omar, and Baharum (2018) was used. The minimum sample size required to for Cronbach’s alpha to be 0.8 is approximately 19. Calculation of sample size is based on 8 statement scale evaluated on 7-point Likert scale.

The information avoidance score also varies between the statements. For instance, Table 6 provides the summary statistics for the information avoidance measure on the item scale. Considering mean for each item, the most avoidant behavior in the data was exhibited for questions “I can think of the situation in which I would rather not know the balance” and “I want to know immediately.” Overall, the evidence of information avoidance is pronounced in the data, although the majority of participants have low information avoidance scores.

Table 6. Average IAS item scale

Item	Scale mean	Standard Deviation
IAS_Q1	2,9	1,69
IAS_Q2	2,25	1,39
IAS_Q3	2,65	1,64
IAS_Q4	2,8	1,52
IAS_Q5	2,55	1,45
IAS_Q6	4	1,79
IAS_Q7	3,15	1,71
IAS_Q8	3,4	1,69
Total average	2,962	1,11

Note. The total average the average of the all item scores, not the average score subjects obtained.

Form the parameters of the probability weighting function, it is possible to determine the probabilistic risk attitude. The median β and α are 1.266 and 1.006, respectively, whereas β and α based on the median data are 1.282 and 0.897. Figure 6 shows that the median weighting function is convex. Further, median and mean β are above 1, meaning that most of the subject in the data can be classified as pessimistic.

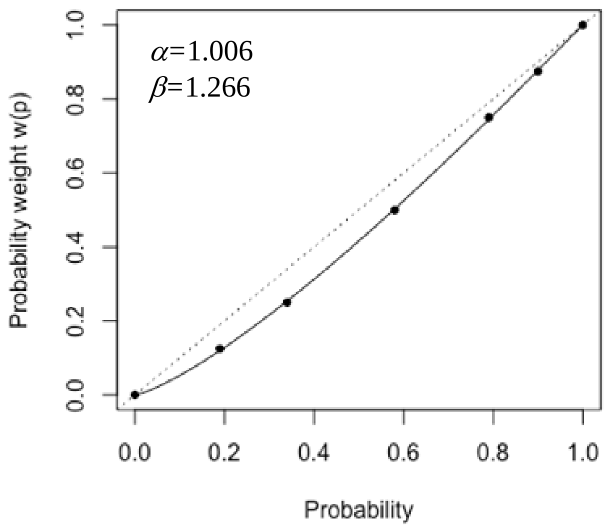


Figure 6. Median probability weighting function with parameters β and α are 1.266 and 1.006.

To examine the relationship between optimism and the information avoidance score, scatter plot and correlation tests were used. Figure 7 shows that the scatter plot does not show a clear linear relationship. Furthermore, Table 7 shows negative non-significant correlation between β and IAS score using Pearson's correlation test. Pearson's test assumes normal distribution of the variables. Although, IAS score is approximately normally distributed, variable of β is skewed to the right (see Appendix G). Therefore, to test the correlation between the variables rank correlation tests are used that do not assume normality in the data. Table 7 shows that the relationship between the variables appears to be positive using Spearman's ρ and Kendall's τ tests. However, the null hypothesis that there is no association between β and information avoidance score cannot be rejected as rank correlation tests do not show significant results. The sign change of correlation coefficients could be an indication of the non-linear relationship between the variables, because Pearson's test assumes linear relationship.

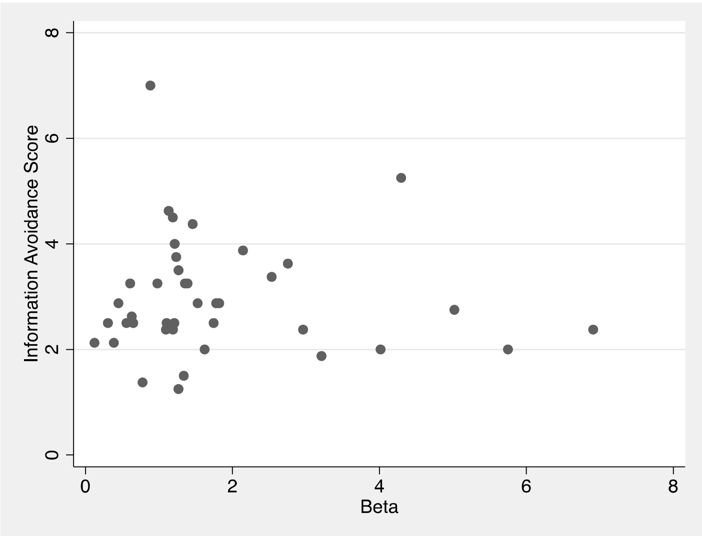


Figure 7. Scatter plot showing correlation of IAS score and β.

Table 7. Tests for correlation between IAS score and β

Correlation test	β
Pearson's ρ	-0.0543
	(0.7391)
Kendall's τ	0.0038
	(0.9813)
Spearman's ρ	0.0104
	(0.9494)

Note. P-values are reported in parenthesis.

Furthermore, polynomial transformations were used to test the non-linearity of the relationship between information avoidance and optimism. Table 8 shows the regression results with IAS score as a dependent variable. Based on the regression results of Model 1 and 3 it can be seen that the second-degree polynomial is a better predictor of the relationship between IAS score and β.[10] Based on the main hypothesis, it is expected that β and information avoidance level are negatively correlated. It can be seen from Table 8 in Model 4, that IAS score is positive at the small levels of β (β coefficient is 0.452), and at high levels of β it is negative (β^2 coefficient is -0.076). However, the coefficients of β are not statistically significant.

Table 8. OLS regression analysis determinants of information avoidance.

	IAS score			
	Model 1	Model 2 with controls	Model 3	Model 4 with controls
β	-0.040	-0.031	0.351	0.452
	(0.704)	(0.761)	(0.287)	(0.321)
β^2			-0.063	-0.076
			(0.131)	(0.228)
Constant	3.034***	7.508	2.675***	6.720**
	(0.000)	(0.003)	(0.000)	(0.011)
R^2	0.003	0.301	0.029	0.326
Observations	40	40	40	40

Note. Model 2 and Model 4 include control variables *α, variance, time preferences, male, age, educational level, individualistic country*, and *economic student* which are omitted from this table. P-values are reported in parenthesis. The significance level of 5% and 1% is indicated ** and ***, respectively. Standard errors are robust to heteroscedasticity.

6.3 Additional Results

To see whether the non-significant association between the variables is caused by the quality of the elicitation of the values on the utility and the probability weighting functions, or parametric specification of the probability weighting function further analysis is needed. First of all, the elicited values on the utility functions are analyzed. It is crucial to assess the quality of the elicited values, because the prospects to elicit probability weighting function are based on the elicited values of the utility midpoints for each participant. Furthermore, it is possible to analyze and check the quality of the elicited probability weighting function on the individual data. The information avoidance is further analyzed based on the classification groups by the shape of the probability weighting functions from the individual data.

[10] Higher degrees of polynomials were also tested but did not show any significant improvements from the results in Model 3.

6.3.1 Midpoints of the Utility Function

The linearity of the utility midpoint was analyzed with Wilcoxon signed-rank test. The median value of x_1 and x_2 are 83 and 107, respectively.[11] The linearity of the midpoints on the utility function can be rejected at 10% significance level when the equality of medians of the first differences between x_1 - x_0, and $x_2 – x_0$ denoted as $\Delta_i' = |x_i - x_{i-1}|$ (Abdellaoui, 2000) is tested (Wilcoxon signed-rank tests, z = 1.741, p = 0.0816). This result suggests non-linearity of the utility function. On the contrary, a linear utility for prospects with low values is established in the literature (Wakker & Deneffe, 1996; Abdellaoui et al., 2007; Van De Kuilen & Wakker, 2011).

The curvature of the utility function was assessed based on the classification of convex, concave, and linear shapes. To determine the curvature of the utility function within midpoints at the individual level, the sign of the second differences between the elicited x_i, calculated as $\Delta_j'' = \Delta_{i+1}' - \Delta_i'$ (Abdellaoui, 2000; Belichrodt & Pinto, 2000). When Δ_j'' is positive (negative) the slope of function can be classified as concave (convex), when Δ_j'' is equal to 0 it can be assumed that the slope on the midpoints is linear. Here, only midpoints of the sequence of the outcomes are elicited. Therefore, the classification is adopted to approximate the slope of the utility function between x_0, x_1, and x_2.[12] Using this classification, 13 participants exhibit concave utility function, 20 convex, and 7 have a linear utility function. When determining whether there are more convex utility functions than concave and the rest of the forms the binomial test is performed with H_0: p = 1/2; H_a: p > 1/2 and H_0: p = 1/3; H_0: p > 1/3, respectively. Comparing only convex and concave utility functions, it cannot be concluded that there are significant differences between the number of convex and concave utility functions at the individual level (p=0.148, one-sided test). Furthermore, taking into account all the shapes of the utility functions, the null hypothesis is rejected at 5% significance level, indicating that there are more convex utility functions in the data than the rest of the form (p=0.021, one-sided test).

[11] The median values are rounded to the nearest whole number.

[12] Literature suggests a stricter classification of the curvature of the utility functions. For instance, if three out of five Δ_j'' is positive (negative) the function is classified as concave (convex) (Abdellaoui, 2000; Belichrodt & Pinto, 2000).

A similar number of convex and concave utility functions at the individual level was found in the study of Van De Kuilen and Wakker (2011).[13]

6.3.2 Probability Weighting Function

The non-linearity in the perception of probabilities is observed when the probability functions were analyzed at the individual level. Table 9 shows that the results based on the one-sided Wilcoxon signed-rank test show that the probabilities were significantly underweighted, except probabilities related to the probability weights $w^{-1}(6/8)$ and $w^{-1}(7/8)$. Although, the underweighting of probabilities was also observed by Van De Kuilen and Wakker (2011), other studies show overweighting of small probabilities and underweighting of large probabilities (Abdellaoui, 2000; Belichrodt & Pinto, 2000).

Table 9. Summary of the probability weighting function

	w-1(p)-p		Summary statistics		
p	>0	<0	Median	Mean	Standard deviation
1/8	23*** (0.0049)	17	0.160	0.228	0.174
2/8	27*** (0.0009)	13	0.340	0.379	0.196
4/8	30** (0.0110)	10	0.615	0.604	0.233
6/8	27 (0.1087)	13	0.840	0.776	0.176
7/8	22 (0.4996)	18	0.900	0.842	0.154

Note. P-values are reported in parenthesis. The significance level of 5% and 1% are indicated by ** and *** respectively.

Additionally, the curvature of the probability weighting function was determined at the individual level to distinguish between the convex and concave probability weighting functions. The curvature between the elicited points can be determined by the sign of change in the average slope of the probability weighting function between the elicited points on the function (Belichrodt & Pinto, 2000). The following formula is used to calculate the average slope of the weighting function between the elicited points

$$\partial_{i-1}^{i} = \frac{w(p_i)-w(p_{i-1})}{p_i-p_{i-1}}. \quad (4)$$

[13] The findings of Van De Kuilen and Wakker (2011) show that there are 32 convex and 26 concave utility functions out of the sample of 64 university students.

The change in the average slope is denoted as ∇_{i-1}^{i}, which is the difference between $\partial_{i-1}^{i}$and ∂_{i-2}^{i}. To classify individual weighting function as convex (concave) at least three changes in the average slope between the elicited points on the function should be positive (negative), and the function should not have lower (upper) subadditivity (Bleichrodt & Pinto, 2000). Lower and upper subadditivity are the properties of the probability weighting function (Abdellaoui, 2000). Firstly, when $\nabla_{1/8}^{2/8}$ on the first two probability intervals is negative, a probably weighting function is classified as lower subadditive (Bleichrodt & Pinto, 2000).[14] When lower subadditivity is pronounced on the individual's probability weighting function, it means that individual places higher preference for a change from impossible events to possible than a change from possible to highly possible (Bleichrodt & Pinto, 2000). Similarly, when $\nabla_{7/8}^{1}$ on the last two intervals is positive, the function can be classified as upper subadditive.[15] This implies that a change from possible events to highly possible is preferred over a change from impossible to possible (Bleichrodt & Pinto, 2000).[16] Furthermore, a weighting function is classified to have an inverse-S shape form when the function exhibits both lower and upper subadditivity at the same time (Tversky & Wakker, 1995).

Based on the classification of the above-mentioned curvature of the probability weighting function, it is possible to distinguish between inverse-S shape, convex, and concave forms. Table 10 shows that 32.5% of the participants have inverse-S shape probability weighting function, 27.5% of the functions are concave, and 40% are convex. Probability functions on the individual level can be seen in Appendix H. Using binomial test to assess whether there are more convex probability weighting functions than concave and the rest of the forms, the test result shows that it cannot be concluded that there are significantly more convex probability weighting functions ($p=0.221$, $p=0.23$, one-sided, respectively).

Table 10. Probability weighting function classification

Shape	Proportion of subjects
Inverse-S shape	32.5%
Convex	40%
Concave	27.5%

[14] Lower subadditivity means that lower interval on the probability weighting function has a higher decision weight than the middle interval (Tversky & Wakker, 1995).
[15] When upper subadditivity is pronounced, the upper interval has a higher decision weight than the middle interval (Tversky & Wakker, 1995).
[16]In the literature lower and upper subadditivity are also referred as "possibility effect" and "certainty effect", respectively (Abdellaoui, 2000; Bleichrodt & Pinto, 2000).

Shape	Proportion of subjects
Lower Subadditivity	50%
Upper Subadditivity	60%

Note. Classification is based on the slope of the weighting function.

To show the relationship between information avoidance and optimism, only convex and concave probability weighting functions were used. Due to the fact that optimism depends on the curvature capacity of the probability weighting function, individuals that belong to inverse-S shape function can be either optimistic or pessimistic. The optimism within that category depends on the magnitude of the overestimation of small probabilities and underestimation of large probabilities. However, individual that belong to just concave or convex group can be only optimistic or pessimistic, respectively.

To test whether the information avoidance level is different for the optimistic and pessimistic groups, non-parametric and parametric analyses were used. Firstly, it is tested whether the distribution of IAS scores is different between the groups. It cannot be concluded that the distribution is different for optimistic and pessimistic groups (Mann-Whitney U: p=0.77). Further, OLS regression with concave as an independent dummy variable was performed, which is 1 when the individual probability weighting function is classified as concave and 0 if it is classified as convex. Table 11 shows that the relationship between IAS score and concave probability weighting function is positive, indicating that compared to pessimistic individuals, belonging to the optimistic (concave) group increases information avoidance by 0.033 points. However, the coefficients of concave variable are not statistically significant for Model 5 and Model 6.

Table 11. OLS regression analysis determinants of information avoidance.

	IAS score	
	Model 5	Model 6 with controls
Concave (optimistic)	0.044	0.033
	(0.906)	(0.945)
Constant	2.797***	5.874*
	(0.000)	(0.078)
R^2	0.0005	0.296
Observations	27	27

Note. Model 6 include control variables *variance, time preferences, male, age, educational level, individualistic country,* and *economic student* which are omitted from this table. P-values are reported in parenthesis. The significance level of 10% and 1% is indicated * and ***, respectively. Standard errors are robust to heteroscedasticity.

7. Discussion and Limitations

7.1 General Discussion

In this study, the relationship between information avoidance and optimism measured using β parameter of the Prelec (1998) probability weighting function was analyzed. It was hypothesized that information avoidance and the measure of optimism have a positive correlation. The β parameter increases with pessimism, meaning that based on the hypothesis, information avoidance score is negatively correlated with β. Based on the results, the relationship between the variable of β and information avoidance appears to be non-linear. The regression analysis shows that the model with the second degree of polynomial better explains the relationship between information avoidance measure and optimism, measured by the β parameter of the probability weighting function, than other forms. This indicates that when the level of β is low, more optimistic profile, the information avoidance increases with β, but for the high level of β, more pessimistic profile, the information avoidance decreases with β. However, the regression results and correlation tests did not find any significant association between the variables of information avoidance and β parameter. Therefore, it cannot be concluded from the regression analysis that β parameter is one of the predictors of information avoidance.

Additionally, the relationship between information avoidance and optimism, measured by the concavity of the probability weighting functions at the individual level was also examined. Although, the parametric analysis is found to approximate the shape of probability weighting function well (Gonzalez & Wu, 1999), it is arguable that the specification of the probability weighting function can influence the form of its shape.[17] Therefore, the analysis on relationship between the information avoidance score and optimism was performed using classification of shapes of the probability weighting functions at the individual. For this analysis, only concave and convex probability weighting functions were used to assess the relationship between information avoidance and individuals who belong to only optimistic or pessimistic group. The correlation between the variables of information avoidance score and optimistic group is positive, but the coefficient of optimistic group is highly insignificant.

[17] The relationship between the variables were also analyzed using similar two-parameter Goldstein and Einhorn (1987) probability weighting function. The same sign and significance of the correlation between information avoidance and optimism was found.

Therefore, it cannot be concluded that when individuals are optimistic, they have higher information avoidance level than pessimistic individuals.

Based on the results obtained in Section 6, no significant associations between the variables of optimism and information avoidance is found. Hence, it cannot be concluded that there is a connection between the information avoidance in the financial domain and optimism, measured by the β parameter of probability weighting function and by the curvature of the functions on the individual level. The non-significant results can be an indication of no relationship between the information avoidance and optimism measured using probability weighting function. However, the quality of the elicited variables needs to be discussed before drawing conclusions about the true association between information avoidance and optimism.

First of all, the obtained information avoidance scores in this study is compared to the information avoidance level found in the literature that uses similar scales to measure information avoidance. The results show that people in the current sample are somewhat not avoidant for the given scenario. Moreover, the internal consistency of the information avoidance measure is high using Cronbach's alpha. When comparing the information avoidance scores to the original study that introduced IAS scale, the mean value of the information score in this study is comparable to the results of Howell and Shepperd (2016).[18] Although, Howell and Shepperd (2016) have different domains of information avoidance that have been tested with the scale, such as health, attractiveness and partner faithlessness. Thus, comparing the current level of avoidance to the studies that analyzed it within similar domain can give better insights on the accuracy of the avoidance score in this study. Interestingly, the study of Ho et al. (2018) that previously used the same scenario about the foregone opportunities of investments for retirement funds shows higher avoidance level than it is found in this research.

Furthermore, based on the results in this study, the median probability weighting function is convex, which is comparable to the results of Van De Kuilen and Wakker (2011), although, contradicting findings of well-established literature on the shape of probability weighting function. Several scholars established that on average the probability function is concave on the interval with small probabilities and convex for the large probabilities, representing an inverse-S function (Abdellaoui, 2000; Bleichrodt, & Pinto, 2000; Abdellaoui,

[18] Howell and Shepperd (2016) present the results that show mean item scale varies from 2.3 to 2.6 points for health domain with Cronbach's alpha above 0.88, from 3.9 to 4.2 points for personal attractiveness with Cronbach's alpha above 0.85, and from 1.5 to 2 points for partner faithlessness.

Bleichrodt, & l'Haridon, 2008). On the contrary, this study did not find any evidence to confirm that the probability weighting function takes an inverse-S shape, confirming results from the study of Van De Kuilen and Wakker (2011). Moreover, there are also other scholars that find evidence against the established shape of the probability weighting function (Birnbaum & Chavez, 1997; Armantier & Treich, 2009). Hence, it is plausible that different methods of elicitation have an impact on the shape of the probability weighting function or there are some limitations in the elicitation method that was used in this study.

Moreover, the quality of elicited values on the utility function can influence the accuracy of the results of the probability weighting function. The analysis of the concavity of the utility function at the individual level show that there are more convex utility functions than the other forms. Other scholars that elicit utility and probability weighting functions using high value prospects, found that the median utility function is concave, contrary to the results of this study (Tversky & Kahneman, 1992; Abdellaoui, 2000). In this study, small values were used in the prospect to elicit utility midpoints. Van De Kuilen and Wakker (2011) found that the elicited midpoints form linear utility function for the small value prospects. Based on the obtained results and the findings in the literature, it is plausible to assume that the obtained utility midpoints are subject to an elicitation error. Although, predominance of convex utility function can be also seen in the study of Jullien and Salanié (2000), Goeree, Holt, and Palfrey (2002), and Van De Kuilen & Wakker (2011).

A possible explanation that the relationship between optimism and the information avoidance score is not significant in this study, can be due to the differences in definitions of optimism. There are notable distinctions in the evaluation of the optimistic profile used in the literature. Psychology scholars test for optimism in a way how people think about positive and negative events (Scheier et al., 2001). For instance, the most common approach is to test for dispositional optimism using Life Orientation Test (LOT) (Scheier & Carver, 1985, 1987). On the other hand, economic literature evaluates optimism by the revealed preferences (Kahneman & Tversky, 1979; Wakker, 2001). It is important to note that there are some studies that indicate a relation between optimistic emotion and whether people attach subjective probabilities to the events. For instance, Bleichrodt, L'Haridon, and Van Ass (2018) have tested optimism of professional hockey players by establishing the properties of probability weighting function. However, there is little research done on the actual correlation of the two concepts of optimism. Hence, it cannot be assumed that optimism in general is not correlated to the information avoidance, albeit the insignificant correlation in this study.

7.2 Limitations

Given the findings in this study, it is important to discuss the limitations that have possibly affected the outcome of analyses. First of all, the considerably low sample size used in this study might have an impact on the regression analysis results. Due to the importance of the personal interview, it is hard to gain a large sample size. Other scholars that elicit probability weighting function mostly do not have a much larger sample size than it is used in this study (Abdellaoui, 2000; Bleichrodt, & Pinto, 2000; Etchart-Vincent, 2009; Van De Kuilen & Wakker, 2011). Therefore, the validity of the measure of optimism using probability weighting function should not be affected by the small sample size. Although, it is plausible that to assess the true association between variables of information avoidance and optimism, measured using β parameter, a much larger sample size should be used. Furthermore, the quality of the data is subject to how well participants understood the prospects. As it was discussed in Section 4, personal interview is crucial in the elicitation process. During the interviews, I observed that many participants did not pay attention to the prospects, even when the changes between the prospects were pointed out. Thus, almost 15% of the participants was excluded from the original sample and it is questionable whether the rest of the responses were reliable. Moreover, the elicitation of utility midpoints was done only once, which deviates from the original midweight method of Van De Kuilen & Wakker (2011). This limitation can affect the validity of the elicited midpoints in this study. Additionally, there were no consistency questions in the utility function elicitation, compared to the study of Abdellaoui (2000). Thus, including the questions to check the consistency of the answers for the midpoints on the utility could have helped to make the results more reliable.

8. Conclusion

This study aimed to analyze the relationship between information avoidant behavior and optimism. It is important to assess the relationship between these two concepts within personal financial decision-making, because recent surveys in financial literature indicate that consumers of financial products lack the desire to obtain the information that can help them make optimal decisions for their personal finances. It was hypothesized that people who are more optimistic show more avoidant behavior towards financial information. To test this hypothesis, an experiment was conducted. The data were collected at Erasmus University Rotterdam, and each individual was interviewed personally.

Several measures were used in the experiment. IAS with a combination of the financial scenario from IPS were used to elicit information avoidant behavior. The optimistic profile of participants was measured by the parameters of probability weighting function. The probability weighting functions of each individual were elicited using a non-parametric elicitation method designed by Van De Kuilen and Wakker (2011). Further, the parameters of the probability weighting functions were determined using parametric analysis with Prelec (1998) probability weighting function.

Based on the results in this study, participants on average can be identified as pessimistic and somewhat not avoidant. The results show that the median β parameter is above one, which is an indication that the majority of the participants in the sample have a pessimistic profile. The median probability weighting function is convex, contrary to well-established literature that finds an inverse-S shape median probability weighting function. Concerning the information avoidance score, on average participants were somewhat not avoidant to the provided financial scenario.

The regression analysis suggests that the relationship between variables of information avoidance and optimism is non-linear. However, no significant correlation between the variables was found. Additional results also do not establish significant correlation between information avoidance score and optimistic group of participants. Hence, in this study, there is no indication that optimism is significantly correlated with information avoidance in the financial domain. Nevertheless, it cannot be concluded that optimism does not influence the level of avoidance due to the differences in a measure of optimism in economic and psychology literature.

For the future research, there are some important limitations in this study that should be addressed. First of all, a larger sample size is needed to assess the relationship between information avoidance and optimism, measured using parameters of probability weighting function. A large sample size would allow to determine whether the insignificance is due to the low sample size of due to the no correlation between the variables. Besides having a large sample size, it is also important to make sure whether the sample is diverse. This study used only university students due to time and availability constraints, further research can expand the sample to the more representative body of participants. Moreover, the results regarding utility and probability weighting functions do not confirm the results from well-established literature in behavioral economics. Although, the results of this study are comparable with the results of midweight methods used to elicit the probabilistic risk attitude. Hence, to have a more defined conclusion about the relationship between information avoidance and optimism, other elicitation methods for probability weighting function need to be used. Further research can also benefit from not only establishing optimistic profile with probability weighting function, but also using alternative tests from psychology literature. The results then can show whether optimism, using various definitions, is associated with information avoidant behavior. Besides using different measures for optimism, it can be beneficial to examine other measures of information avoidance. Although in this study, the IAS scale was found to have high internal consistency and reliability, observing actual behavior as a measure of information avoidance can provide additional insights into the behavior of participants by eliminating the subjective interpretation of statements and biased responses.

References

Abdellaoui, M. (2000). Parameter-free elicitation of utility and probability weighting functions. *Management science*, *46*(11), 1497-1512.

Abdellaoui, M., Bleichrodt, H., & l'Haridon, O. (2008). A tractable method to measure utility and loss aversion under prospect theory. *Journal of Risk and uncertainty*, *36*(3), 245.

Abdellaoui, M., l'Haridon, O., & Zank, H. (2010). Separating curvature and elevation: A parametric probability weighting function. *Journal of Risk and Uncertainty*, *41*(1), 39-65.

Akter, S., & Bennett, J. (2013). Preference uncertainty in stated preference studies: facts and artefacts. *Applied Economics*, *45*(15), 2107-2115.

Armantier, O., & Treich, N. (2009). Subjective probabilities in games: An application to the overbidding puzzle. *International Economic Review*, *50*(4), 1079-1102.

Armin, F., Becker, A., Dohmen, T., Huffman, D., & Sunde, U. (2016). The Preference Survey Module: A Validated Instrument for Measuring Risk, Time, and Social Preferences. *SSRN Electronic Journal*.

Armor, D. A., & Taylor, S. E. (1998). Situated optimism: Specific outcome expectancies and self-regulation. In *Advances in experimental social psychology* (Vol. 30, pp. 309-379). Academic Press.

Arrow, K. J. (1972). Economic welfare and the allocation of resources for invention. In *Readings in industrial economics* (pp. 219-236). Palgrave, London.

Åstebro, T., Mata, J., & Santos-Pinto, L. (2014). Skewness seeking: risk loving, optimism or overweighting of small probabilities?. *Theory And Decision*, *78*(2), 189-208.

Beattie, J., & Loomes, G. (1997). The Impact of Incentives Upon Risky Choice Experiments. *Journal of Risk and Uncertainty*, 14(2), 155-168.

Ben-David, I., Graham, J. R., & Harvey, C. R. (2013). Managerial miscalibration. *The Quarterly Journal of Economics*, *128*(4), 1547-1584.

Blajer-Gołębiewska, A., Wach, D., & Kos, M. (2018). Financial risk information avoidance. *Economic research-Ekonomska istraživanja*, *31*(1), 521-536.

Bleichrodt, H., L'Haridon, O., & Van Ass, D. (2018). The risk attitudes of professional athletes: Optimism and success are related. *Decision*, *5*(2), 95-118.

Bleichrodt, H., & Pinto, J. (2000). A Parameter-Free Elicitation of the Probability Weighting Function in Medical Decision Analysis. *Management Science*, *46*(11), 1485-1496.

Birnbaum, M. H., & Chavez, A. (1997). Tests of theories of decision making: Violations of branch independence and distribution independence. *Organizational Behavior and human decision Processes*, *71*(2), 161-194.

Brunnermeier, M. K., & Parker, J. A. (2005). Optimal expectations. *American Economic Review*, *95*(4), 1092-1118.

Budescu, D. V., & Fischer, I. (2001). The same but different: an empirical investigation of the reducibility principle. *Journal of Behavioral Decision Making*, *14*(3), 187-206.

Bujang, M., Omar, E., & Baharum, N. (2018). A Review on Sample Size Determination for Cronbach's Alpha Test: A Simple Guide for Researchers. *Malaysian Journal Of Medical Sciences*, *25*(6), 85-99.

Camerer, C. F. (1989). An experimental test of several generalized utility theories. *Journal of Risk and uncertainty*, *2*(1), 61-104.

Caplan, L. S. (1995). Patient delay in seeking help for potential breast cancer. *Public health reviews*, *23*(3), 263-274.

Carrillo, J., & Mariotti, T. (2000). Strategic Ignorance as a Self-Disciplining Device. *Review Of Economic Studies*, *67*(3), 529-544.

Davidson, L. B., & Cooper, D. O. (1976). A simple way of developing a probability distribution of present value. *Journal of Petroleum Technology*, *28*(09), 1-069.

Diecidue, E., & Wakker, P. (2000). On The Intuition Of Rank-Dependent Utility. *SSRN Electronic Journal*.

Elliot, A., Chirkov, V., Kim, Y., & Sheldon, K. (2001). A Cross-Cultural Analysis of Avoidance (Relative to Approach) Personal Goals. *Psychological Science*, *12*(6), 505-510.

Etchart-Vincent, N. (2009). Probability weighting and the 'level' and 'spacing' of outcomes: An experimental study over losses. *Journal of Risk and Uncertainty*, *39*(1), 45-63.

Fehr-Duda, H., & Epper, T. (2012). Probability and Risk: Foundations and Economic Implications of Probability-Dependent Risk Preferences. *Annual Review Of Economics*, *4*(1), 567-593.

Fehr-Duda, H., Epper, T., Bruhin, A., & Schubert, R. (2011). Risk and rationality: The effects of mood and decision rules on probability weighting. *Journal of Economic Behavior & Organization*, *78*(1-2), 14-24.

Fennema, H., & Wakker, P. (1997). Original and cumulative prospect theory: A discussion of empirical differences. *Journal of Behavioral Decision Making*, *10*(1), 53-64.

Frank, J. M. (2011). Do credit card users systematically underestimate their interest rates? Evidence from the Survey of Consumer Finances. *Journal of Public Policy & Marketing*, *30*(1), 133-139.

Galai, D., & Sade, O. (2006). The "ostrich effect" and the relationship between the liquidity and the yields of financial assets. *The Journal of Business*, *79*(5), 2741-2759.

Ghirardato, P., Maccheroni, F., Marinacci, M., & Siniscalchi, M. (2003). A Subjective Spin on Roulette Wheels. *Econometrica*, *71*(6), 1897-1908.

Gliem, J. A., & Gliem, R. R. (2003). Calculating, interpreting, and reporting Cronbach's alpha reliability coefficient for Likert-type scales. Midwest Research-to-Practice Conference in Adult, Continuing, and Community Education.

Goeree, J. K., Holt, C. A., & Palfrey, T. R. (2002). Quantal response equilibrium and overbidding in private-value auctions. *Journal of Economic Theory*, *104*(1), 247-272.

Goldstein, W. M., & Einhorn, H. J. (1987). Expression theory and the preference reversal phenomena. *Psychological review*, *94*(2), 236.

Golman, R., Hagmann, D., & Loewenstein, G. (2017). Information Avoidance. *Journal Of Economic Literature*, *55*(1), 96-135.

Golman, R., & Loewenstein, G. (2016). Information gaps: A theory of preferences regarding the presence and absence of information. *Decision*, *5*(3), 143-164.

Gonzalez, R., & Wu, G. (1999). On the shape of the probability weighting function. *Cognitive psychology*, *38*(1), 129-166.

Hershey, J., & Schoemaker, P. (1985). Probability Versus Certainty Equivalence Methods in Utility Measurement: Are they Equivalent?. *Management Science*, *31*(10), 1213-1231.

Ho, E., Hagmann, D., & Loewenstein, G. (2018). Measuring Information Preferences. *SSRN Electronic Journal*.

Hofstede, G. (2001). *Culture's consequences: Comparing values, behaviors, institutions, and organizations across nations*. Thousand Oaks, CA: Sage Publications.

Holt, C., & Laury, S. (2002). Risk Aversion and Incentive Effects. *SSRN Electronic Journal*.

Howell, J., & Shepperd, J. (2016). Establishing an Information Avoidance Scale. *Psychological Assessment*, *28*(12), 1695-1708.

Huck, S., Szech, N., & Wenner, L. M. (2017). *More effort with less pay: On information avoidance, optimistic beliefs, and performance* (No. SP II 2015-304r2). WZB Discussion Paper.

Jang, S., Shen, W., Allen, T., & Zhang, H. (2017). Societal individualism-collectivism and uncertainty avoidance as cultural moderators of relationships between job resources and strain. *Journal Of Organizational Behavior*, *39*(4), 507-524.

Jullien, B., & Salanié, B. (2000). Estimating preferences under risk: The case of racetrack bettors. *Journal of Political Economy*, *108*(3), 503-530.

Kahlor, L., Dunwoody, S., Griffin, R., & Neuwirth, K. (2006). Seeking and Processing Information about Impersonal Risk. *Science Communication*, *28*(2), 163-194.

Kahneman, D., Diener, E., & Schwarz, N. (Eds.). (1999). *Well-being: Foundations of hedonic psychology*. Russell Sage Foundation.

Kahneman, D.., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, *47*(2), 363-391.

Karlsson, N., Loewenstein, G., & Seppi, D. (2009). The ostrich effect: Selective attention to information. *Journal Of Risk And Uncertainty*, *38*(2), 95-115.

Lench, H. C. (2009). Automatic optimism: The affective basis of judgments about the likelihood of future events. *Journal of Experimental Psychology: General*, *138*(2), 187.

Lewandowski, M. (2017). Prospect theory versus expected utility theory: Assumptions, predictions, intuition and modelling of risk attitudes. *Central European Journal of Economic Modelling and Econometrics*.

Losee, J., Shepperd, J. A., & Webster, G. D. (2018). Financial Resources and Decisions to Avoid Information about Environmental Perils.

McCloud, R., Jung, M., Gray, S., & Viswanath, K. (2013). Class, race and ethnicity and information avoidance among cancer survivors. *British Journal Of Cancer*, *108*(10), 1949-1956.

Meechan, G., Collins, J., & Petrie, K. (2002). Delay in seeking medical care for self-detected breast symptoms in New Zealand women. *The New Zealand Medical Journal (Online)*, *115*(1166).

Miles, A., Voorwinden, S., Chapman, S., & Wardle, J. (2008). Psychologic predictors of cancer information avoidance among older adults: the role of cancer fear and fatalism. *Cancer Epidemiology and Prevention Biomarkers*, *17*(8), 1872-1879.

Oster, E., Shoulson, I., & Dorsey, E. (2016). Optimal Expectations and Limited Medical Testing: Evidence from Huntington Disease: Corrigendum. *American Economic Review, 106*(6), 1562-1565.

Prelec, D. (1998). The probability weighting function. *ECONOMETRICA-EVANSTON ILL, 66*, 497-528.

Ruggeri, M., & Coretti, S. (2015). Do Probability and Certainty Equivalent Techniques Lead to Inconsistent Results? Evidence from Gambles Involving Life-Years and Quality of Life. *Value In Health*, *18*(4), 413-424.

S&P 500 Historical Annual Returns. (2019). Retrieved 23 September 2019, from https://www.macrotrends.net/2526/sp-500-historical-annual-returns

Scheier, M. F., & Carver, C. S. (1985). Optimism, coping, and health: assessment and implications of generalized outcome expectancies. *Health psychology*, *4*(3), 219.

Scheier, M. E., & Carver, C. S. (1987). Dispositional optimism and physical well-being: The influence of generalized outcome expectancies on health. *Journal of personality*, *55*(2), 169-210.

Scheier, M. F., Carver, C. S., & Bridges, M. W. (2001). Optimism, pessimism, and psychological well-being. *Optimism and pessimism: Implications for theory, research, and practice*, *1*, 189-216.

Schreier, S. S., Heinrichs, N., Alden, L., Rapee, R. M., Hofmann, S. G., Chen, J., Oh, K. J., & Bögels, S. (2010). Social anxiety and social norms in individualistic and collectivistic countries. *Depression and anxiety*, *27*(12), 1128-1134.

Shah, P., Harris, A., Bird, G., Catmur, C., & Hahn, U. (2016). A pessimistic view of optimistic belief updating. *Cognitive Psychology*, *90*, 71-127.

Sicherman, N., Loewenstein, G., Seppi, D. J., & Utkus, S. P. (2015). Financial attention. *The Review of Financial Studies*, *29*(4), 863-897.

Sullivan, P. S., Lansky, A., Drake, A., & HITS-2000 Investigators. (2004). Failure to return for HIV test results among persons at high risk for HIV infection: results from a multistate interview project. *JAIDS Journal of Acquired Immune Deficiency Syndromes*, *35*(5), 511-518.

Sweeny, K., Melnyk, D., Miller, W., & Shepperd, J. (2010). Information Avoidance: Who, What, When, and Why. *Review Of General Psychology*, *14*(4), 340-353.

Taber, J., Klein, W., Ferrer, R., Lewis, K., Harris, P., Shepperd, J., & Biesecker, L. (2015). Information Avoidance Tendencies, Threat Management Resources, and Interest in Genetic Sequencing Feedback. *Annals of Behavioral Medicine*, *49*(4), 616-621.

Tversky, A., & Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal Of Risk And Uncertainty*, *5*(4), 297-323.

Tversky, A., & Wakker, P. (1995). Risk Attitudes and Decision Weights. *Econometrica*, *63*(6), 1255.

Van De Kuilen, G., & Wakker, P. P. (2011). The midweight method to measure attitudes toward risk and ambiguity. *Management Science*, *57*(3), 582-598.

Vind, K. (1991). Independent preferences. *Journal Of Mathematical Economics*, *20*(1), 119-135.

Wakker, P. (2001). Testing and Characterizing Properties of Nonadditive Measures Through Violations of the Sure-Thing Principle. *Econometrica*, *69*(4), 1039-1059.

Wakker, P., & Deneffe, D. (1996). Eliciting von Neumann-Morgenstern Utilities When Probabilities Are Distorted or Unknown. *Management Science*, *42*(8), 1131-1150.

Webb, C., & Zank, H. (2011). Accounting for optimism and pessimism in expected utility. *Journal Of Mathematical Economics*, *47*(6), 706-717.

Weinstein, N. D. (1980). Unrealistic optimism about future life events. *Journal of personality and social psychology*, *39*(5), 806.

Yang, Z., & Kahlor, L. (2012). What, Me Worry? The Role of Affect in Information Seeking and Avoidance. *Science Communication*, *35*(2), 189-212.

Appendix A

Original Information Avoidance Scale

Table A1

Item Stems for the Information Avoidance Scale

Item number	Stem
1	I would rather not know _______.
2	I would avoid learning _______.
3	Even if it will upset me, I want to know _______. (R)
4	When it comes to _______, [sometimes] ignorance is bliss.
5	I want to know _______. (R)
6	I can think of situations in which I would rather not know _______.
7	It is important to know _______. (R)
8	I want to know _______ immediately. (R)

Notes: R = reverse coded. For Item 4. 'sometimes' is optional.

Appendix B

Rank-dependent models

RDU and CPT models allow determining the rank of the worst and the best outcomes to estimate the decision weights attached to the probabilities of outcomes (Fehr-Duda & Epper, 2012). Under RDU the decision weights (πi) are defined as

$$\pi_i = \begin{cases} w(p_1) & for\ i = 1, \\ w\left(\sum_{k=1}^{i} p_k\right) - w\left(\sum_{k=1}^{i-1} p_k\right) & for\ 2 \le i \le n, \end{cases} \qquad (1)$$

for the prospect P = (x_1: p_1, …, x_n: p_n), where x_i is the prospect outcome, p_i is the probability and $x_1>\ldots>x_n$ (Fehr-Duda & Epper, 2012). The utility function and the weighting function are continuous and strictly increasing, with u(0) = 0 and w(0) = 0 and w(1) = 1. The RDU formula takes the following form

$$V_{RDU}(P) = \sum_{i}^{n} \pi_i u(x_i). \qquad (2)$$

Under CPT, the decision weights are determined by the probability distribution (Tversky & Kahneman, 1992; Fehr-Duda & Epper, 2012). The rank and the sign of the outcomes are modeled with respect to the reference point (Fehr-Duda & Epper, 2012). Empirically, the probability weighting function is defined as $w^+(p_i)$ for gains and $w^-(p_i)$ for losses (Abdellaoui, 2000). The CPT formula for the prospect P = (x_1: p_1, …, x_n: p_n) has the following form with $x_1>\ldots>0>\ldots>x_n$

$$V_{CPT}(P) = \sum_{i=1}^{k} \pi_i^- u(x_i) + \sum_{i=k+1}^{n} \pi_i^+ u(x_i), \qquad (3)$$

where π^+ is a decision weight for gains and π^- is a decision weight for losses.[19]

[19] Where decision weights are determinate by $\pi^+ = w^+(p_i+\ldots+p_n)-w^+(p_{i+1}+\ldots+p_n)$ for k+1<i<n-1 and $\pi^-=w^-(p_1+\ldots+p_i)-w^-(p_1+\ldots+p_{i-1})$ for 2<i<k (Fennema & Wakker, 1997).

Appendix C

Tradeoff method

By using the TO method, the sequence of outcomes can be determined when prospects have two reference outcomes R and r, where R≥r, and the starting outcome $x_{0.}$ Then, x_j is determined by indifference between the prospects [p:R, 1-p, x_{j-1}] and [p:r, 1-p, x_1], where R≥x_{j-1} and r≥$x_{j,}$ for the standard sequence of outcomes for which U(x_i)-U(x_{i-1})=U(x_j)-U(x_{j-1}) for 1≤i, j≤k (Wakker & Deneffe, 1996; Bleichrodt & Pinto, 2000). These outcomes, x_0, …, x_n, are then used to determine the standard sequence of probabilities. Firstly, the standard sequence of probabilities can be measured with the indifference (x_i:1, x_0) ~ (x_n: p_i; x_0: 1-p_i), with i=1, …, n-1(Abdellaoui, 2000). Then the probability function can be elicited as the probabilities are determined in a sequence using the indifferences and based on the cumulative theories $w(p_i) = \frac{i}{n}$ (Abdellaoui, 2000)

Appendix D

Midweight Method Elicitation Techniques

The highest point for the indifference interval is set to x_0+96 (Van De Kuilen & Wakker, 2011). Thus, the first point interval, which contains x_1, is [x_0, x_0+96]. For the first question, participants are presented with x_1 value which is calculated as an average between the lowest and the highest point on the first interval, (x_0+(x_0+96))/2. Further, the interval is being narrowed down depending on the subject's choice. If subject chooses left prospect it means that midpoint (x_0+(x_0+96))/2 exceeded x_1 and the interval is reduced to [x_0, (x_0+(x_0+96))/2]. If right prospect is chosen, then the interval is between (x_0+(x_0+96))/2 and x_0+96.[20] For each question, x_1 is being narrowed down with the length of $96*2^{-i}$, with i≥2. Furthermore, the same procedure is used for x_2 elicitation.[21] Van De Kuilen and Wakker (2011) elicit utility midpoints twice for each participant and take the average of elicited x_1 and x_2 to ensure the reliability of the measure.

For probability weighting function elicitation, the elicitation process starts with obtaining probability $w^{-1}(4/8)$ using indifference (x_1:1, x_0) ~ (x_2: a+g_i; x_0: 1-a+g). In the midweight method a+g is the midpoint used between the lowest (0) and the highest (1) probabilities. More specifically, the first indifference is between getting x_1 with the certainty and a lottery that consist of getting x_2 with probability 0.5 and x_0 with probability (1-0.5). The indifference interval starts from [0,1]. If the subject chooses left (right) prospect, then the midpoint of [0,1] is larger (smaller) than 0.5. Thus, depending on the choice between left and right prospects, the interval is narrowed down with a length of 2^{-i}, with i≥2 for five subsequent questions.

Further, low probabilities, $w^{-1}(1/8)$ and w^{-1} (2/8), are elicited differently than the large probabilities, $w^{-1}(6/8)$ and $w^{-1}(7/8)$. The elicited probability $w^{-1}(4/8)$ is used for the next indifference (x_1: $w^{-1}(4/8)$, x_0:1- $w^{-1}(4/8)$) ~ (x_2: a+g_i; x_0: 1-a+g) to elicit probability w^{-1} (2/8) with interval [0, $w^{-1}(4/8)$). At the same time, $w^{-1}(4/8)$ is used to determine $w^{-1}(6/8)$ with the indifference interval (x_2: $w^{-1}(4/8)$, x_1:1- $w^{-1}(4/8)$) ~ (x_2: a+g_i; x_0: 1-a+g) and the interval [$w^{-1}(4/8)$, 1].

[20] For the consequent questions, if x_0 denotes as l and x_0+96 as u then the indifference interval varies for left prospect choices as [l^{i+1},(l^{i+1}+u^{i+1})/2) and for the right prospect choice [l^{i+1}+u^{i+1})/2,u^{i+1}) with i=1, 2, … 5.
[21] To be able to elicit x_2, the value of elicited x_1 should be placed instead of x_0.

Appendix E

Subjective uncertainty measure

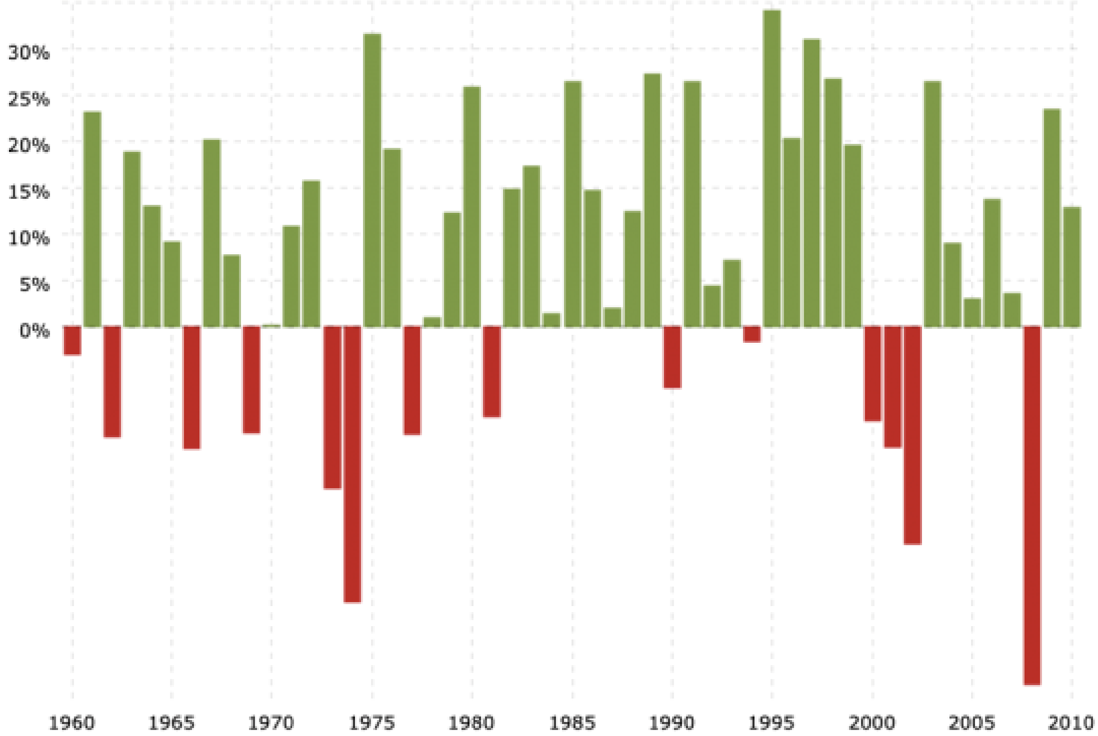
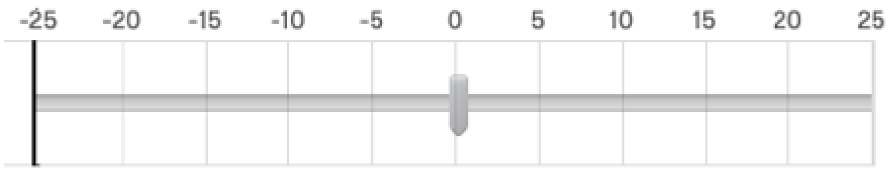
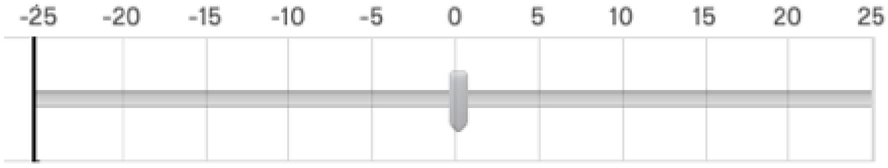


Figure B1. Historical return of hypothetical fund B used in the survey. Reprinted from the Macrotrends LLC, S&P 500 Historical Annual Returns, 2019, Retrieved from https://www.macrotrends.net/2526/sp-500-historical-annual-returns.

What is the highest annual average percentage return on fund B that you would expect over the investment period of 10 years?



What is the lowest annual average percentage return on fund B that you would expect over the investment period of 10 years?



Appendix F

Experimental instructions

General instruction received in the beginning of the survey

Dear Participant,

Thank you for taking time to participate in the research for my master thesis. This research is aimed to estimate the connection between information preferences and probabilistic risk attitude. Please be assured that the collected information will be kept with strict confidentiality.

During this session, I will ask you several questions. Please be aware that there are no incorrect answers and try to answer each question as accurately and honestly as possible.

Your participation is highly valuable for this research. Participation is voluntary, and you may refuse to participate at any time. For participating in this survey, you will have a chance to participate in the lottery by providing your email address at the end of the survey. The prizes for the lottery are 25 Euro, 10 Euro and 5 Euro.

If you have any questions during the survey, please do not hesitate to ask them.

Instruction before elicitation of probability weighting function

In this section, you will be asked to make a number of choices between two so-called "prospects." Both prospects yield prizes depending on the roll of the two 10-sided dice, similar to the ones that are on your table right now.

As you can see, one 10-sided die has the values 0, 1, 2, 3, 4, 5, 6, 7, 8, and 9 and the other 10-sided die has the values 00, 10, 20, 30, 40, 50, 60, 70, 80, and 90.

Prospect *L*			Prospect *R*		
Roll	Probability	Prize	Roll	Probability	Prize
1 to 40	40%	€100	1 to 20	20%	€150
41 to 100	60%	€50	21 to 100	80%	€20

If we code the sum of the roll “a 0 and a 00” as 100, then the sum of a roll with both 10-sided dice yields a random number from 1 up to 100. The prospects from which you have to choose are called **Prospect L (left)** and **Prospect R (right)**, and are presented in the following way:

In this case, Prospect L yields a prize of 100 Euro if the sum of the roll with both 10-sided dice is 1 up to 40 and if the sum of a roll is 41 up to 100, Prospect L yields a prize of 50 Euro. Similarly, Prospect R yields a prize of 150 Euro if the sum of a roll with both 10-sided dice is 1 up to 20 and otherwise Prospect R yields a prize of 20 Euro. You can use the dice on your table to better understand the prospects above. Both the prizes, as well as the probabilities of yielding certain prizes can vary across decisions.

When you feel comfortable with these concepts, please switch to the Excel file on this computer for further instructions.

In this part you will be asked a series of questions similar to the example question you just saw. If you have troubles understanding the example question, please come back to it and read the explanation one more time.

In each following question you will need to choose between Prospect L and Prospect R by indicating "L" or "R" in the Choice box (you can use drop down list). It is not possible to indicate an indifference between the prospects. If you feel that the prospects are similar to you, indicate the one which explains your preferences the most. Please do not leave the Choice box empty. Keep in mind that there is no "right" or "wrong" answer. Try to answer each question as accurately and honestly as possible. In case you have any questions about the following Prospects, please do not hesitate to ask.

To continue press the "next" button below.

Appendix G

Additional results- *distribution of IAS and β*

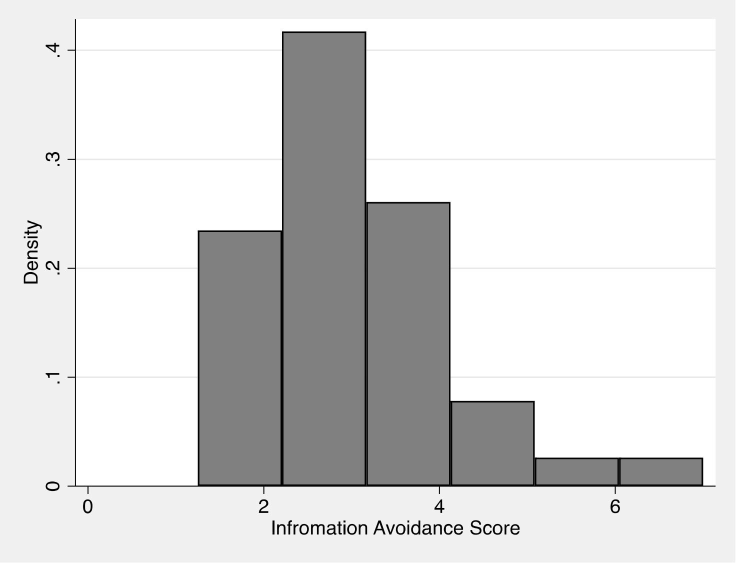


Figure G1. Histogram of information avoidance scores.

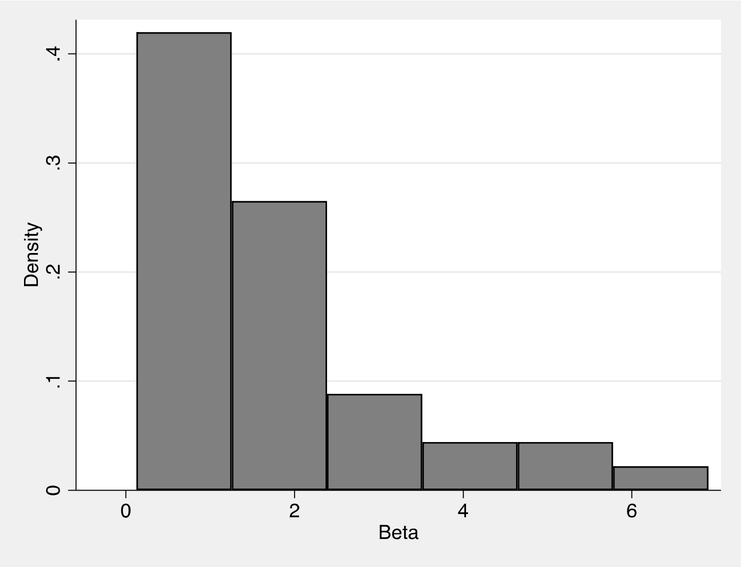
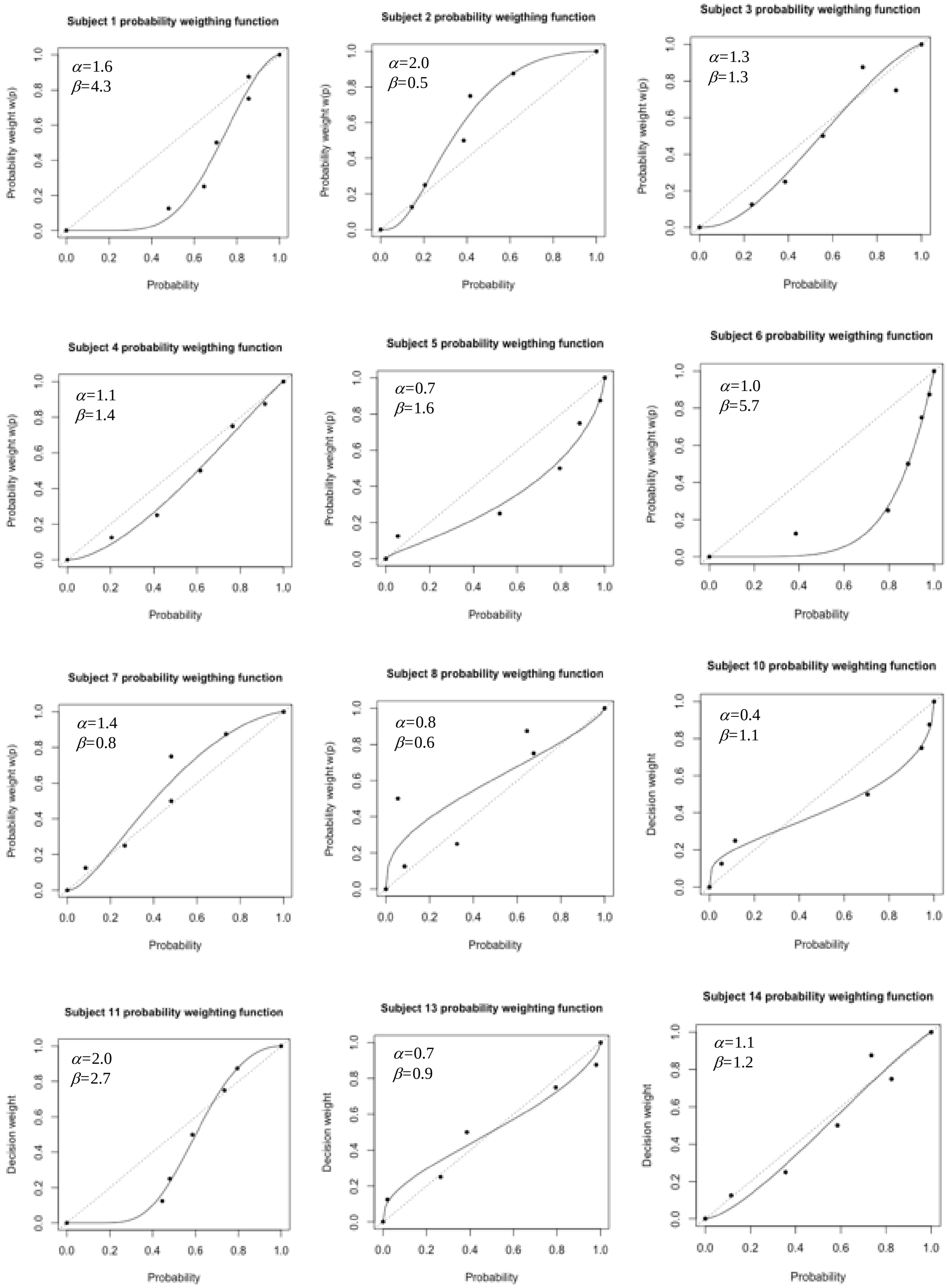
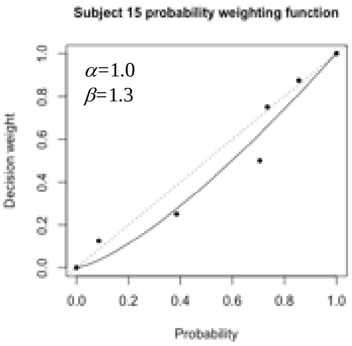


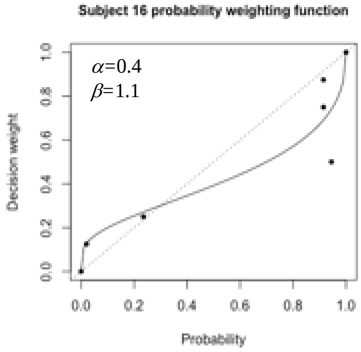
Figure G2. Histogram of β parameter.

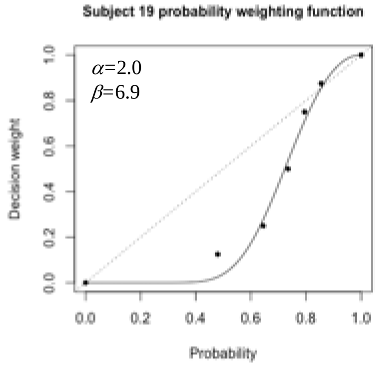
Appendix H

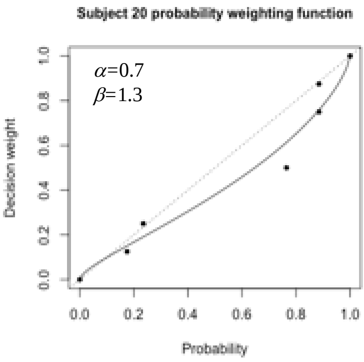
Probability weighting functions on individual level

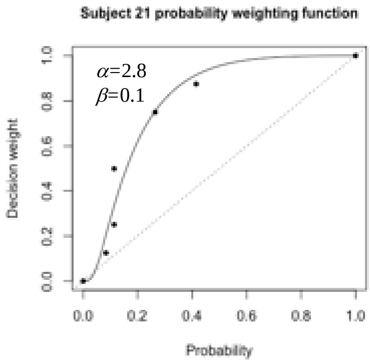


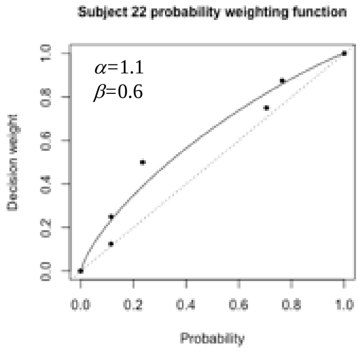

Subject 15 probability weighting function
α=1.0
β=1.3
Decision weight
Probability

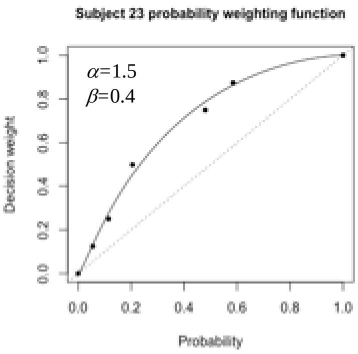

Subject 16 probability weighting function
α=0.4
β=1.1
Decision weight
Probability

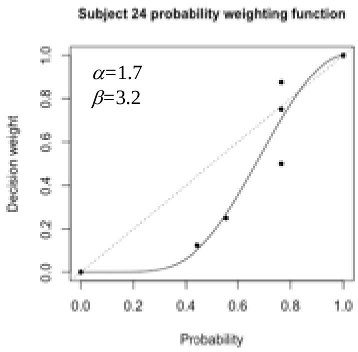

Subject 19 probability weighting function
α=2.0
β=6.9
Decision weight
Probability

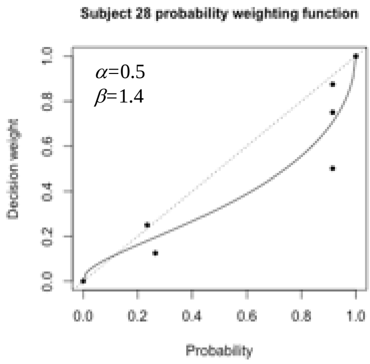

Subject 20 probability weighting function
α=0.7
β=1.3
Decision weight
Probability

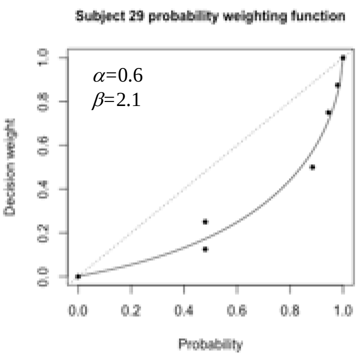

Subject 21 probability weighting function
α=2.8
β=0.1
Decision weight
Probability

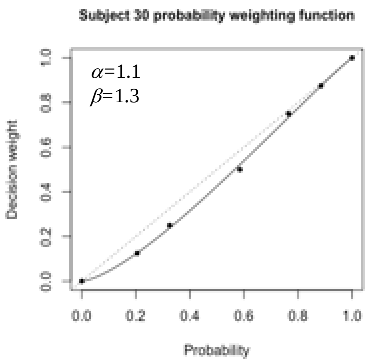

Subject 22 probability weighting function
α=1.1
β=0.6
Decision weight
Probability

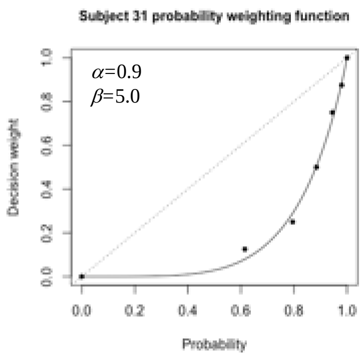

Subject 23 probability weighting function
α=1.5
β=0.4
Decision weight
Probability

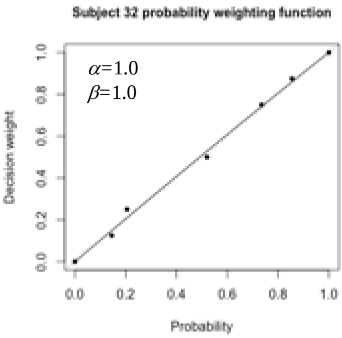
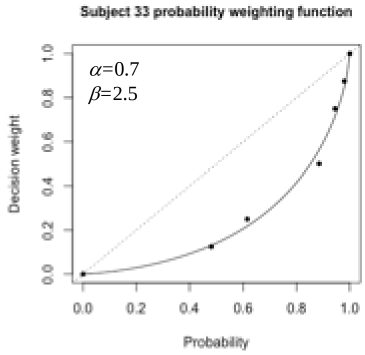
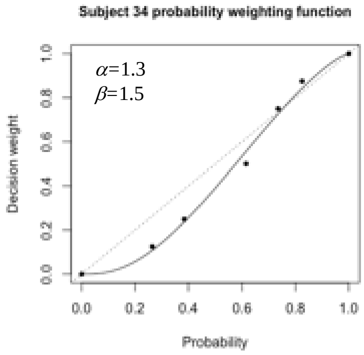
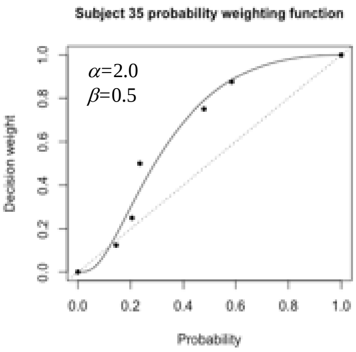
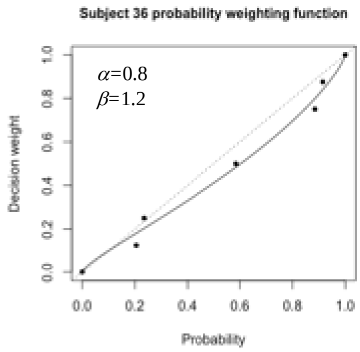
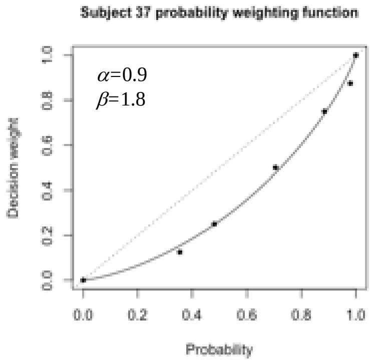
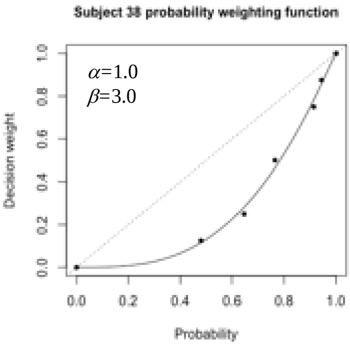
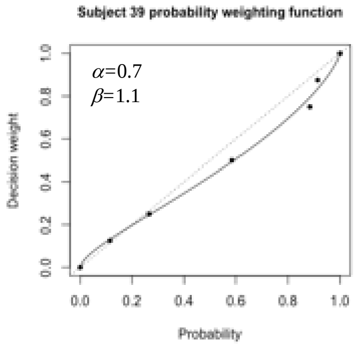
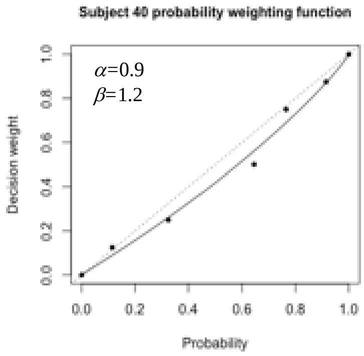
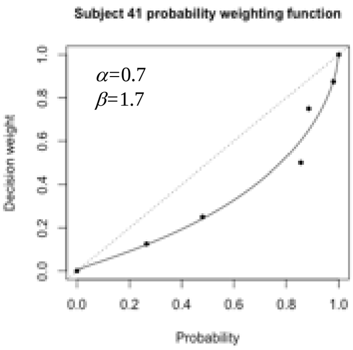
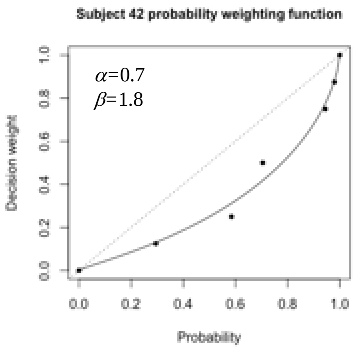
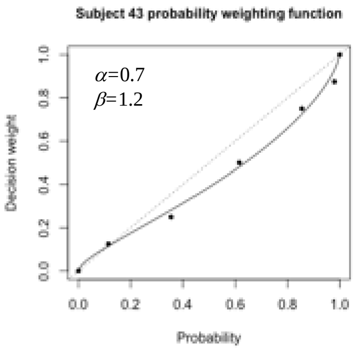

Subject 24 probability weighting function
α=1.7
β=3.2
Decision weight
Probability

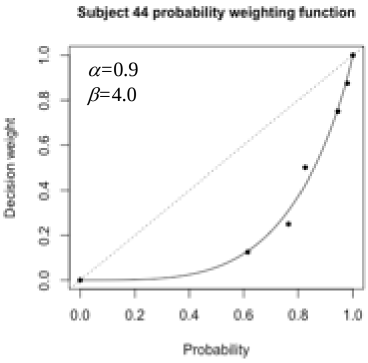

Subject 28 probability weighting function
α=0.5
β=1.4
Decision weight
Probability

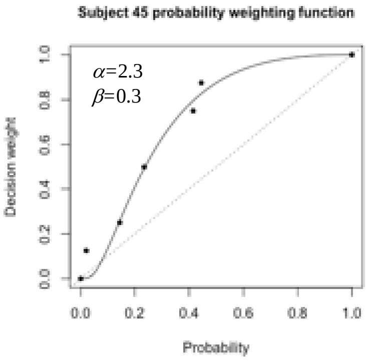

Subject 29 probability weighting function
α=0.6
β=2.1
Decision weight
Probability

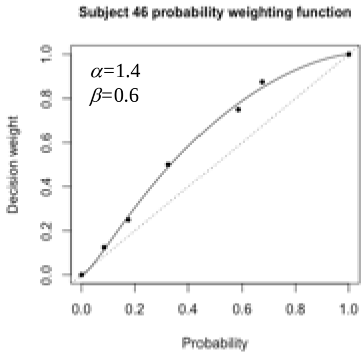

Subject 30 probability weighting function
α=1.1
β=1.3
Decision weight
Probability

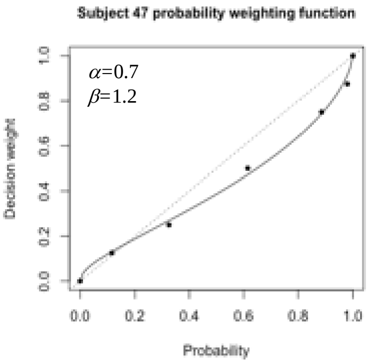

Subject 31 probability weighting function
α=0.9
β=5.0
Decision weight
Probability


Subject 32 probability weighting function
α=1.0
β=1.0
Decision weight
Probability

Subject 33 probability weighting function
α=0.7
β=2.5
Decision weight
Probability

Subject 34 probability weighting function
α=1.3
β=1.5
Decision weight
Probability

Subject 35 probability weighting function
α=2.0
β=0.5
Decision weight
Probability

Subject 36 probability weighting function
α=0.8
β=1.2
Decision weight
Probability

Subject 37 probability weighting function
α=0.9
β=1.8
Decision weight
Probability

Subject 38 probability weighting function
α=1.0
β=3.0
Decision weight
Probability

Subject 39 probability weighting function
α=0.7
β=1.1
Decision weight
Probability

Subject 40 probability weighting function
α=0.9
β=1.2
Decision weight
Probability

Subject 41 probability weighting function
α=0.7
β=1.7
Decision weight
Probability

Subject 42 probability weighting function
α=0.7
β=1.8
Decision weight
Probability

Subject 43 probability weighting function
α=0.7
β=1.2
Decision weight
Probability


Subject 44 probability weighting function
α=0.9
β=4.0
Decision weight
Probability
0.0 0.2 0.4 0.6 0.8 1.0


Subject 45 probability weighting function
α=2.3
β=0.3
Decision weight
Probability
0.0 0.2 0.4 0.6 0.8 1.0


Subject 46 probability weighting function
α=1.4
β=0.6
Decision weight
Probability
0.0 0.2 0.4 0.6 0.8 1.0


Subject 47 probability weighting function
α=0.7
β=1.2
Decision weight
Probability
0.0 0.2 0.4 0.6 0.8 1.0