Master Thesis Economics and Business – Behavioural Economics

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Optimism - Economics & Psychology: Two Sides of the Same Coin?

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31-10-2017

Abstract: This paper investigates a possible correlation between the economic concept of optimism as measured by the parameters of the probability weighting function and the psychological concept of optimism as measured with the revised version of the Life-Orientation Test. 39 students of the Erasmus University Rotterdam were individually interviewed to measure these two types of optimism. Even though the existing literature points towards a possible correlation between economic and psychological optimism, no such correlation is found in this study. However, optimism is a broad term containing several different types of optimism. It is therefore possible that the difference between what literature suggests and the findings of this paper can be explained by the fact that they refer to different types of optimism.

Key words: Optimism, Probabilistic Risk Aversion, LOT-R, Parameter-Free Elicitation Method, Utility, Probability Weighting, Cumulative Prospect Theory, Decision Making, Trade-Off Method

Key messages:

- In general, participants exhibit a concave utility function, overweight small probabilities and underweight medium and large probabilities. Subjects are thus optimistic when faced with small probabilities and pessimistic when faced with medium and large probabilities.
- Correlation and regression analysis reveals that there is no significant correlation between optimism as measured by probability weighting and optimism as measured by the revised Life-Orientation Test

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1. Introduction

In 1979, Kahneman and Tversky, published their paper on prospect theory. By assigning individual decision weights to probabilities, optimism could now be measured. An optimist in this context is someone who thinks that the probability of a favourable (unfavourable) event happening is more (less) than the objective probability of that event happening (Hey, 1984). Thus, by looking at the elevation of the probability weighting function, it is possible to determine what the individual's probabilistic risk attitude is and thereby determine whether the individual is optimistic or pessimistic (Wakker, 2001). Economists were not alone in this new found interest in optimism. Around the same period, psychology also developed a way to measure optimism. In 1985, Scheier and Carver designed the Life Orientation Test (LOT), which was meant to measure dispositional optimism as a trait. Scheier and Carver defined dispositional optimism as a global generalized tendency to expect that an individual will generally experience more good outcomes than bad outcomes in life (Andersson, 1996). Simultaneously, several other psychological measurements were developed, such as the Attributional Style Questionnaire (ASQ; Peterson et al., 1985) and the Optimism/Pessimism Scale (OPS; Dember, Martin, Hummer, Howe & Melton, 1989).

Using these methods, scientists began exploring the role of optimism in physical and mental well-being. Originally mainly focusing on the domain of health (e.g. Fitzgerard et al., 1993; Scheier et al. 1989; Tindle et al., 2009), but later also expanding to the context of social relations (e.g. Andersson 2012), and economic concepts such as ambiguity aversion and economic choice in general (e.g. Pulford, 2009; Puri & Robinson, 2007). Not only has research focused on the effects of optimism, several studies also focused on comparing different psychological measures of optimism (e.g. Burke, Joyner, Czech & Wilson, 2000; Chang, D'Zurilla & Maydeu-Olivares, 1994; Hjelle, Belongia & Nesser, 1996; Kamen, 1989; Gillham, Tassoni, Engel, DeRubeis, and Seligman, 1998; Scheier & Carver, 1992). Nevertheless, no such research has been done comparing dispositional optimism to optimism as a probabilistic risk attitude. Yet, there are several findings in literature that could suggest some level of correspondence between these two types of optimism. Firstly, Pulford (2009) studied the relation between optimism and ambiguity aversion. Pulford found that participants that scored low on optimism were significantly more ambiguity averse than participants that scored high on the optimism scale. Pulford also found that this difference is not due to the absence of pessimism, but due to the presence of optimism. Optimistic participants seem to have more faith in the random nature of luck, maybe even believing that they are lucky.

Moreover, Pulford (2009) further mentions that Einhorn and Hogharth's (1985) proposal that optimists and pessimists might adjust subjective probabilities by weighting them seems to be supported. This adjustment of perceived probabilities is mainly done by the least optimistic, leading to more ambiguity aversion. This seems to indicate a link between the economic definition of optimism and optimism as measured in psychology (in this case by an extended version of the LOT). Secondly, Bleichrodt, l'Haridon & Van Ass (2016), using the economic definition of optimism, found that professional hockey players were more optimistic for gains, indicating that there might be a relation between success in sports and differences in optimism. They note that this result is consistent with several psychological studies on the relation between dispositional optimism and success. Lastly, Graham, Harvey & Puri (2013) concluded that there exists a positive relation between risk tolerance amongst CEOs and dispositional optimism. The economic measurement of optimism also relates optimism to risk tolerance, where more optimism implies more risk tolerance. Overall, these three studies thus seem to hint at a possible overlap between probabilistic risk seeking ('economic optimism') and dispositional optimism.

This paper thus presents an interdisciplinary approach to optimism, measuring both the economic 'optimism profile' and the psychological 'optimism profile' of an individual. By doing this, it is possible to see whether there is a correlation between the economic approach towards optimism and the psychological perspective on optimism. Using this within subject approach, the following research question will be answered:

Is there a positive correlation between an individual's probabilistic risk attitude and his or her dispositional optimism profile?

This research question is answered by interviewing 39 students of the Erasmus University Rotterdam. During this interview, which took on average 55 minutes, the students completed the revised version of the Life Orientation Test (LOT-R) and their probability weighting function is elicited using the parameter-free elicitation method of Abdellaoui (2000). From the data it can be concluded that there is no indication of a correlation between optimism as measured economically and optimism as measured psychologically. Several other conclusions are also drawn. First of all, it can be concluded that there are significantly more concave shaped utility functions for gains than other shaped functions. This thus confirms the theory of Kahneman & Tversky (1989) and is in line with the results of Abdellauoui (2000). Secondly, on average subjects are likelihood insensitive, meaning that they overweight small probabilities and underweight medium and large probabilities. Lastly, regarding the LOT-R, this data of this paper seems to support the unidimensional nature of the LOT-R, although the sample size is too small to draw any real conclusions on this matter.

The structure of the paper is as follows. First a theoretical framework will further discuss results of studies related to optimism, psychological measures of optimism, the economic approach to measuring optimism. Subsequently, the method used for data collection and the resulting data will be addressed in section 3 and 4. The results will be presented in section 5, this includes a subsection discussing the reliability of the elicited probability weighting function and other results regarding the economic or psychological optimism measures. The discussion and conclusion will follow in section 7 and 8 respectively.

2. Literature Review

In this section, research concerning optimism and different psychological measurements of optimism are discussed. Furthermore, the economic measurement of optimism using probability weighting according to prospect theory is explained.

2.1 Optimism Overall

In both economics and psychology, optimism is usually regarded as a bias (Wakker, 2010; Dember et al., 1989). However, contrasting to other behavioural biases, there is a vast amount of literature suggesting that this bias is associated with better outcomes instead of being harmful to an individual. As briefly touched upon in the introduction, research on the effect of optimism was first mainly focused on the domain of health. In this domain, Fitzgerard et al. (1993) indicated that optimists are less distressed before a surgery and are more satisfied with their life after surgery compared to more pessimistic individuals. In some studies this effect on life satisfaction lasted even up to five years after surgery (Scheier et al. 1989). Optimists were also the least distressed after a disappointing event, as indicated by Litt, Tennen, Affleck, Klock, (1992) in a study on vitro fertilization. Additionally, optimists are generally thought of to be approach copers[1], meaning that they continue trying to solve the problem and thus as having a more fighting spirit (Scheier, Carver & Bridges, 2001). Optimism can thus be seen as a predictor of persistence (Carver & Scheier, 2014). Optimists also appear to take action to minimize health risks (Carver, Scheier & Segerstrom, 2010), are less likely to die of diseases such as cancer and cardiovascular disease (Tindle et al., 2009) and are less likely to

[1] Contrastingly, pessimists are generally thought of to be avoidant copers, meaning that pessimists let themselves be distracted by things that do not solve the problem or sometimes even stop trying to solve the problem. This occasionally leads to a feeling of hopelessness (Scheier, Carver & Bridges, 2001)

suffer from a stroke (Kim, Park & Peterson, 2011). Moreover, optimists show symptoms of life-threatening diseases later and are able to survive longer than more realistic or pessimistic individuals (Seligman & Csikszentmihalyi, 2000).

In a more economic and social context, it was found that if students are optimistic during their first semester, they were more likely to complete college and to have higher salaries ten years later (Solberg Nes, Evans & Segerstrom, 2009). These higher salaries could be explained by the findings of Creed, Patton and Bartrum (2002). They found that individuals with a high optimism score reported higher levels of career planning and exploration, were more satisfied about career related decisions and set more goals related to their career. Optimists are also found to be more efficient in balancing multiple goals (Segerstrom & Solberg Nes, 2006), to have a greater and more diverse social circle (Andersson, 2012) and to be more successful in their relationships (Carver, Scheier & Segerstrom, 2010).

Overall, the future of an optimist thus seems to look quite optimistic. There are however also some drawbacks of optimism. Optimists might be more likely to develop gambling problems. This is because optimists have more positive expectations for the outcomes of the gambles than pessimists and they are less likely to stop gambling after poor outcomes (Gibson & Sanbonmatsu, 2004). Optimists also experience greater goal conflict since they are less likely to consider defeat when there is no alternative task at hand. However, optimists are more effective in balancing expectancy, value and cost of goal pursuit than pessimists (Wrosch, Scheier, Carver & Schulz, 2003). Lastly, Puri and Robinson (2007) note that too much optimism might have an adverse effect on the individual’s economic well-being, although being moderately optimistic is related to better decision-making.

2.2 The Life Orientation Test

In most of the studies mentioned above, optimism was measured by means of one of the psychological measurements of optimism. Of these measures of (dispositional) optimism, the Life Orientation Test (LOT) or its revised version (LOT-R) are most frequently used (Herzberg, Glaesmer & Hoyer, 2006). The original LOT is a self-report measure that consists of four positively worded statements, four negatively worded statements and four filler statements. These statements are meant to assess generalized expectancies for positive versus negative outcomes and to result in an unidimensional optimism scale[2] (Scheier & Carver,

[2] There is an ongoing debate about whether the LOT(-R) is indeed unidimensional or whether it is actually bidimensional and the negatively worded and positively worded items should thus be scored separately (Herzberg, Glaesmer, & Hoyer, 2006; Chang, D’Zurilla & Maydeu-Olivaries, 1994; Rauch, Schweizer & Moosbrugger, 2007; Vautier, Raufaste, & Cariou, 2003).

1985). Although the LOT is the most commonly used method in research on optimism, it did receive some criticism. Smith, Pope, Rhodewalt and Poulton (1989) noted that the LOT might also measure a third variable; trait anxiety. Similarly, Marshall and Lang (1990) had a similar critique, but then concerning self-mastery instead of trait anxiety. Upon closer examination of these critiques, Scheier, Carver & Bridges (1994) stated that both these concepts each have at least one additional quality that is different from optimism and that these concepts are only moderately correlated, concluding that the criticism should not be a problem for the predictive value of the LOT. Nevertheless, they did make some improvements to the LOT. First of all, two positively worded statements related to coping were left out. Secondly, in order to keep three positive and three negatively worded items, one negatively worded statement was removed and a new positively worded statement was added (Scheier, Carver & Bridges, 1994). The revised version of the LOT (LOT-R) thus consists in total of six items related to optimism and four filler items. Hence, the major benefit of the LOT-R is its briefness, which allows it to be easily combined with other measures.

2.3 The Optimism/Pessimism Scale

Another measure of dispositional optimism is the Optimism/Pessimism Scale (OPS). This is also a self-report measure, consisting of 56 items, based on the Pollyanna Principle (Dember et al., 1989). The Pollyanna Principle, coined by Matlin & Stang (1978), is a general tendency to favour and accentuate pleasant information over unpleasant information. Dember et al. (1989) state that optimism/pessimism might predict this positive bias. Their measurement of optimism/pessimism consists of 18 items measuring optimism, 18 items measuring pessimism and 24 filler items. After an internal consistency analysis, Dember et al. concluded that the OPS might not be bipolar. Chang, D'Zurilla and Maydeu-Olivaries (1994) determined that the scale is actually a multidimensional scale.

When testing the test-retest reliability of the OPS, Dember & Brooks (1989) mentioned that the OPS is very similar to the LOT. Even though both the LOT(-R) and the OPS are measures related to future oriented expectancies, there does appear to be an important difference in measurement. Given that the OPS asks respondents to answer according to how they currently feel, it might actually be measuring state optimism and pessimism, thus being more related to the mood of the subject. The LOT(-R) on the other hand, may be measuring trait optimism and pessimism, hence it is more related to the individual's personality (Burke, et al., 2000).

2.4 The Attributional Style Questionnaire

Dispositional optimism as measured by the LOT(-R) and OPS is not the only type of optimism within the realm of positive psychology being put in the spotlight. Where dispositional optimism is a more future focused and expectancy related type of optimism, optimism can also be determined by means of how individuals explain events. In 1982, Peterson et al., designed the Attributional Style Questionnaire (ASQ), which measures the explanatory style of an individual based on how people perceive the cause of twelve hypothetical situations. An optimist (pessimist) in this context is someone that has a habit of assigning stable, global and internal causes to good (bad) events, whereas unstable, specific and external causes are assigned to bad (good) events (Peterson & Seligman, 1984). Having a pessimistic explanatory style is associated with being more susceptible to depression and other related helplessness deficits (Peterson & Seligman, 1984). Interestingly, even though explanatory style and dispositional optimism have commonly been studied in isolation of each other, findings in literature on each type of optimism parallel each other (Gillham, Shatté, Reivich & Seligman, 2001). This seems to suggests that there is a correlation between these two concepts. However, research investigating the correlation between the LOT and ASQ results in various correlations, ranging from below 0.2 to 0.77, the relation between dispositional optimism and explanatory style thus remains opaque (Gillham. Shatté, Reivich & Seligman, 2001). Moreover, one difference between explanatory style and dispositional optimism is that according to Seligman (1991), individuals with a pessimistic explanatory style can learn to adapt a more optimistic perspective (learned optimism), whereas learning this with respect to dispositional optimism is deemed impossible.

2.5 Probabilistic Risk Attitudes

An individual's risk attitude is partly determined by how probabilities are perceived (Wakker, 1994). If an individual overweights (underweights) the probability of a positive event, then this illustrates probabilistic risk seeking and thus optimism (pessimism). Utility, on the other hand, describes an intrinsic appreciation of money prior to probability or risk (Wakker, 1994). Only if an individual is probabilistically risk neutral and the weighted probability is equal to the actual probability, the individual fits the Expected Utility (EU) theory. This probabilistic risk neutrality is however seldom observed and various empirical flaws of the EU model were thus exposed (Qui & Steiger, 2011). Hence, Kahneman &

Tversky (1979) introduced with Prospect Theory (PT) a second factor to risk attitudes, namely the weighting of probabilities.

To elicit these utility and probability weighting functions, the parameter-free elicitation method of Abdellaoui (2000) is used. This method or a slightly moderated version is also adapted in several other papers (Bleichrodt & Pinto, 2000; Qui & Steiger, 2011). The two-step method first elicits the utility function and then the weighting functions under cumulative prospect theory (CPT). The first step consists of obtaining a standard sequences of positive outcomes which needs the construction of n indifferences $(x_{i-1}, p; R) \sim (x_i, p; r)$, where 0 $\leq r < R < x_{i-1} < x_i$. Hence, the trade-off of x_0 for x_1 equals the trade-off of x_1 for x_2, x_2 for x_3, …, and x_{n-1} for x_n. The resulting outcomes are thus equally spaced on the utility axis, leading to a standard sequence of $x_0, x_1, \ldots, x_n$.

Step two then consists of using the standard sequence of outcomes to determine a sequence of probabilities. For each $x_i, i = 1, \ldots, n-1$, a p_i is established to make the individual indifferent between $(x_n, p_i; x_0)$ and (x_i). According to CPT, this indifference implies that $w(p_i) = \frac{u(x_i) - u(x_0)}{u(x_n) - u(x_0)}$, which can be simplified to $w(p_i) = \frac{i}{n}$ for i = 1, …, $n-1$ because of the standard sequence of positive outcomes as obtained in step one. The shape of the probability weighting function can thus be estimated.

3. Method

In this section, the data collection procedure is discussed in details. Section 3.1 discusses the general procedure. Section 3.2 then gives a precise account of the elicitation of the economic optimism profile and section 3.3 provides a comprehensive account of the elicitation of the psychological optimism profile.

3.1 Participants & Procedure

To obtain data, a total of 39 participants were personally interviewed. By conducting personal interviews, the data quality is improved. Apart from these 39 participants, an additional four subjects participated in the pilot study, which allowed for correcting errors in the elicitation procedure. The personal interview sessions took on average 55 minutes, with a minimum of approximately 30 minutes and a maximum of 80 minutes. Participants were each individually recruited and consisted of Economic & Business bachelor and master students at the Erasmus University Rotterdam, with a majority specializing in Behavioural Economics. Since the participants were all Economic & Business students, they were familiar with probabilities and expectations. The participants voluntarily took part in the collection of data and were not paid. This also means that the prospects shown to the participants during the elicitation of the economic optimism profile were purely hypothetical. Some researchers argue that real incentives are important in experiments (Holt & Laury, 2002). However, there is also a vast amount of literature that argues that there is no or little effect of using real incentives in contrast to purely hypothetical situations, except that the latter might lead to slightly noisier responses (Bardsley et al., 2010; Camerer, Hoghart, Budescu & Eckel, 1999; Dohmen et al., 2011; Read, 2005). For example, Beattie and Loomes (1997), performed an experiment using both hypothetical and real tasks. They found that when tasks were one-stage lotteries, the responses to the hypothetical and real tasks did not differ significantly. Moreover, because of the recruitment procedure, it is likely that the participants were incentivised by intrinsic motivation.

The order of the economic and psychological questionnaires were counterbalanced. As such, 22 participants answered the psychological questions first and the other 17 participants were first presented with the economic questions. This precaution was taken to avoid order effects. The instructions and the psychological measurement of optimism were both verbally explained and handed to the participants on a sheet of paper where the participant also had to write down his/her age, gender, nationality and current study (see appendix A1.1 & A1.2). Moreover, the participants were not aware of the aim of the study. These preventative measures were taken to avoid experimenter demand effect and self-classification. If the participants were interested, the aim of the study was explained after the session was finished. Hence, a vast majority of the participants is informed about the aim of the study after the individual interview.

3.2 Eliciting the Economic Optimism Profile

The economic elicitation of the optimism profile is based on a two-step parameter free approach as proposed by Abdellaoui (2000). The same amounts (converted to euros) and probabilities are used during this study as those that were used in the study of Abdellaoui. However, in order to keep the sessions as short as possible, only the utility and weighting functions for gains are elicited, whereas Abdellaoui also elicited the functions for losses. By using a series of choice questions the outcomes and probabilities are obtained. These questions each consist of an outright choice between two prospects. The prospects were both verbally explained as well as displayed as a pie chart (see appendix A1.3). Using a pie chart might help the participants to visualise the prospects. Moreover, the task is explained before the start of the elicitation procedure. Since the personal interview makes it possible to ask questions and to provide further explanation if necessary, there were no trial questions. Because the trade-off answers for the outcomes were used as input in the elicitation of weighting functions, the construction of the standard sequence of outcomes must always precedes the elicitation of the probability weighting function.

3.2.1 Eliciting the Utility Function

To elicit the utility function, thirty pairs of prospects were presented to the participants. The participants were instructed to indicate which prospect they prefer, with the possibility to indicate indifference if they really could not choose between the two prospects. Fourteen participants made used of this possibility and indicated an indifference between the two prospects at least once during the session.

For each participant, a standard sequence of six outcomes (x_1,…., x_6), was constructed. Each of these outcomes is obtained by means of asking five questions. The outcomes x_0, r and R were set similar to Abdellaoui (2000), namely to €200, €0 and €100, respectively[3]. The participants thus faced prospects $A = (x_{i-1}, p; 100)$ and $B = x_i^j, p; 0)$. The interval of feasible outcomes ranged from x_{i-1} to $x_{i-1} + €800$. x_i^j was then taken as the midpoint of this interval of feasible outcomes corresponding to the j-th question. Table 1 displays the procedure of eliciting x_1 for a subject who chooses prospect A in questions 1, 3 and 4. After the fifth question, the outcome ends up in the interval [750; 780], the midpoint of this interval is then chosen as x_1. All values are rounded up to the closest multiple of ten. The values are manually updated and calculated with the use of an Excel sheet (see appendix A1.4). Since different studies set the probability (p) differently (Fennema & van Assen, 1998; Bleichrodt & Pinto, 2000), the present study gives the probability p the value of 2/3 similar to Abdellaoui (2000). This value of p also makes it slightly more difficult to calculate the expected value of the prospects. This might ensure that only the subjects that in real life would calculate the expected value, do so in this setting. When the standard sequence is obtained, the participants have to choose again between two prospects corresponding to the fourth question of two of the obtained outcomes. This is done to check the reliability of the participant's answers. The two questions that are repeated are randomly selected.

[3] The amounts used by Abellaoui were FF 1,000 ($200), 0 and FF 500 ($100) respectively. These dollar amounts were converted to euros and rounded to hundreds.

Table 1 Assessing x_1 Through Bisectional Method for Gains

Question	Prospects	Outcome interval	Choice
1	A= (200, 2/3;100, 1/3) B = (600, 2/3; 0)	[200; 1000]	A
2	A= (200, 2/3;100, 1/3) B = (800, 2/3; 0)	[600; 1000]	B
3	A= (200, 2/3;100, 1/3) B = (700, 2/3; 0)	[600; 800]	A
4	A= (200, 2/3;100, 1/3) B = (750, 2/3; 0)	[700; 800]	A
5	A= (200, 2/3;100, 1/3) B = (780, 2/3; 0)	[750; 800]	B
		[750;780]	
x_1		770	

3.2.2 Eliciting the Probability Weighting Function

After obtaining the standard sequence of outcomes, the probability weighting function is elicited. For this second step, the participant again had to answer 30 choice questions aiming to determine the probabilities $p_1, \dots, p_5$ that result in an indifference between prospects $A = x_i$ and $B = (x_6, p; x_0)$. Similar to Abdellaoui (2000), a sixth probability p_2' is elicited such that $(x_3, 1) \sim (x_4, p_2'; x_2)$, this is to check the reliability of the elicitation method.

Each switching probability is assessed by asking six choice questions. As can be seen in table 2, the procedure is similar to the procedure for outcome x_1, except that p_1 is elicited by means of six instead of five binary choice questions. The probabilities were all rounded up to the closest integer. Special precautions were taken to avoid the problem of "framed probabilities" and possible biases due to scale compatibility[4]. The problem of "framed probabilities" arises when some participants reframe the questions to elicit the probability weighting function as if they were mixed lotteries. If they reframe the probabilities in this way, then the prospects might be coded as "gains" and "losses" relative to a fixed amount for sure and thus changing the reference point from 0 to S. This type of reframing is less likely during the elicitation of the standard sequence of outcomes (Hershey & Schoemaker, 1985). The taken precautions consist of not successively sequencing the assessment of a given probability p. Instead, the sequence of questions first asks the first question for each probability $p_i^1, i = 1, \dots, 5$ and p_*^1, and then the second question for each probability $p_i^2, i =$

[4] Scale compatibility is the tendency of individuals to give more weight to the attribute that is most compatible with the response scale (Tversky, Sattath & Slovic, 1988).

$1, \ldots, 5$ and p_*^2, continuing this sequence till all six questions are asked for all probabilities. This way, it might seem like the elicitation is actually trying to find a certainty equivalent instead of a probability equivalent and this might thus solve the abovementioned problems. When all the probabilities were elicited, the participants again had to answer three randomly selected choice questions of the fourth question for each probability $p_i^4, i = 1, \ldots, 5$ and p_*^4. This step is taken to assess the participants reliability in the elicitation of the probability weighting function.

Table 2 Assessing $\boldsymbol{p_1}$ Through Bisectional Method for Gains

Question	Prospects	Probability interval (x1%)	Choice
1	A = $(x_1,1)$ B = $(x_6,50;x_0)$	[0; 100]	A
2	A = $(x_1,1)$ B = $(x_6,75;x_0)$	[50; 100]	B
3	A = $(x_1,1)$ B = $(x_6,63;x_0)$	[50; 75]	A
4	A = $(x_1,1)$ B = $(x_6,57;x_0)$	[50; 63]	A
5	A = $(x_1,1)$ B = $(x_6,60;x_0)$	[57; 63]	B
6	A = $(x_1,1)$ B = $(x_6,62;x_0)$	[60; 63]	B
		[60; 62]	
p_1		61	

3.2.3 Determining the Optimism Profile

Once the probability weighting functions are elicited, the optimism profiles can be determined. There are several ways to classify optimism. The first classification is by means of the probability weighting function introduced by Prelec (1998):

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

In this function, α is used as an index of likelihood insensitivity and β measures the degree of optimism/pessimism. If α is between 0 and 1, then it means that the individual is likelihood insensitive and thus overweights small probabilities and underweights large probabilities, which results in an inverse s-shaped pattern. When α is larger than 1, the individual is oversensitive to likelihoods and thus overweights large probabilities and underweights small probabilities, this results in an s-shaped pattern. If β falls between 0 and 1, then the probability weighting function captures optimism, if β is larger than 1, then it captures pessimism (Åstebro, Mata & Santos-Pinto, 2015).

Another method to classify optimism is introduced by Goldstein and Einhorn (1987), which estimates the probability weighting functions by means of the following formula:

$$w(p) = \frac{\delta p^{\gamma}}{\delta p^{\gamma} + (1-p)^{\gamma}}$$

This form allows for the most common shapes of the probability weighting function. In this function, δ is an indication of optimism, with higher values corresponding to more optimism. Using the five data points obtained during the elicitation of the probability weighting function, $p_i, i = 1, \ldots, 5$, α, β, δ and γ can be estimated for each individual using nonlinear least squares. The functions of Goldstein and Einhorn and Prelec both contain a parameter for optimism and one for likelihood insensitivity and these parameters are highly correlated, making them almost indistinguishable (Åstebro, Mata & Santos-Pinto, 2015; Bleichrodt, l'Haridon & Van Ass, 2016). Gonzalez and Wu (1999) also showed that both functions fit the data equally well.

Qui & Steiger (2011) on the other hand, propose a vastly different but rather intuitive method to categorize optimism. In their method, the area below the drawn probability weighting function is used to obtain a ratio (τ_{p}) between 0 and 1. The size of this ratio indicates if an individual, in general, overweights or underweights probabilities. Qui & Steiger (2011) then classify the individuals as pessimistic, neutral or optimistic when $\tau_{\mathrm{p}} < 0.47$, $0.47 \leq \tau_{\mathrm{p}} \leq 0.53$ and $\tau_{\mathrm{p}} > 0.53$, respectively. Even though Qui & Steiger (2011) found a high correlation between τ_p and δ and concluded that τ_p captures probability weighting reasonably well, it is not fool proof. An individual with an almost horizontal probability weighting function and an individual with a linear probability weighting function would have the same τ_p, whereas the former is actually quite optimistic for small gains and pessimistic for large gains and the latter does not weight probabilities. Hence, this paper's primary research will be analysed using Prelec's probability weighting function to measure optimism, as a robustness check however, the results are also analysed by means of Goldstein & Einhorn's probability weighting function and these results can be found in appendix A5.

3.3 Eliciting the Psychological Optimism Profile

Research has shown that individual risk attitudes are relatively stable over time (Harrison, Johnson, McInnes & Rutström, 2005; Sahm, 2007; Zyphur, Narayanan, Arvey & Alexander, 2009). It is therefore likely that the economic measure of optimism as used in this paper can be seen as a form of 'trait' optimism. A possible correlation between economic and psychological optimism is therefore most likely found between two measures of trait optimism. As previously discussed, the LOT(-R) might be measuring this type of optimism, whereas the OPS most likely measures state optimism. Not only is a correlation most likely found between dispositional optimism as measured by the LOT(-R) and probabilistic risk seeking, the LOT(-R) is also the most widely used measure of optimism within the domain of psychology and its briefness allows it to be easily combined with other measures. The psychological optimism profile will thus be determined by means of the LOT-R.

As discussed in section 2.2, the LOT-R consists of three positively worded statements, three negatively worded statements and four filler items (for instructions and statements see appendix A1). Subjects have to indicate their degree of agreement to the ten statements along a 5-point Likert-scale, ranging from 'strongly disagree' (= 0) to 'strongly agree' (= 4). By reverse scoring the negatively worded items, a total score can be calculated, ranging from 0 to 24. Moreover, because of the dispute about the dimensionality of the LOT-R, the positively and negatively worded items are also scored separately. This results in an overall unidimensional optimism score, and two specific bidimensional optimism and pessimism sub-scores.

4. Data Sample and Variables

As discussed in the previous section, 39 students were individually interviewed to ensure high quality data. Several variables were derived from these individual interviews, namely *age*, *gender*, *nationality*, *study*, *order*, $x_1, x_2, x_3, x_4, x_5, x_6, p_1, p_2, p_3, p_4, p_5, p'_2$, *LOT-R*, *optimist* and *pessimist*. *Order* is a binary variable, taking the value of 1 if the participants first answered the LOT-R and zero otherwise. *Optimist* and *pessimist* are the separate optimism and pessimism sub-scores obtained if the LOT-R is seen as a bidimensional scale. Both *gender* and *nationality* are binary variables, taking the value 1 when the respondent is male and Dutch, respectively. Lastly, *study* is a categorical variable, taking the value of 1 when the participant is a master in Behavioural Economics student, 2 if (s)he is an (international) bachelor of Economics student and 3 when the participant studies a different master in Economics or Business.

The variables p_1, p_2, p_3, p_4 and p_5 are then used to estimate Prelec's and Goldstein & Einhorn's probability weighting functions and thus to obtain α, δ, γ and δ. Using the statistical software tool R, it was possible to determine these variables for 38 of the 39 participants. Upon closer investigation, it was found that the participant of which R could not estimate the α, δ, γ and δ most likely made an error in answering the first stage of the elicitation thus leading to a faulty standard sequence of outcomes. This resulted in a p_1, p_2, p_3, p_4 and p_5 of 0.94, 1.00, 1.00, 1.00 and 1.00 respectively, which would mean that the individual is extremely pessimistic. This individual is dropped from the data, resulting in a total of 38 observations.

Table 3 shows that the sample is reasonably balanced, with 19 Dutch and 19 non-Dutch participants and 22 male compared to 16 female participants. Moreover, as can be seen in appendix A2, table 9, 50% of the participant are behavioural economics students, 29% of the participants follow a bachelor in economics and 21% of the participants pursue a different economic or business master[5].

Table 3 Descriptive Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
α	38	0.6867047	0.3560615	0.1615367	2.180021
β	38	3.475129	12.42421	0.6253567	77.72644
γ	38	0.7531757	0.4521685	0.1829277	2.582912
δ	38	0.7230222	0.4557009	0.0041465	1.697098
LOT-R	38	16.18421	3.555394	6	22
Optimist	38	8.473684	2.190111	4	12
Pessimist - reversed	38	7.710526	2.091267	2	11
Age	38	22.73684	2.355949	18	27
Nationality	38	0.5	0.5067117	0	1
Gender	38	0.5526316	0.5038966	0	1

5. Results

In this section, the results obtained from the individual interviews is discussed. Section 5.1 examines the reliability and the consistency of the participants choices. Then, the relation between the economic concept of optimism and the psychological concept of optimism is discussed in section 5.1. Lastly, separate results relating to economic optimism or psychological optimism are examined in sections 5.2 and 5.3 respectively.

[5]These masters are Health Economics (1), Economics of Management & Organisations (2), International Economics (3), Finance & Investments (1) and Global Business & Sustainability (1).

5.1 Reliability & Consistency

During the elicitation of the probability weighting functions, several precautions were taken to check and ensure the reliability of the elicitation method. As discussed in section 3.2, the reliability of the participants responses can be tested by checking how often they expressed the same preference for the same pair of prospects. The percentage of times the participants expressed the same preference for the same pair of prospects can thus determine whether the participant was consistent in his or her answers and whether the standard sequence of outcomes and probabilities obtained from the elicitation process is reliable. This consistency is important since the responses are chained and an error made early in the elicitation process (for example at i =1 or 2) can bring about error propagation in the standard sequence, leading to a distortion in the measurement of the probability weighting function (Abdellaoui, 2000). For 50 out of 186 of the repeated questions, the respondent changed his or her answer and thus showed a preference reversal. This means that there was an overall consistency rate of 73.11%. Even though this rate is lower than the overall consistency rate obtained by Abdellaoui (2000), it is still higher than other choice experiments, where inconsistency rates of up to 33% are common (Stott, 2006). Using this measure of consistency, some preference reversals can be expected, since participants are very close to or already at their indifference point. This could also be seen from the fact that most participants had to think longer about which prospects they preferred when they came closer to indifference. A preference reversal might in this case thus not necessarily be an indication of the unreliability of the elicited standard sequences.

The reliability of the elicitation method can also be checked by testing whether the elicited p_2' is equal to 0.5, as is predicted when the results are reliable. If this is the case, then the standard sequence of outcomes obtained in the first step produced the genuine standard sequence of outcomes. Therefore, a one sample t-test is performed to determine whether on average p_2' is equal to 0.5. According to this test, p_2' is not significantly different from 0.5 (p = 0.77) and overall the elicited standard sequences thus seem reliable.

As discussed in section 3.1, the order of tests was alternated. This was done to avoid experimenter demand and order effects. If participants noticed that the first test measured optimism, then it could be the case that they answered the second test according to their answers of first test in order to be consistent. To test whether such order effects are at work, both a two-sample t-test and a Mann-Whitney U test are performed for the LOT-R (sub-)scores and for α and β. If there is a significant difference in these scores between the group that first answered the LOT-R and the group that first answered the elicitation questions, then order effects might be at work. These order effects could then result in an unreliable correlation between the LOT-R and the α and β. This does not seem to be the case since *α, β, LOT-R, Optimist* and *Pessimist* are not significantly different for participants that answered the LOT-R first and participants that answered the LOT-R afterwards (t-test: p = 0.43, p = 0.31, p = 0.65, p = 0.34 & p = 0.93, Mann-Whitney-U: p = 0.55, p = 0.84, p = 0.95, p = 0.66 & p = 0.88, respectively). Moreover, on average subjects spend the same amount of time answering the LOT-R (approximately 2 minutes), irrespective of whether this test was performed before or after the economic choice experiment.

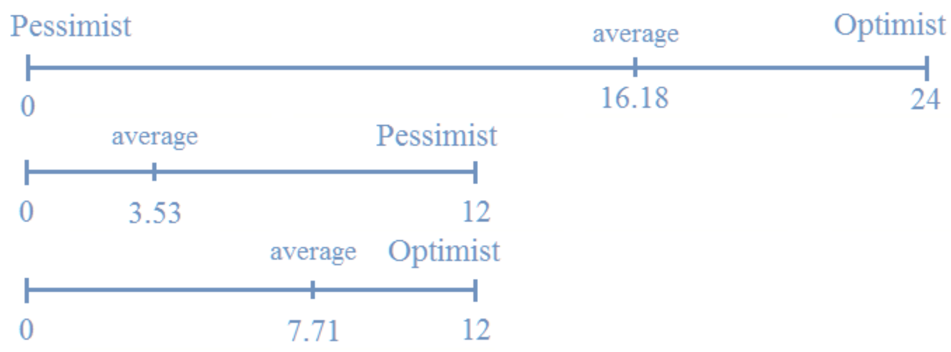
To test the internal consistency of the LOT-R, Cronbach's Alpha is determined. Cronbach's Alpha is a measure of scale reliability and measures how closely related the different items of the LOT-R are as a group. A higher level of Cronbach's Alpha illustrates a higher rate of internal consistency. Cronbach's Alpha for the LOT-R found in this study is 0.68. Although a higher alpha is preferred, DeVellis (1991) still considers an alpha of 0.65 as acceptable. Additionally, the alpha for each separate sub-scale is rather low (0.6 for optimism, 0.59 for pessimism). It is however questionable how accurate this alpha is, since the sample size of this study is quite small and the highest eigenvalue obtained from principal component analysis is 2.35 (see appendix A4, table 11 & 12). According to Yurdugül (2008), Cronbach's Alpha can be accurate for a small sample size (in his study a sample size of n = 30), when the highest eigenvalue is sufficiently large. However, with an eigenvalue of 2.35, it is highly likely that the alpha found in this study is biased. If the alpha currently found is higher than the actual alpha, it could mean that the LOT-R is not reliable or inconsistent, this would be the case if Cronbach's Alpha is below 0.6. However, previous research has proven the LOT-R to be a reliable measure of optimism, and a biased alpha in this study does not necessarily mean that the LOT-R is thus unreliable.

5.2 Optimism Overall

The average LOT-R score is 16.18 out of a maximum of 24. Moreover, when looking at the optimism and reversed pessimism score separately, it can be seen that on average participants tend to disagree more with pessimistic statements (average score of 8.47 out of 12) than they tend to agree with positively worded statements (average score 7 out of 12). These scores are quite close to scores found in other research. Creed, Patton and Bartrum (2002), for example, found average scores of 16.47, 7.47 and 8.94, respectively. However, higher and lower scores are also observed in literature (Burke et al., 2000; Lai & Yue, 2000).

Overall, the LOT-R (sub)scores seem to indicate that the participants were relatively optimistic, both measured on a unidimensional scale and on a bidemensional scale (see figure 1).

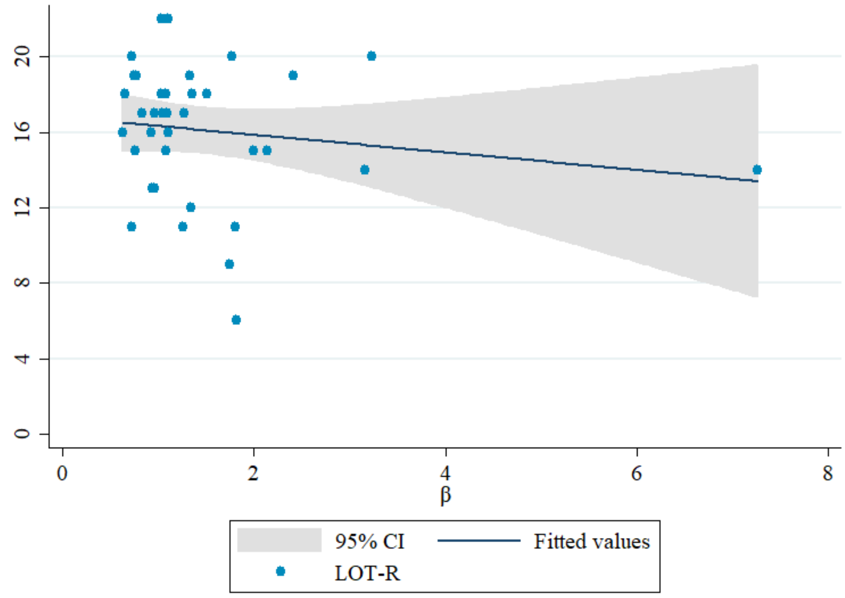
Figure 1 Average LOT-R Score on an Unidimensional and Bidimensional Scale



When looking at the average β (3.48), it seems that economically seen, subjects were rather pessimistic. This average is however skewed by the outlier of 77.72. Nevertheless, the median β is also above 1 (1.09). this seems to indicate that there might not be a correlation between the two measures of optimism. This is confirmed by a Pearson's correlation test between the LOT-R (sub)scores and β. According to this test, there is a non-significant positive correlation between LOT-R and β. Upon closer investigation of the data, it becomes clear that this positive correlation might be due to the individual with a highly pessimistic beta (77.72), but quite optimistic LOT-R score (19). Taken this outlier and the overall skewed distributions of β (see appendix A2, figure 5), ranked correlation analysis seems more appropriate. Therefore, the variables are also tested by means of ranked correlation tests, both using Spearman's Rho and Kendall's Tau. These test still show an insignificant correlation between the LOT-R and β ($\rho = -0.1172, p = 0.4835$ & $\tau = -0.0828, p = 0.4864$). This can also be seen from the scatterplot in figure 2, where the outlier of 77.72 is excluded. The two measures of optimism thus seem to measure a different kind of optimism.

Apart from the correlations, a regression analysis is also performed. This regression will however not result in any causal effects, since it is highly likely that there is reversed causality between the two measures of optimism. Nevertheless, it does allow for confounding factors to be taken into account in the analysis and variables such as *age*, *gender*, *nationality*, *study* and *order* can be added to the regression. The regression is performed both with LOT-R being the dependent variable and with β as the dependent variable. Moreover, as mentioned in section 5.2.2, the variable β is skewed and log-linear and linear-log regression analyses are thus also performed (see appendix A4). From these regressions it can again be concluded that there is no significant relation between the economic concept of optimism and the psychological concept of optimism. The results from the correlations are thus confirmed by these regression analyses.

Figure 2 Scatterplot of LOT-R & Beta, including line of best fit and the 95% CI (excluding the observation with a β of 77.72)



As mentioned in section 3.2.3, the parameters of Goldstein & Einhorn's function are also estimated and are expected to be highly correlated with the parameters of Prelec's function. Indeed, α and γ are significantly correlated and so are β and δ. Since Pearson's correlation coefficient is very sensitive to outliers, results from ranked correlation tests are also reported in table 4.

Table 4 Correlation Between Prelec's and Goldstein & Einhorn's Probability Weighting Function

Correlation test	***α* and *γ***		***β* and *δ***	
	corr.	*p-value*	*corr,*	*p-value*
Pearson's Correlation	0.9519	0.000**	-0.3208	0.0496*
Spearman's Rho	0.8600	0.000**	-0.9759	0.000**
Kendall's Tau	0.6833	0.000**	-0.8862	0.000**

* significant at $\alpha = 5\%$, **significant at $\alpha = 1\%$

Because of the significant correlation between the parameters, it is expected that the results using Goldstein & Einhorn's function support the results found by using Prelec's function. However, even though the parameters γ and δ of Goldstein and Einhorn's (1987) function did not produce any significant correlations to LOT-R either, the coefficients in the regressions are significant (see appendix A5, model 6 & 7). This difference might be explained by the distribution of β & δ, where β is right skewed with three outliers whereas δ is left skewed with no outliers (see appendix A2, figure 5).

5.2 Economic Optimism

The two-step elicitation method gives a rich amount of data from which several conclusions can be drawn. Firstly, the obtained standard sequence of outcomes can be used to determine the curvature of the individual utility functions. Secondly, the elicited probability weighting function can be drawn and several tests can be performed concerning the transformation of probabilities.

5.2.1 The Utility Functions

For gains, the utility function is expected to be concave (Kahneman & Tversky, 1979). This is because of diminishing sensitivity, where an extra 100 euro is valued more when it is an increase from 100 to 200 euros than when it is an increase from 1000 to 1100 euros. To measure the curvature of the utility function, Δ_j'' needs to be measured when j varies. Δ_j'' is the difference between Δ_{i+1}' and Δ_i', j = 1, …, 5 with $\Delta_i' = x_i - x_{i-1}$, i = 1, … , 6. Thus, for a standard sequence that represents gains, the utility function is concave if and only if Δ_j'' is positive for j = 1, …, 5. However, because of response error, this requirement is loosened and participants with at least three out of five positive (negative) Δ_j'' are classified as exhibiting concave (convex) utility functions for gains[6]. Similarly, when a minimum of three out of five Δ_j'' are between -10 and 10 the participant is classified as having a linear utility curve[7]. As Kahneman & Tversky (1979) predicted, a majority of the participants exhibit a concave utility function. More specifically, a total of 17 participants are classified as concave, 7 participants as convex, 6 participants as linear and 8 as exhibiting a mixed shape. By performing a binominal test, both when taking all of these shapes into account ($H_0\!: \pi \leq \frac{1}{4}$, $H_a\!: \pi > \frac{1}{4}$) , and when only taking the convex and concave shapes into account ($H_0\!: \pi \leq \frac{1}{4}$, $H_a\!: \pi > \frac{1}{4}$), it can be concluded that there are significantly more concave utility functions than other shaped functions (p = 0.0023 & p = 0.0113, significant at α = 0.01 and α = 0.05, respectively). Table 6 shows the averaged results for gains and table 7 and show the median results for gains. Interestingly, according to table 6, the utility function for the averaged results is convex shaped, whereas table 7 shows a concave utility function for the median results. This

[6] Abdellaoui (2000), Fennema & van Assen (1998) and Bleichrodt & Pinto (1998) used similar criteria.
[7] This interval is chosen because each x_i is also chosen in an interval rounded to tens. Δ_j'' is therefore also considered positive when $\Delta_j'' \geq 10$ and negative when $\Delta_j'' \leq 10$.

difference between the median and average data is due to the skewedness of x_i for all $i = 1, \ldots, 6$. Moreover, $x_i, i = 4, 5$ & 6, also contain several outliers (see appendix A2, figure 6).

Table 5 Averaged Results N=38

i	x_i	Δ'_i	Δ''_j
1	486 (230)	286	-57
2	715 (390)	229	47
3	991 (567)	276	26
4	1293 (745)	302	-2
5	1593 (912)	300	-24
6	1869 (1036)	276	

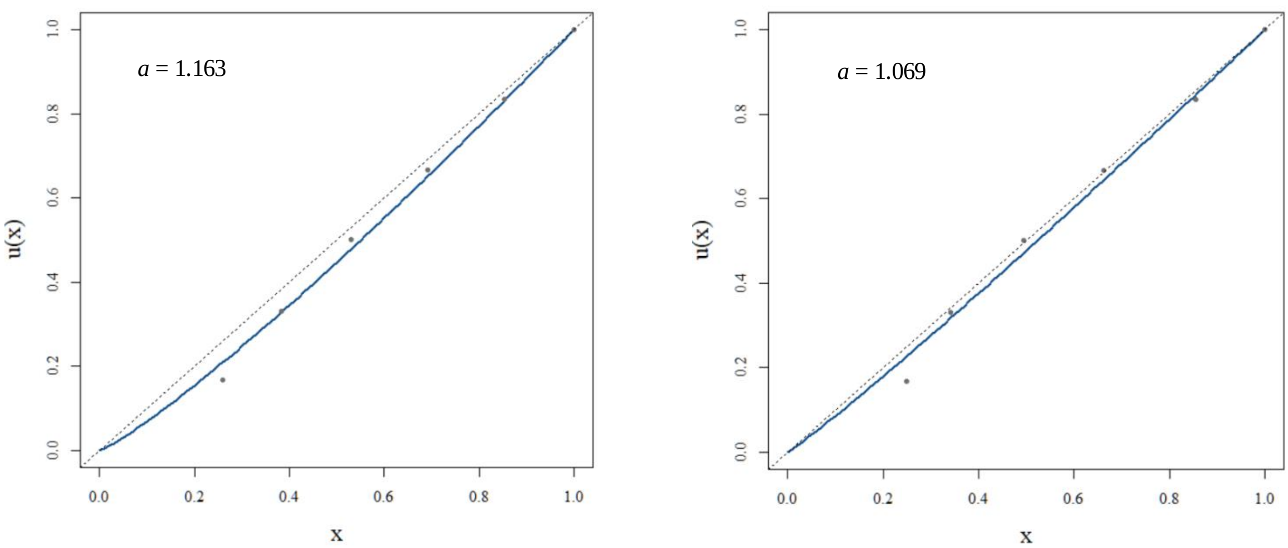
* standard deviations between parentheses

Table 6 Median Results N=38

i	x_i	Δ'_i	Δ''_j
1	380	180	-40
2	520	140	95
3	755	235	20
4	1010	255	40
5	1305	295	-75
6	1525	220	

Apart from the previous mentioned classification, the utility curve is also estimated by the power function (x^a). If $a > 1$, then the utility function for gains can be classified as convex, whereas $a < 1$ indicates a concave utility function. In order to estimate a by nonlinear least squares, the domain of U is normalized to [0,1] by dividing every x_i, $i = 1, \ldots, 6$ by x_6. However, this power function paints a different picture (see figure 3). A total of 8 participants can be classified as having a concave utility curve, compared to 30 participants with a convex shaped curve, which is significantly more (p = 0.000). This difference in results can be explained by the loosened classification of the former method compared to the strict classification of the latter method. According to Wakker & Deneffe (1996), the curvature of the utility curve becomes more pronounced and thus easier to classify when sufficiently large outcomes are used.

Figure 3 The Elicited Utility Functions based on Average (left) and Median (right) Results



5.2.2 The Probability Weighting Functions

To test whether participants indeed transform probabilities and whether they overweight or underweight them, a one-sided sign test of $H_0: w(p_i) = p_i$ is performed. The assessed values are the values of $w(p_i)$ at p = $i/6$, i = 1, …, 5 and p = 0.05, 0.95, as estimated by Prelec's function. Table 8 gives means, medians and standard deviations of the corresponding distributions. In general it is expected that participants overweight small probabilities and underweight medium and large probabilities, as is theorized by Tversky & Kahneman (1979) and confirmed, for instance, by Abdellaoui (2000). From the sign-test (see table 8), it can be concluded that participants did transform probabilities for gains. In particular, the data confirms the overweighting of small probabilities and underweighting of moderate and high probabilities except for p = 1/6. Generally, participants thus tend to be likelihood insensitive, as can also be inferred from the median α of 0.583.

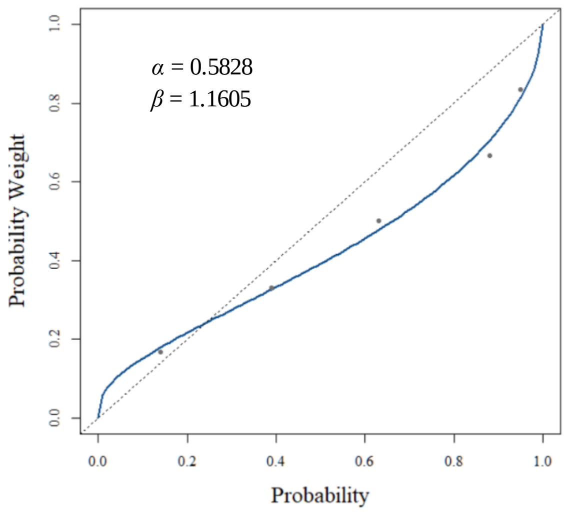
Table 7 One-Tailed Sign-test for w(p) – p and descriptive statistics for w(p)

w(p)-p	**>0**	**<0**	**Median**	**Mean**	**Std. Dev**
p= 0.05	26**	12	0.099	0.120	0.094
p = 1/6	22	16	0.193	0.193	0.122
p = 2/6	14*	24	0.313	0.279	0.147
p = 3/6	9	29***	0.513	0.508	0.168
p = 4/6	6	32***	0.484	0.477	0.181
p = 5/6	2	36***	0.640	0.625	0.174
p= 0.95	0	38***	0.849	0.799	0.135

* significant at α = 10%, *** significant at α= 5%, *significant at α=1%

To illustrate the probability weighting function, individual graphs are drawn. Figure 4 shows this graph for the median data, the individual graphs can be found in appendix A3. For the median data, the graph indeed shows likelihood insensitivity, with an overweighting of probabilities smaller than approximately p = 0.25 and underweighting of probabilities larger than p = 0.25.

Figure 4 Elicited Probability Weighting Function for the Median Data



As mentioned in section 4.1, the average β without the outlier of 77.72 is quite high, namely 1.47. However, when taking a more detailed look at the data, it can be seen that the median of the entire sample is 1.095. A majority of the sample could thus be classified as being pessimistic. Indeed, 13 individuals have a β which is smaller than 1, compared to 25 individuals with a β above 1. Comparing this median beta to other studies, it appears to be quite similar to the median β (1.19) found for recreational hockey players in a recent study of Bleichrodt, L'Haridon & Van Ass (2016). For professional hockey players this beta was significantly lower (0.70). In a different study, Bleichrodt & Pinto (2000) reported an average β of 0.938. Lastly, Stott (2006) found a median β of 1.0 in a sample of 96 university students. Overall, the obtained β's thus seem to lie somewhere around 1.0, meaning that on average participants are neither very optimistic nor pessimistic.

5.3 Psychological Optimism

Apart from the economic optimism profile, several tests are also performed related to the psychological optimism profile. Firstly, a Mann-Whitney-U test is performed to test for possible gender and nationality differences. Previous research on a possible gender difference in optimism leads to varying results. Burke et al. (2000) found no gender difference, both measuring optimism by the LOT-R and the OPS. Dawson (2017) on the other hand speaks of 'female pessimism', noting that females are generally more pessimistic than men, with a tendency to be overly pessimistic. Delving deeper into the descriptive statistics and excluding the outlier of 77.72 from the data, the difference between the average male and female LOT-R score is 0.74, males scoring slightly higher on average. However, as can be seen in appendix A4, this difference is not significant.

Table 8 Optimism and Pessimism Scores Sorted by Gender (N = 16 for Male, N = 21 for Female)

Variable	**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**
LOT-R	16	15.6875	3.646345	9	22
	21	16.42857	3.561714	6	22
Optimist	16	7.5625	2.159282	3	11
	21	7.761905	2.119074	2	10
Pessimist	16	3.875	2.5	0	8
	21	3.333333	1.983263	0	8
β	16	1.478747	0.6732406	0.6540205	3.235207
	21	1.460405	1.450556	0.6253567	7.269787

Similarly, Chang (2002) found a significant difference between Asian and Caucasian American College students in optimism. This indicates that an individual's background might play a role when it comes to optimism. As can be seen in appendix A2, table 9, Dutch participants score higher on both the LOT-R score (17 vs 15.17) and the Optimism subscale (7.89 vs 7.4) and lower on the Pessimism subscale (2.89 vs 4.28). However, from the Mann-Whitney-U test it can be concluded that this difference is only significant for the pessimism sub-score at a 10% -level (p = 0.0984).

Secondly, given the debate on the dimensionality, *Optimist* and *Pessimist* are tested for correlation both using Pearson's Correlation and ranked correlation tests. This correlation gives some indication on whether the LOT-R is best perceived as an unidimensional or bidimensional measurement. From Pearson's Correlation coefficient, it can be seen that the Optimism and Pessimism sub-scores are significantly and negatively correlated ($\rho = -0.3789, p = 0.019$). This is confirmed by Spearman's rho (ρ = -0.3143, p = 0.0546) and Kendall's tau (τ = -0.2392, p = 0.0598), which also show a significant negative correlation. It can thus be concluded that both sub-scales are not independent and a unidimensional scale thus seems appropriate. However, a larger sample is necessary to be able to make strong conclusions on the dimensionality of the LOT-R and to confirm these results with a factor analysis.

6. Discussion & Limitations

This section discusses several limitations, improvements and possible extensions of this research. In section 6.1, the two-step approach is discussed more elaborately together with insights into the choice process obtained by the individual interviews. Afterwards, section 6.2 provides a critical note on the terminology, elaborating on different uses of the term optimism and possible confusions.

6.1 The Two-Step Approach

Because of the individual interviews, it was possible to get extra insight into the choice process of the participants. From these interviews several things became clear. First of all, while eliciting the standard sequence of outcomes, there was an overall tendency to create some sort of pattern in answers[8]. This tendency might have been an attempt of the participants to seem somewhat rational or consistent and might have led to answers that were not truly based on preferences of the participants. It is possible that participants would have answered

[8] These patterns differ per individual, however an often observed pattern A frequently observed pattern in answers is that the participants switch or state indifference when the difference between the certain amount in prospect B and the uncertain amount of prospect A is equal to 100

differently when the prospects regarding the elicitation of the standard sequence of outcomes were asked in a different order. However, the order of the questions cannot be changed in the trade-off method. What might help however, is changing the amount of questions asked, for example the first three questions for each x_i, $i = 1, \dots, 6$ could be asked via binary choice questions and then the indifference value of the closed in interval can be asked directly. This method was already applied by Bleichrodt, L'Haridon & Van Ass (2016).

Another striking observation is that the pattern in answers usually developed during the process, therefore the first set of choices regarding x_1 and often also the set of choices regarding x_2 did not follow this pattern yet. A frequently observed pattern in answers is that the participants switch or state indifference when the difference between the certain amount in prospect B and the uncertain amount of prospect A is equal to 100 (the value of R). The value at which R is set thus seems to highly influence the choices made.

Relatedly, participants often also expressed that the 100 euros was a lot when faced with prospects that had smaller monetary amounts compared to prospects with larger monetary amount. This thus seems to confirm diminishing sensitivity to money. For example, one individual noted during the first question while obtaining x_1 that "100 euros is also already a lot", while during the first question to obtain x_4 she noted that "100 euros means almost nothing anymore". Yet another mentioned that "with the large amounts of money, 100 euro seems to decrease in value" and "a difference of 400 euro is less in case of 1400 vs 1800 euros than when it's 400 vs 800 euros". An interesting observation however, is the fact that often once the larger amounts were elicited (x_5& x_6), participants had sometimes anchored to these amounts and were more risk seeking when faced again with smaller amounts, as was the case during the reliability check and the elicitation of probabilities. This was also often mentioned by the participants themselves. One participant first said when the fourth question of x_1 was repeated as a reliability test that "you start to think differently now that you have seen all the high amounts of money". This seems to indicate that individuals perception of what a large amount of money is also changes during the elicitation process, where 200 and 100 euros were first seen as large amounts but after seeing even larger amounts the same 200 and 100 euros become negligible. This means that the individuals reference point to which they make decisions (which was assumed to be set at 0), seems to change during the process.

Several participants also noted that the choice between the prospects would depend on their state and mood. However, as discussed previously, risk attitude has been proven to be relatively stable over time and the choice between the prospects should therefore not be state or mood dependent. Whether these participants are thus correct in stating that their choice is mood-dependent could be investigated further by creating a panel data study.

Additionally, multiple participants noted that they did not really feel like they had a point of indifference, but more an interval between which they would be indifferent. This interval of indifference, referred to as the imprecision interval by Butler & Looms (2007), is often observed and could possibly account for the preference reversal phenomenon. According to Butler & Looms (2007), the final indifference point picked in the indifference interval is influenced heavily by various anchors. One anchor they observed was the starting point in the elicitation process, having both an impact on the location of the interval and the final point of indifference. Overall, Butler & Looms concluded that there exists some degree of imprecision in participants' preferences and that this might play a role in explaining preference reversals. The existence of imprecision intervals became especially clear during the elicitation of the probability weighting function. Participants often felt as if they had already seen a prospect before, whereas the probability actually changed by a few percentage points. However, when this was noted they still said that it felt like the same prospect. Asking six question per p_i might thus be redundant, since a change in the probability by 1% is hardly noticed by participants. Moreover, several participants also noted that they rounded the probabilities to the nearest 5% instead of looking at it as it was.

This suggests that choices were generally also made by performing some sort of calculations, as is confirmed by the participants. For the elicitation of the standard sequence of outcomes, several participants calculated the expected value and then made a choice purely on which expected value was higher or by comparing the two expected values and then taking into account whether it was worth the extra risk. Additionally, the differences between x_{i-1} & x_i^j and R & x_i^j were also often used as a basis to make the decision. For the standard sequence of outcomes, the main focus thus seemed to lie on the monetary amounts to be gained for both prospects. Scale compatibility might thus play a role in the decision making process for the elicitation of the standard sequence of outcomes. It is important to note that even if the difference between x_{i-1} & x_i^j and R & x_i^j were used as a basis to make decisions, respondents still did not frame them as mixed lotteries and the "problem of framed probabilities" as discussed in section 3.2.2 did not seem a problem in this case.

The economic or mathematical approach to answering the choice questions might be due to the economic background of the participants. Hence, individuals with a different background might have a different approach to answering the questions. Having this homogenous group of subjects is thus beneficial to the internal validity of the results, however external validity is low. One added benefit of using subjects with an economic background is that they are familiar with probabilities and are less likely to make mistakes interpreting them. However, it would be interesting to see whether the results are vastly different with a group of psychology students which are familiar with the LOT-R instead of the economic elicitation method or just generally with a more heterogeneous group of subjects.

Another step that can be taken to improve the external validity of the elicitation method is to have either real monetary incentives or to increase the amount of money at stake. Increasing the outcomes results in utility functions with a more pronounced curvature (Wakker & Deneffe, 1996). Nevertheless, as mentioned in section 3.1, whether responses differ when using real incentives in experiments compared to hypothetical experiments is debatable. Additionally, the shape of the probability weighting function and the parameter estimates found in this study are similar to those found in other studies that did have real incentives. Because of the individual interviews, it was also possible to ask for the motivation behind certain choices. Overall, the motivation behind the choices showed that respondents were engaged during the process and had clear reasons why they stated a certain preference. This suggests that the hypothetical design of this study did not influence the data significantly. Nevertheless, Bleichrodt & Pinto (2000) proposed a version of the elicitation method without monetary outcomes but in the context of medical decision making. In this context, they found a more elevated probability function compared to research using monetary outcomes. According to this, individuals would be more optimistic when faced with medical outcomes compared to monetary outcomes. This might however be due to an inability of the participants to fully interpret outcomes. Therefore, instead of using monetary outcomes with real incentives, the probability weighting function could also be elicited in the context of medical decision making. This could also provide a better fit with the LOT-R, for which research is often performed in the realm of health.

Lastly, instead of actual statement of indifferences, response time might also be a used as a measurement of indifference. During the elicitation process, subjects often had to think longer about a choice between prospects that were closer to indifference than the ones at the beginning of the elicitation of x_i and p_i, *i=1,….,5 (& 6)*. Using response time to infer indifferences is actually proven to be a valid method by Konovalov and Krajbich (2017). They propose an elicitation procedure were several questions are asked and where the response time of the answers is measured. From this, it can be inferred that the questions with the longest response times are the ones where the participant is roughly indifferent.

6.2 The Optimism Umbrella

Optimism as discussed in this paper should not be confused with optimism bias[9], although these terms are interrelated (Windschitl & O'Rourke Stuart, 2015). Optimism bias is the difference between an individual's expectation of what will happen and the actual outcome. If the expectation is more positive (negative) than the outcome, then there is an optimistic (pessimistic) bias. This bias is one of the most consistent, prevalent and robust biases documented in psychology and behavioural economics (Sharot, 2011). Moreover, optimism bias is also seen in how individuals process knowledge. With the optimism bias, information is processed in a biased manner, where more importance is given to information that favours the self or supports the desired conclusion (Flyvbjerg, 2006). As previously mentioned, dispositional optimism is often linked to positive outcomes across a variety of areas. However, there seems to be no correlation, or only a moderate correlation, with specific expectations (e.g. Harris, Giffin & Murray, 2008; Taylor et al., 1992). There is also only a small amount of evidence that dispositional optimism is associated with a bias in those expectations (Radcliffe & Klein, 2002). Moreover, Bränstörm & Brandberg (2010), found that optimism bias often prevents individuals from taking preventive measures for good health since they believe that they are less at risk of getting ill than others. This is in sharp contrast with the previously mentioned relation between dispositional optimism and taking preventative measures to remain in good health (Carver, Scheier & Segerstrom, 2010).

Another interrelated concept is overconfidence. Overconfidence is a more internal concept, where an individual is optimistic about his or her own performance, both in an absolute sense or compared to others. On the other hand, optimism can also be about external events which are out of the control of the individual him- or herself, such as being optimistic about the weather or more related to this study, being optimistic about the chance of obtaining a larger monetary gain. However, optimism and overconfidence still seem two confusing terms and are often used interchangeably or with the definitions interchanged. For example, in an article of the Huffington Post, optimism is actually defined as an attitude, whereas overconfidence is defined as an error in calculating statistical probabilities (McGarvie, 2010). In a paper written by Antonczyk and Salzmann (2014), overconfidence and optimism are only mentioned as the "overconfidence and optimism bias" and the two constructs are not even defined separately. Trevelyan (2008) on the other hand does make a clear distinction between

[9] Optimism bias is also often referred to as unrealistic optimism and the two terms are used interchangeably (Jefferson, Bortolotti, & Kuzmanovic, 2017)

optimism and overconfidence, where optimism is defined as a trait where people have a positive outlook on life and where people hold positive expectations for the future. This definition of optimism thus seems similar to the definition of dispositional optimism. Overconfidence on the other hand is indeed seen as a more internal bias, where individuals are overly confident in their own knowledge or success. However, optimism and overconfidence are viewed as two elements of confidence (Trevelyan, 2008).

Yet another type of optimism often discussed in research is relative optimism. This is quite similar to overconfidence, where people tend to be overly optimistic about themselves relative to the average person and where people believe that negative events are more likely to happen to others than to themselves (Menon, Kyung & Agrawal, 2009).

With all these clarifications given, there still seems to be some overlap between the concepts. Additionally, although these concepts are somewhat different, it is hard to draw a clear distinction between them. The term optimism might thus be best seen as some sort of umbrella term where good (positive) is favoured over bad (negative), which covers various specific types of optimism. However, since it is not always clear which type of optimism is referred to in some cases, drawing clear conclusions about the measurement of optimism also proves to be a difficult task.

7. Conclusion

The central focus of this paper was to determine whether there is a correlation between optimism as measured economically and optimism as measured psychologically. The economic measurement of optimism is by means of measuring the probabilistic risk attitude via the elicitation of the utility and probability weighting functions. Psychological optimism is measured by means of the revised Life-Orientation Test (LOT-R). Findings suggest that there is a small positive, but insignificant correlation between optimism seen economically and psychological optimism and the two concepts thus seem to be unrelated.

The results concerning the elicitation of the utility function confirm the overall view of a dominance of the concave utility function over other shapes. This is in accordance with diminishing sensitivity to outcomes, which was also sometimes noticed by the participants. The results of the probability weighting function as estimated by the function proposed by Prelec (1998) show that in general, participants are likelihood insensitive. Moreover, the majority of the sample can be classified as pessimistic as estimated by the probability weighting function since the median optimism parameter β was above 1.

Psychologically, individuals seem rather optimistic, with an average LOT-R score of 16.18/24. Moreover, there is a significant negative correlation between the optimism sub-score and the pessimism sub-score of the LOT-R, indicating that for this sample the LOT-R can be analysed using an unidimensional scale. However, to be able to make any real conclusions about the dimensionality of the LOT-R, a larger sample size is necessary.

When estimating the probability weighting function using the specification of Goldstein & Einhorn (1987), a regression analysis resulted in a significant relation between the LOT-R and the optimism parameter δ. However, due to reversed causality, this relation cannot be interpreted as causal.

While evidence in previous literature thus points towards a correlation between the two optimism profiles, no such significant correlation is found in this study. However, the fact that no such correlation was found in this study while literature on optimism does suggest such a correlation might also be due to the various different definitions of optimism available and the interrelatedness of the concepts, as mentioned in section 6.2. Moreover, it might be that these two types of optimism are not correlated, but if economic optimism is measured differently it would be correlated with the LOT-R. For example, Puri & Robinson (2007) created a novel measure of optimism comparing self-reported life expectancy to the life expectancy as implied by statistical tables. They did find a significant correlation between their measure of optimism and the LOT-R and beliefs about future economic conditions.

This study is also not without limitations. First of all, participants were not incentivised by anything other than possible intrinsic motivation. However, this might have led to hurried or unreliable responses. The design of this study could thus undoubtedly be improved with more resources. Moreover, to be able to really make any clear conclusions, the sample needs to be improved. Not only is a larger sample size necessary, but a more heterogeneous sample might also represent the general population better.

Further research should thus improve the design of the study, while increasing the sample size. Moreover, using several different measurements of optimism might also give more conclusive results regarding a possible correlation between psychological and economic optimism. If it however turns out that the psychological concept of optimism and the economic concept of optimism are indeed unrelated, then the overlaps in literature regarding the effects of optimism measured economically and psychologically is surprising. However, as mentioned in section 6.2, there are various types of optimism and their interrelatedness often causes that the different types are used somewhat interchangeably or that papers only generally refer to optimism without specifying exactly which type of optimism is meant. This could be a possible explanation for the unrelatedness of dispositional optimism and probabilistic risk attitudes. It is therefore highly recommended to be careful when using the term optimism, making sure to use it in the right context and to be clear which concept or type of optimism is referred to.

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Appendix A1: Procedure

A1.1 Instructions when the Life Orientation Test-Revised was before the elicitation of probability weights.

Dear Participant,

Thank you very much for participating in this research for my master thesis.

I will ask you a lot of questions, but please be as honest and accurate as you can throughout. Try not to let your response to one statement influence your responses to other statements. Keep in mind that there are no "correct" or "incorrect" answers. Answer according to your own feelings, rather than how you think "most people" would answer. Please take your time when answering the questions and don't be afraid to think out loud.

Please fill in this form before we start.

Gender	o Male o Female
Age	__ years
Nationality	________________
Current Study	________________

Please indicate how much you agree with the following statements:

	I disagree a lot	I disagree a little	I neither agree nor disagree	I agree a little	I agree a lot
In uncertain times, I usually expect the best	O	O	O	O	O
It's easy for me to relax	O	O	O	O	O
If something can go wrong for me, it will	O	O	O	O	O
I'm always optimistic about my future	O	O	O	O	O
I enjoy my friends a lot	O	O	O	O	O
It's important for me to keep busy	O	O	O	O	O
I hardly ever expect things to go my way	O	O	O	O	O
I don't get upset too easily	O	O	O	O	O
I rarely count on good things happening to me	O	O	O	O	O
Overall, I expect more good things to happen to me than bad	O	O	O	O	O

A1.2 Instructions when the Life Orientation Test-Revised was after the elicitation of probability weights.

Page 1:

Dear Participant,

Thank you very much for participating in this research for my master thesis.

I will ask you a lot of questions, but please be as honest and accurate as you can throughout. Try not to let your response to one statement influence your responses to other statements. Keep in mind that there are no "correct" or "incorrect" answers. Answer according to your own feelings, rather than how you think "most people" would answer. Please take your time when answering the questions and don't be afraid to think out loud.

Please fill in this form before we start.

Gender	o Male o Female
Age	__ years
Nationality	_________________
Current Study	_________________

Page 2:

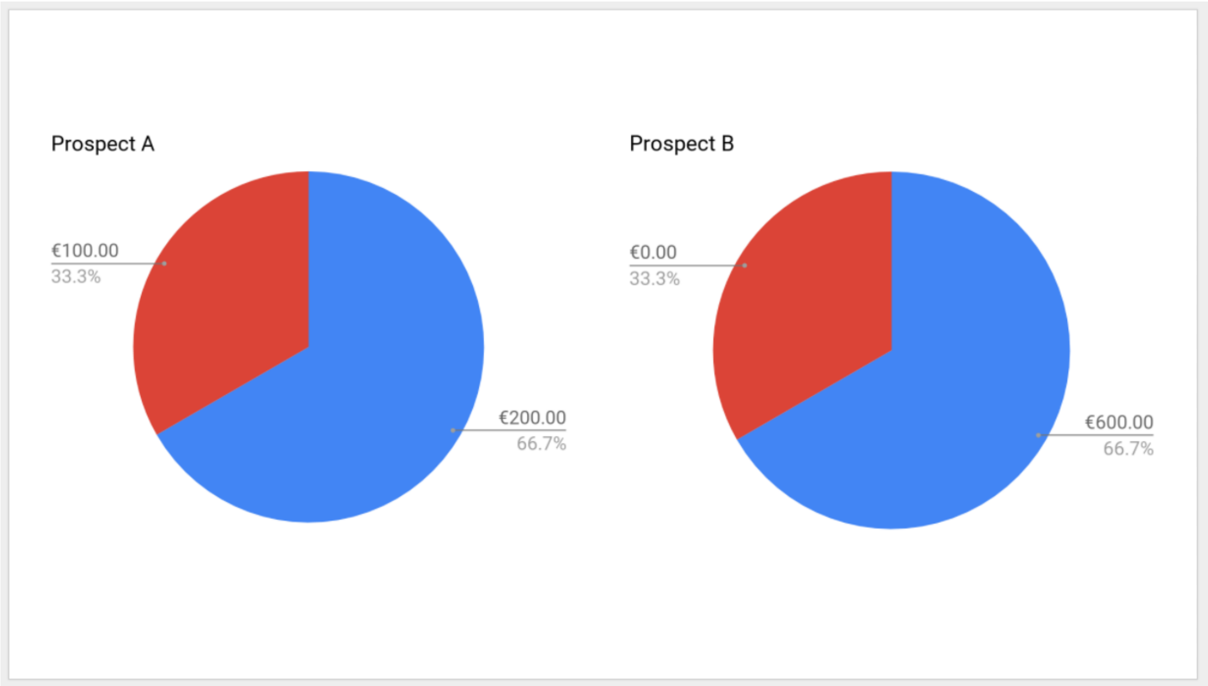
Please be as honest and accurate as you can throughout. Try not to let your response to one statement influence your responses to other statements. Keep in mind that there are no "correct" or "incorrect" answers. Answer according to your own feelings, rather than how you think "most people" would answer.

Please indicate how much you agree with the following statements:

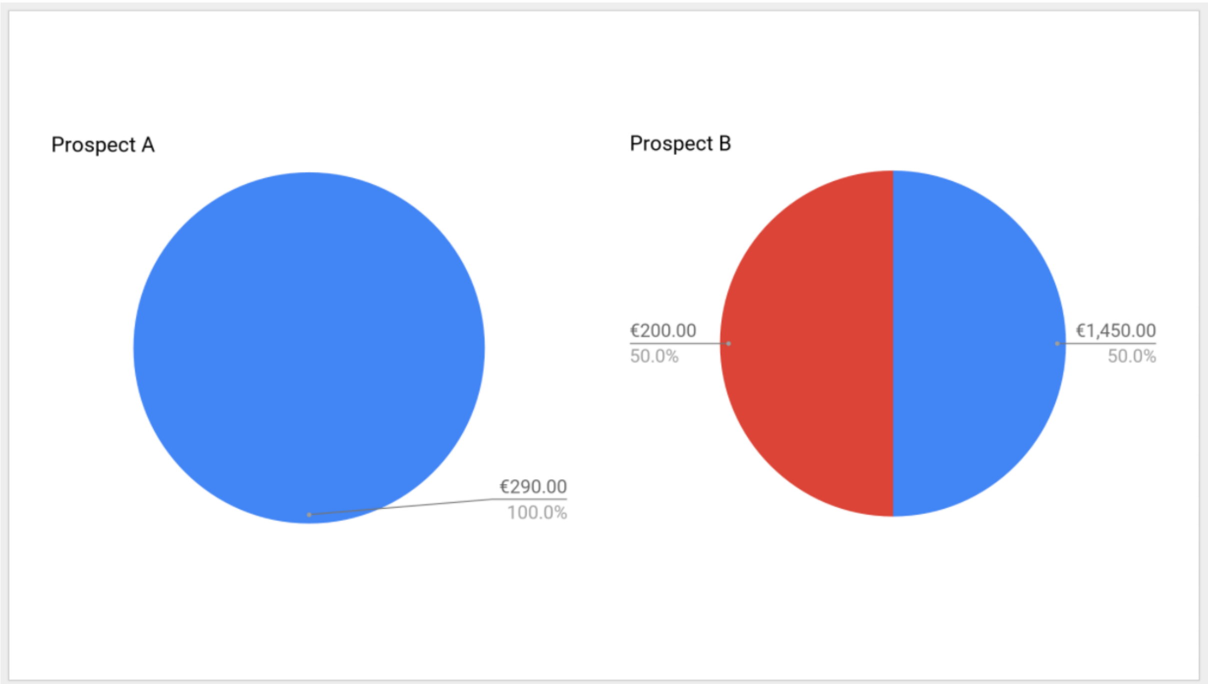
	I disagree a lot	I disagree a little	I neither agree nor disagree	I agree a little	I agree a lot
In uncertain times, I usually expect the best	O	O	O	O	O
It's easy for me to relax	O	O	O	O	O
If something can go wrong for me, it will	O	O	O	O	O
I'm always optimistic about my future	O	O	O	O	O
I enjoy my friends a lot	O	O	O	O	O
It's important for me to keep busy	O	O	O	O	O
I hardly ever expect things to go my way	O	O	O	O	O
I don't get upset too easily	O	O	O	O	O
I rarely count on good things happening to me	O	O	O	O	O
Overall, I expect more good things to happen to me than bad	O	O	O	O	O

A1.3 Choice display of x_1^1 and p_1^1 of first participant

Display in stage 1: Elicitation of Utility (x_1^1)



Display in stage 2: Elicitation of Probabilities (p_1^1)



A 1.4 Screen shots of Excel sheets used during sessions

Excel sheet used during stage 1: Elicitation of Utility[10]

x1										Interval		Choice	delta	800
A	200	2/3	100	1/3	B	600	2/3	0	1/3	200	1000			
A	200	2/3	100	1/3	B	400	2/3	0	1/3	200	600			
A	200	2/3	100	1/3	B	300	2/3	0	1/3	200	400			
A	200	2/3	100	1/3	B	250	2/3	0	1/3	200	300			
A	200	2/3	100	1/3	B	230	2/3	0	1/3	200	250			
										200	230			
									x1	**220**				
x2														
A	220	2/3	100	1/3	B	620	2/3	0	1/3	220	1020			
A	220	2/3	100	1/3	B	420	2/3	0	1/3	220	620			
A	220	2/3	100	1/3	B	320	2/3	0	1/3	220	420			
A	220	2/3	100	1/3	B	270	2/3	0	1/3	220	320			
A	220	2/3	100	1/3	B	250	2/3	0	1/3	220	270			
										220	250			
									x2	**240**				
x3														
A	240	2/3	100	1/3	B	640	2/3	0	1/3	240	1040			
A	240	2/3	100	1/3	B	440	2/3	0	1/3	240	640			
A	240	2/3	100	1/3	B	340	2/3	0	1/3	240	440			
A	240	2/3	100	1/3	B	290	2/3	0	1/3	240	340			
A	240	2/3	100	1/3	B	270	2/3	0	1/3	240	290			
										240	270			
									x3	**260**				
x4														
A	260	2/3	100	1/3	B	660	2/3	0	1/3	260	1060			
A	260	2/3	100	1/3	B	460	2/3	0	1/3	260	660			
A	260	2/3	100	1/3	B	360	2/3	0	1/3	260	460			
A	260	2/3	100	1/3	B	310	2/3	0	1/3	260	360			
A	260	2/3	100	1/3	B	290	2/3	0	1/3	260	310			
										260	290			
									x4	**280**				
x5														
A	280	2/3	100	1/3	B	680	2/3	0	1/3	280	1080			
A	280	2/3	100	1/3	B	480	2/3	0	1/3	280	680			
A	280	2/3	100	1/3	B	380	2/3	0	1/3	280	480			
A	280	2/3	100	1/3	B	330	2/3	0	1/3	280	380			
A	280	2/3	100	1/3	B	310	2/3	0	1/3	280	330			
										280	310			

[10] If choice column is empty, then interval is set as if choice was B

									x5	**300**				
x6														
A	300	2/3	100	1/3	B	700	2/3	0	1/3	300	1100			
A	300	2/3	100	1/3	B	500	2/3	0	1/3	300	700			
A	300	2/3	100	1/3	B	400	2/3	0	1/3	300	500			
A	300	2/3	100	1/3	B	350	2/3	0	1/3	300	400			
A	300	2/3	100	1/3	B	330	2/3	0	1/3	300	350			
										300	330			
									x6	**320**				
Reliability Check														
A	200	2/3	100	1/3	B	250	2/3	0	1/3	200	300			
A	220	2/3	100	1/3	B	270	2/3	0	1/3	220	320			
A	240	2/3	100	1/3	B	250	2/3	0	1/3	220	270			
A	260	2/3	100	1/3	B	310	2/3	0	1/3	260	360			
A	280	2/3	100	1/3	B	330	2/3	0	1/3	280	380			
A	300	2/3	100	1/3	B	350	2/3	0	1/3	300	400			

Excel sheet used during stage 2: Probability Weighting[11]

p1							Interval		Choice
A	220	1	B	320	50	200	0	100	
A	220	1	B	320	25	200	0	50	
A	220	1	B	320	13	200	0	25	
A	220	1	B	320	7	200	0	13	
A	220	1	B	320	4	200	0	7	
A	220	1	B	320	2	200	0	4	
							0	2	
						p1	**1**		
p2									
A	240	1	B	320	50	200	0	100	
A	240	1	B	320	25	200	0	50	
A	240	1	B	320	13	200	0	25	
A	240	1	B	320	7	200	0	13	
A	240	1	B	320	4	200	0	7	
A	240	1	B	320	2	200	0	4	
							0	2	
						p2	**1**		
p3									
A	260	1	B	320	50	200	0	100	
A	260	1	B	320	25	200	0	50	
A	260	1	B	320	13	200	0	25	

[11] If choice column is empty, then interval is set as if choice was B

A	260	1	B	320	7	200	0	13	
A	260	1	B	320	4	200	0	7	
A	260	1	B	320	2	200	0	4	
							0	2	
						p3	**1**		
p4									
A	280	1	B	320	50	200	0	100	
A	280	1	B	320	25	200	0	50	
A	280	1	B	320	13	200	0	25	
A	280	1	B	320	7	200	0	13	
A	280	1	B	320	4	200	0	7	
A	280	1	B	320	2	200	0	4	
							0	2	
						p4	**1**		
p5									
A	300	1	B	320	50	200	0	100	
A	300	1	B	320	25	200	0	50	
A	300	1	B	320	13	200	0	25	
A	300	1	B	320	7	200	0	13	
A	300	1	B	320	4	200	0	7	
A	300	1	B	320	2	200	0	4	
							0	2	
						p5	**1**		
p'2									
A	260	1	B	280	50	240	0	100	
A	260	1	B	280	25	240	0	50	
A	260	1	B	280	13	240	0	25	
A	260	1	B	280	7	240	0	13	
A	260	1	B	280	4	240	0	7	
A	260	1	B	280	2	240	0	4	
							0	2	
						p'2	**1**		
reliability check									
A	220	1	B	320	7	200			
A	240	1	B	320	7	200			
A	260	1	B	320	7	200			
A	280	1	B	320	7	200			
A	300	1	B	320	7	200			
A	260	1	B	280	7	240			

Appendix A2: Descriptive Statistics and Data

Table 9 Participants sorted by study

Study	Frequency	Percent	Cum.
(International) Bachelor Economics and Business Economics	11	28.95	28.95
Master Behavioural Economics	19	50.00	78.95
Other Master	8	21.05	100.00

Table 10 Optimism and Pessimism Scores sorted by Nationality (N= 19 for Dutch, N=18 for non-Dutch)

Variable	Obs.	Mean	Std. Dev.	Min	Max
LOT-R	18	15.16667	3.761258	6	20
	19	17	3.231787	11	22
Optimist	18	7.444444	2.331932	2	11
	19	7.894737	1.911798	4	10
Pessimist	18	4.277778	2.191039	1	8
	19	2.894737	2.051957	0	7
α	18	0.6603579	0. 2439234	0. .3802158	1.434584
	19	0.6330692	0.2771109	0.1615367	1.116169
β	18	1.392634	1.508706	0. .6253567	7.269787
	19	1.540055	0.7524545	0.7518079	3.235207

Figure 5 Box plots of α, β (excluding the outlier of 77.72), δ & γ

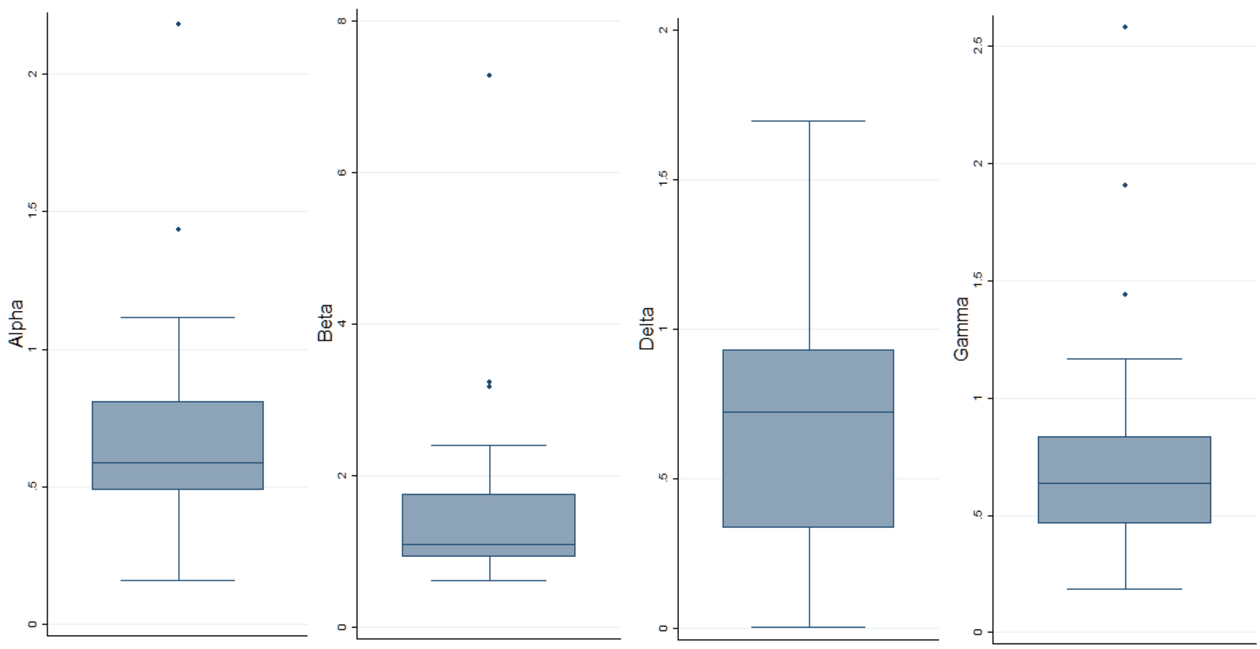
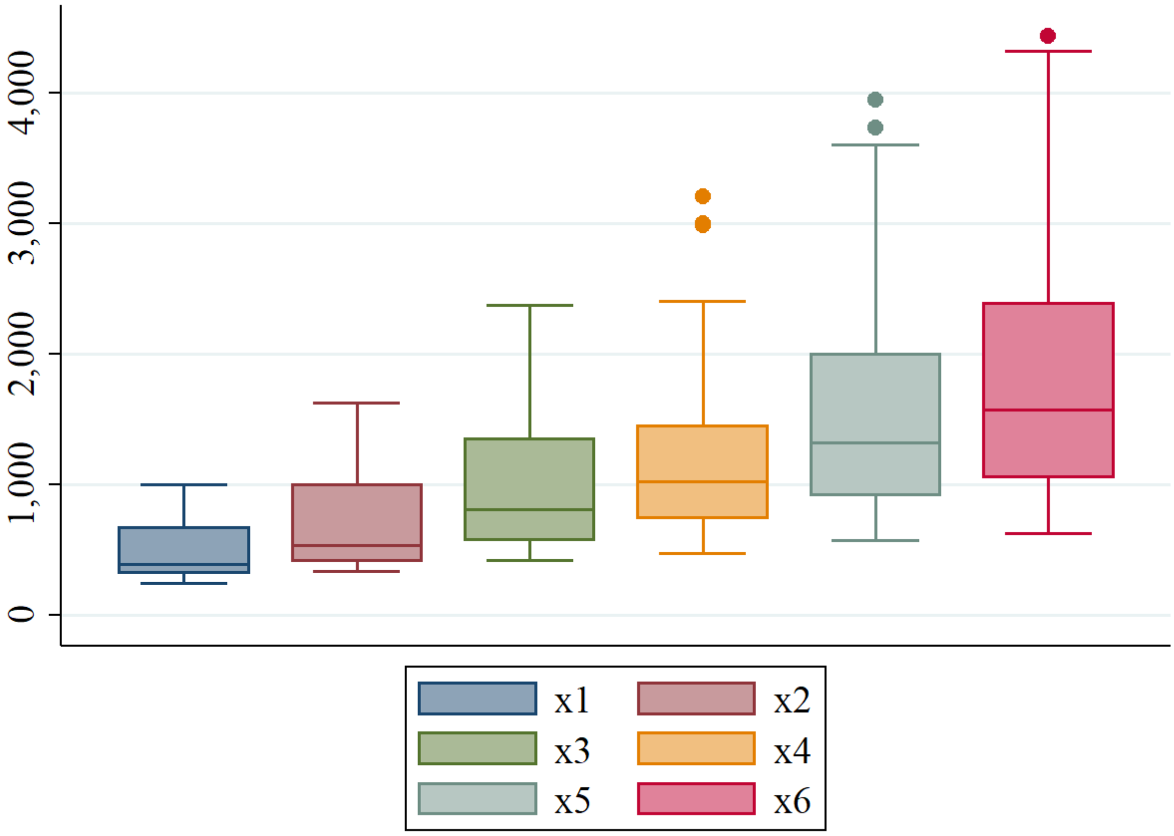
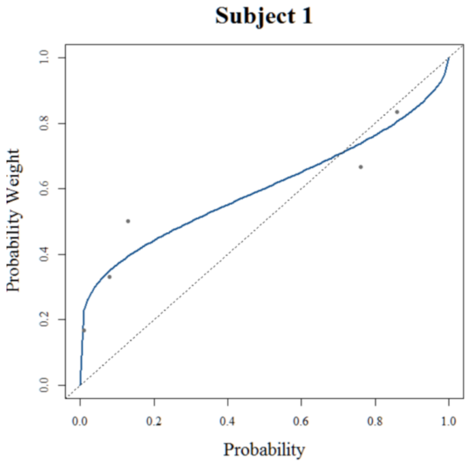
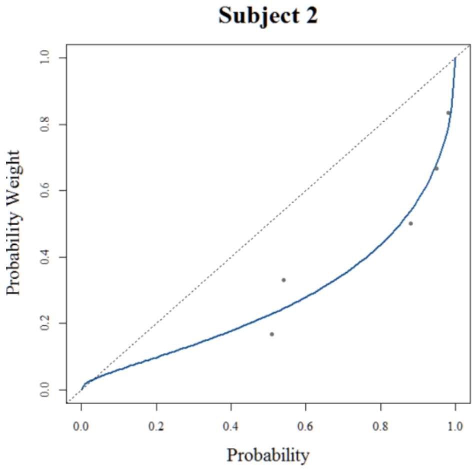


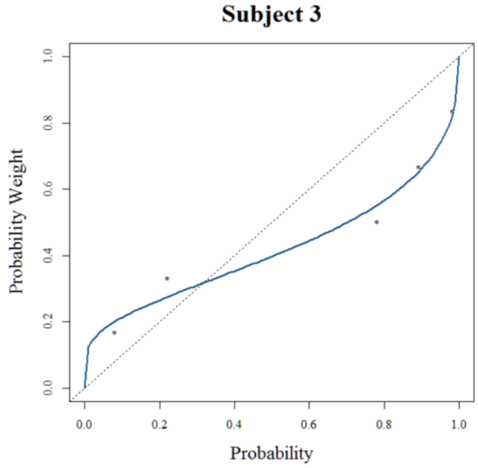
Figure 6 box plots of $x_i, i = 1, \dots, 6$

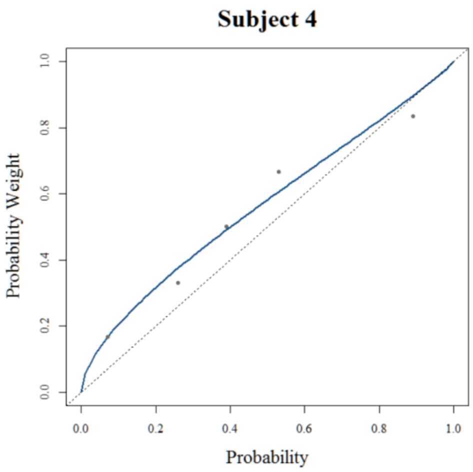


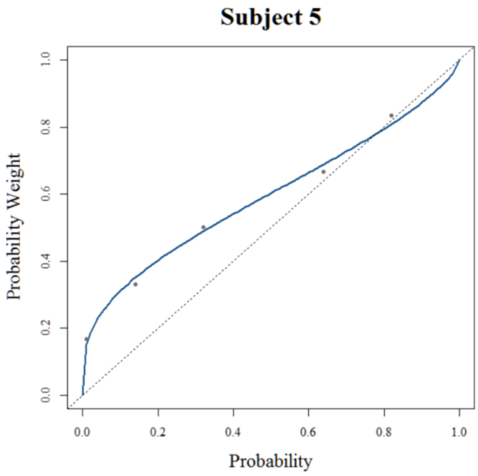
Appendix A3: Elicited Weighting Functions[12]

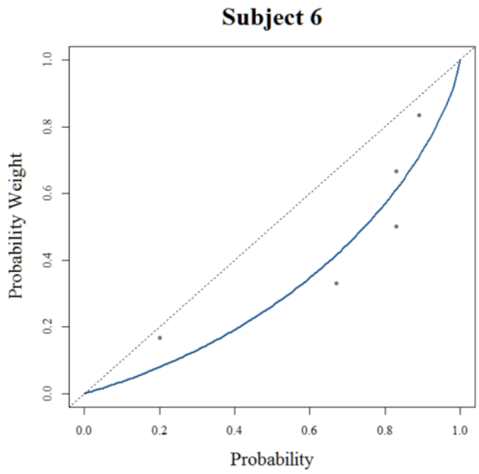


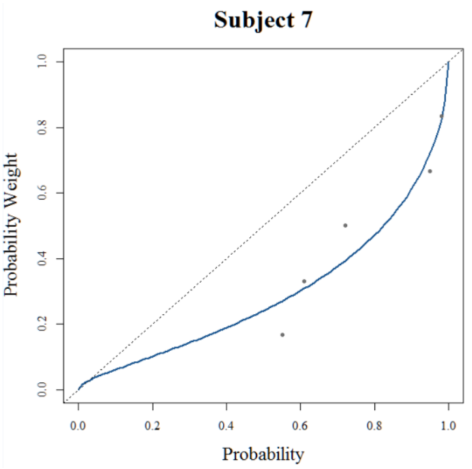


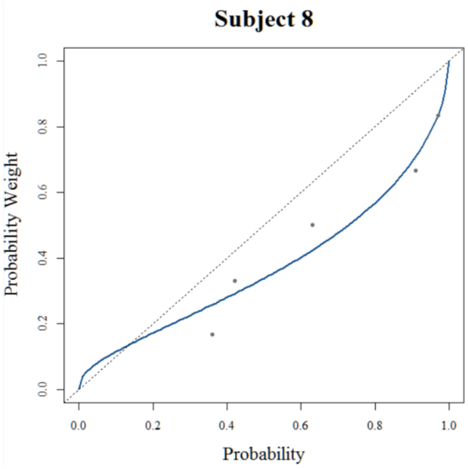


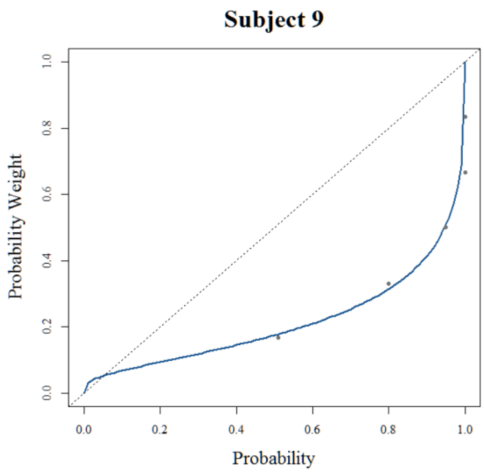




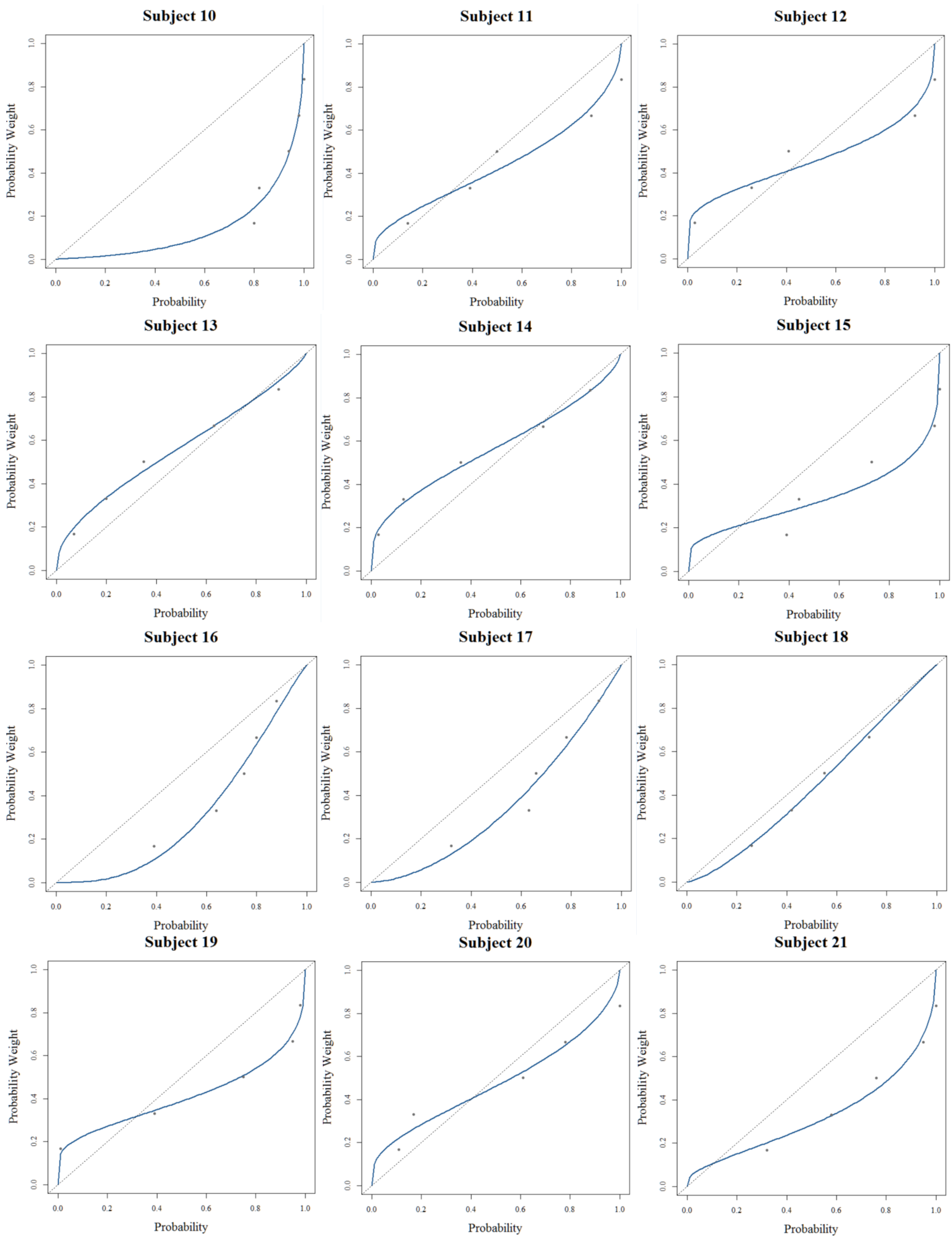


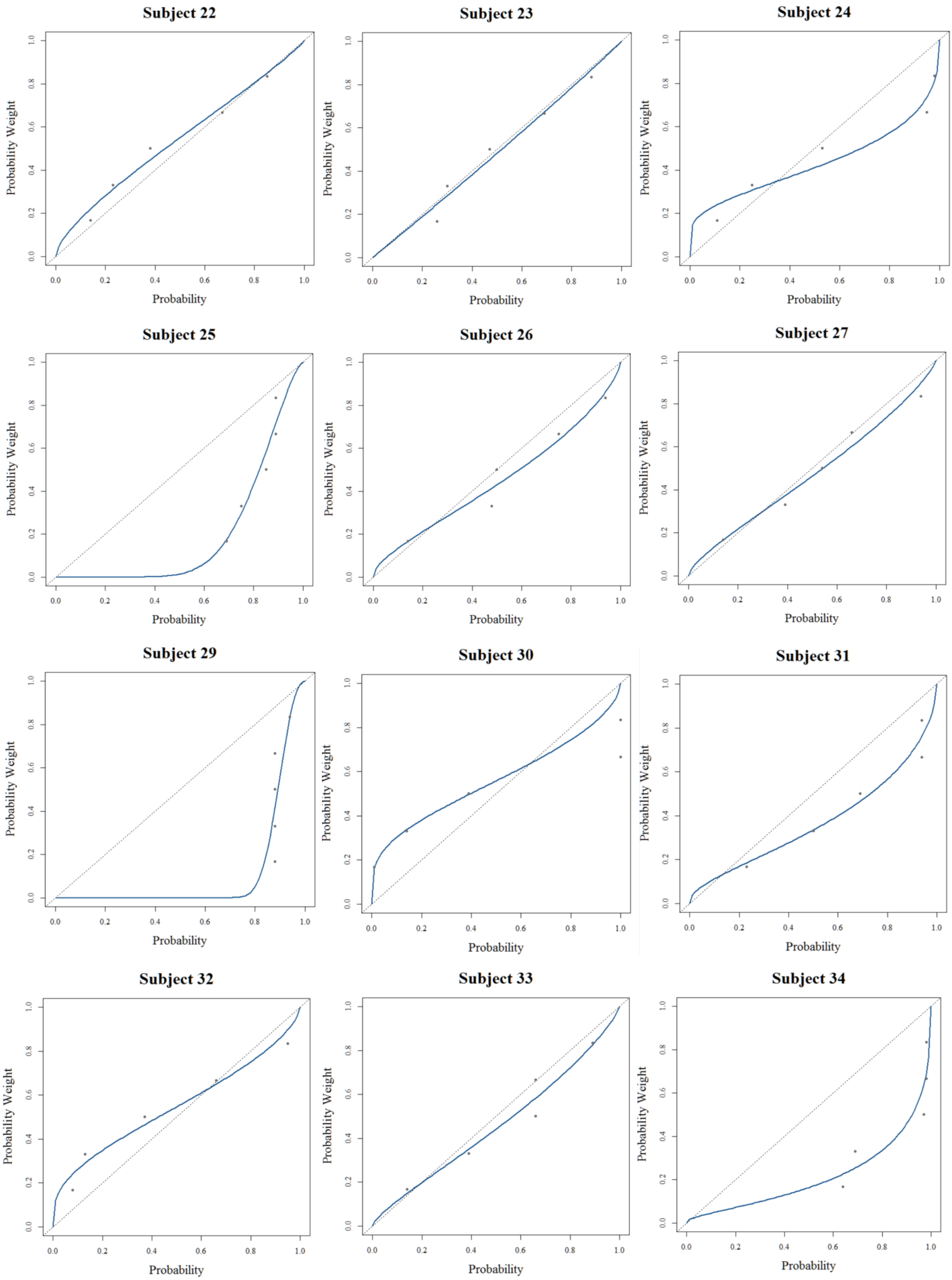


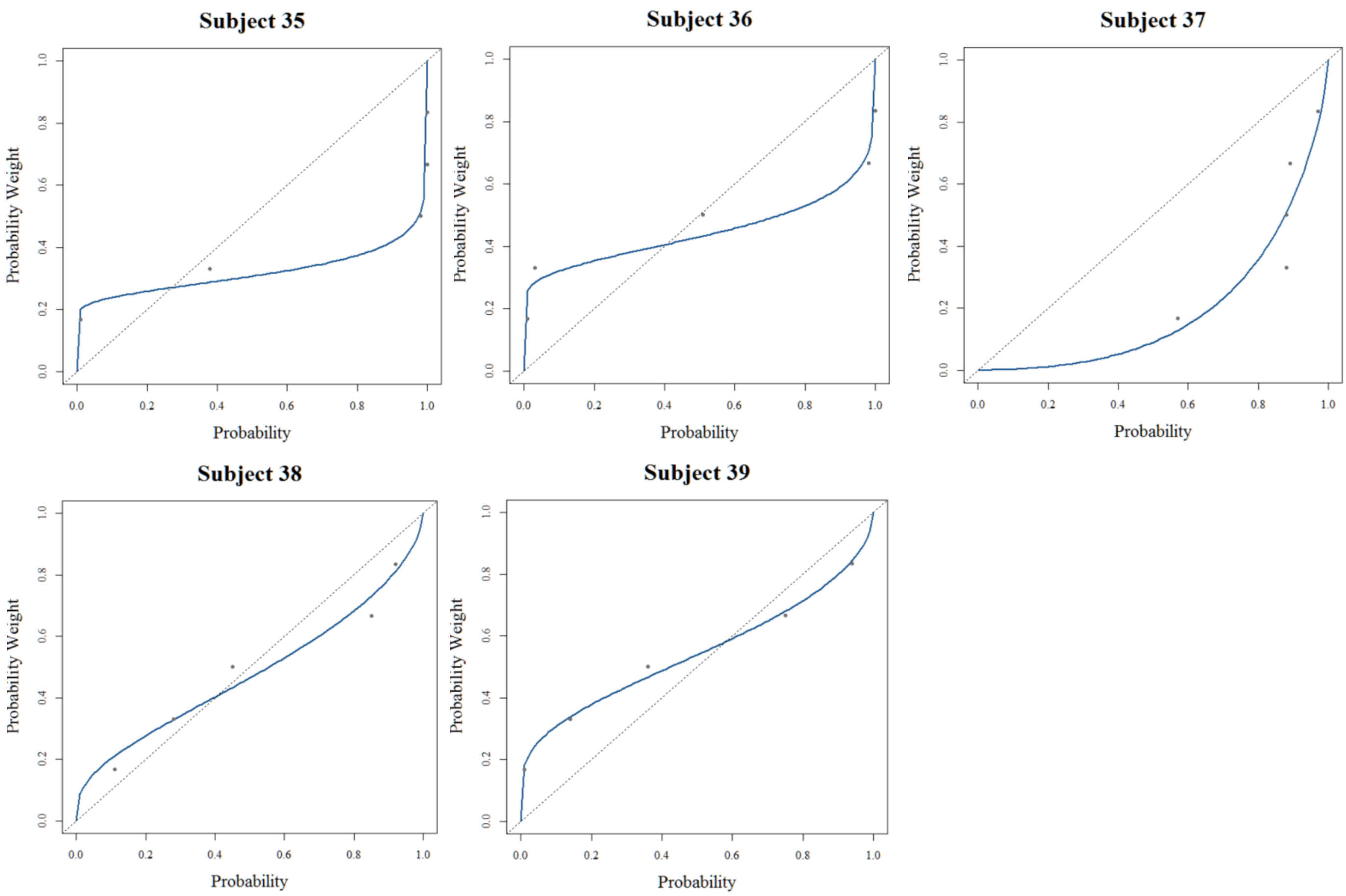




[12] The probability weighing function of subject 28 could not be elicited and is therefore missing


Subject 10
Subject 11
Subject 12
Subject 13
Subject 14
Subject 15
Subject 16
Subject 17
Subject 18
Subject 19
Subject 20
Subject 21
Probability Weight
Probability
0.0
0.2
0.4
0.6
0.8
1.0


Subject 22
Subject 23
Subject 24
Subject 25
Subject 26
Subject 27
Subject 29
Subject 30
Subject 31
Subject 32
Subject 33
Subject 34
Probability Weight
Probability
0.0
0.2
0.4
0.6
0.8
1.0


Subject 35
Subject 36
Subject 37
Subject 38
Subject 39
Probability Weight
Probability
0.0
0.2
0.4
0.6
0.8
1.0

Appendix A4: Tests and Results

Table 11 Principal Component Analysis (N=38)

Component	Eigenvalue	Difference	Proportion	Cumulative
Component 1	2.35454	1.15328	0.3924	0.3924
Component 2	1.20125	0.306967	0.2002	0.5926
Component 3	0.894279	0.198124	0.1490	0.7417
Component 4	0.696154	0.182677	0.1160	0.8577
Component 5	0.513478	0.173159	0.0856	0.9433
Component 6	0.340319	-	0.0567	1.0000

Table 12 Principle Component (Eigenvectors)

Component	Comp 1	Comp 2	Comp 3	Comp 4	Comp 5	Comp 6	Unexplained
Optimism 1	0.2871	0.2570	0.8262	0.4032	-0.0716	0.0364	0
Optimism 2	0.4848	-0.4432	0.0526	-0.0565	0.2898	-0.6918	0
Optimism 3	0.4743	-0.4823	-0.0351	0.0092	0.1799	0.7133	0
Pessimism 1	0.3276	0.5322	0.0897	-0.7102	0.3012	0.0796	0
Pessimism 2	0.4993	0.0984	-0.2325	-0.0816	-0.8220	-0.0686	0
Pessimism 3	0.3179	0.4604	-0.5014	0.5685	0.3349	-0.0165	0

Table 13 Mann-Whitney U test for Optimism and Pessimism Sub-Scores, Sorted by Gender and Nationality

	Optimist, Female	Optimist, Male	Pessimist, Female	Pessimist, Male	Optimist, Dutch	Optimist, Non-Dutch	Pessimist, Dutch	Pessimist, Non-Dutch
Obs.	21	17	21	17	19	19	19	19
Rank sum	422.5	318.5	355	355	383.5	357.5	314.5	426.5
Expected	409.5	331.5	409.5	331.5	370.5	370.5	370.5	370.5
z		-0.389		0.697		-0.386		1.653
Prob > |z|		0.6976		0.4856		0.6992		0.0984

Table 14 Regression Analysis of the determinants of LOT-R

Variables	**Model 1**	**Model 2**	**Model 3**
Constant	14.24581***	7.102978	7.530212
	(1.512291)	(8.925858)	(7.378311)
Alpha	2.965011	3.506091	-
	(2.262973)	(0.268371)	
Beta	-0.0281111	-0.0232121	-
	(0.0458831)	(0.0495144)	
Order		-0.4169057	-0.7190232
		(1.189289)	(1.106865)
Age		0.2497498	0.4217016
		(0.3456061)	(0.2995139)
Nationality		2.12494	2.38172
		(1.475764)	(1.434334)
Gender		0.4558111	-0.1776674
		(1.318923)	(1.288563)
Study		0.0015945	0.3712582
		(1.080946)	(0.9097703)
ln Alpha			3.85902
			(1.535548)
ln Beta			-1.143411
			(0.8451013)
Observations	38	38	38
R-squared	0.0555	0.1624	0.2522
Prob > F	.3685	0.5702	0.2408

Table 15 Regression Analysis of the determinants of Beta (model 3) and the log of Beta (model 4)

Variables	**Model 3**	**Model 4**
Constant	-18.20521	-0.2711711
	(22.51471)	(1.7774)
LOTR	0.5600396	-0.0030878
	(0.6124839)	(0.0416973)
Order	-2.424236	-0.1695441
	(2.596631)	(0.2593377)
Age	0.4496057	0.0201099
	(0.6400747)	(0.592932)
Nationality	-7.817781	-0.1636632
	(7.295009)	(0.4346755)
Gender	-3.156926	-0.2638142
	(3.342546)	(0.2538942)
Study	5.525486	0.3037598
	(4.985111)	(0.3068944)
Observations	38	38
R-squared	0.2040	0.1327
Prob > F	.9666	0.7070

Appendix A5: Goldstein & Einhorn

Table 16 Correlation between LOT-R and parameters of Goldstein & Einhorn

Correlation test	**LOT-R and γ**		***LOT-R* and δ**	
	corr.	*p-value*	*corr,*	*p-value*
Pearson's Correlation	0.1681	0.3129	0.2194	0.1856
Spearman's Rho	0.2589	0.1165	0.1601	0.3370
Kendall's Tau	0.1821	0.1225	0.1183	0.3174

Table 17 *Regression Analysis of the determinants of LOT-R*

Variables	**Model 6**	**Model 7**	**Model 8**
Constant	12.0611***	3.805221	8.273949
	(1.8747)	(7.843799)	(7.337015)
Delta	2.919301**	4.092474**	-
	(1.292096)	(1.50521)	
Gamma	2.665224**	3.482565**	-
	(1.062148)	(1.406827)	
Order		-0.4451985	-0.9182679
		(1.081204)	(1.102422)
Age		0.2518141	0.4063903
		(0.2981017)	(0.2986255)
Nationality		2.889414**	1.945579
		(1.407593)	(1.349288)
Gender		-0.2864023	-0.1985918
		(1.171132)	(1.29152)
Study		0.0250882	0.4503769
		(0.989867)	(0.914881)
ln Gamma			1.311968
			(0.729543)
ln Delta			3.703288
			(1.496014)
Observations	38	38	38
R-squared	0.1391	0.3003	0.2446
Prob > F	0.0364	0.1515	0.2249

Table 18 Regression Analysis of the determinants of Delta (model 9) and the log of Delta(model 10)

Variables	**Model 9**	**Model 10**
Constant	0.4009604	-0.2263903
	(0.9377595)	(2.465822)
LOTR	0.0363541	0.0246304
	(0.0212802)	(0.0559559)
Order	0.0498845	0.2006802
	(0.1510352)	(0.3971445)
Age	-0.0078594	-0.0237112
	(0.0353944)	(0.093069)
Nationality	-0.2548164	0.054762
	(0.158737)	(0.4173961)
Gender	0.1927115	0.3655855
	(0.1507723)	(0.396453)
Study	-0.0558742	-0.02263903
	(0.1144862)	(0.3010395)
Observations	38	38
R-squared	0.2151	0.1299
Prob > F	0.2401	0.5983