ERASMUS UNIVERSITY ROTTERDAM

MASTER THESIS

Correlating Optimism in Psychology with Economics

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Chapter 1

Introduction

For many years psychology and economics were treated as two distinct disciplines. However, in recent years, with the emergence of behavioural economics the gap between these two formerly distinct disciplines is shrinking. In his paper Rabin (1998) writes "Because psychology systematically explores human judgment, behaviour, and well-being, it can teach us important facts about how humans differ from the way they are traditionally described by economists". Camerer, Loewenstein, and Rabin (2011) write: "at the core of behavioural economics is the conviction that increasing the realism of the psychological underpinnings of economic analysis will improve economics on its own terms".

In both psychology and behavioural economics, optimism is a human trait that has been measured and studied with a very large number of implications. In the psychological literature optimism has been studied in a wide range of contexts. These include survivors of missile attacks (Zeidner and Hammer, 1992), people dealing with stresses of childbirth (Carver and Gaines, 1987), better job search outcomes (Kaniel, Massey, and Robinson, 2010) and many more. In the economic literature there have been studies examining optimism in CEO's corporate investment behaviour (Malmendier and Tate, 2005), individual investor behaviour (Ciccone, 2011) and the behaviour of institutions (Lin, Hu, and Chen, 2005).

However, to the best of my knowledge there have been no studies analysing whether optimism measured in psychology correlates with optimism measured in economics. I hope to contribute to the literature by filling this gap. This will be done by applying the Life-Orientation-Test-revised (LOT-R) developed by Scheier, Carver, and Bridges (1994) to measure psychological optimism and the midweight method developed by van de Kuilen and Wakker (2011) to measure optimism in the economics context.

This paper is structured in six chapters. The introduction will be followed by the literature review. Chapter 3 will describe the two methods used to measure optimism in detail, chapter 4 describes the experimental design, the following chapter presents the results and chapter 6 contains a general discussion and the conclusion.

The main findings of my paper are that there is no significant correlation between the psychological and the economic measure of optimism, the median probability weighting function is inverse S-shaped, the median utility function is perfectly linear and most subjects (based on the LOT-R) are neither pessimistic or optimistic but somewhere in between.

Chapter 2

Literature Review

This section provides a detailed account of what has been written in the literature regarding optimism in both the field of economics and psychology. For the sake of a neat and clear structure they will be discussed separately.

2.1 Optimism in Economics

In economics we are often interested in how people make decisions under risk. The literature provides many models for decision making under risk and the best known model is based on maximising expected utility (EU). In the original model as developed by Neumann and Morgenstern (1947) EU was maximised with respect to a given objective probability measure. However, in most real life situation these probabilities are unavailable (Knight, 1921). To model such situations Savage (1954) developed a model in which EU was maximised with respect to subjective probability measures.

Although EU models have many advantages it was shown by Allais (1953) and Ellsberg (1961) that EU models are not descriptively valid. A model was proposed by Handa (1977) to overcome Allais' paradox. It can be mathematically represented as follows:

$$U(P) = \sum_{n=1}^{n} \pi(p_i)u(x_i) \tag{2.1}$$

In the model above π represents the probability weighting function. The model overcomes Allais' paradox, however it violates the axioms of stochastic dominance (the sum of the weights $\neq 1$) as soon as probabilities are transformed non-linearly (Fishburn, 1978). It is this non-linear transformation of probabilities that translates into optimism and pessimism. A more exact definition will be given in section 2.1.2. A model to overcome the violation of dominance was developed by Quiggin (1981, 1982) known as Rank Dependent Utility (RDU) and will be discussed in the next subsection.

2.1.1 Rank Dependent Utility

RDU is a non-EU model and it overcomes the axiomatic violation by weighing the probability of obtaining at least x, and not the probability of obtaining exactly x. The weight attached to an outcome no longer solely depends on the probability of the outcome but also on its rank-ordering.

The first step in computing the RDU is to order the outcomes such that x_1>x_2>...x_n. Then consider prospects of the form P = (p_1:x_1;...p_n:x_n) and compute the decision weight π_i using the following equation:

$$\pi_i = w(p_1 + p_2 ... p_i) - w(p_1 + p_2 ... + p_{(i-1)}) \tag{2.2}$$

The decision weight π_i can be viewed as the 'marginal contribution' of event i to probability weight $w(p_1 + p_2 ... + p_{i-1})$, where $w(p_1 + p_2 ... + p_{i-1})$ is the probability of obtaining at least x_i and $w()$ is the probability weighting function with $w(0) = 0$ and $w(1) = 1$. Once the decision weights have been computer for all i the following equation can be used to determine the RDU of prospect P:

$$RDU(P) = \sum_{n=1}^{n} \pi(p_i)u(x_i) \tag{2.3}$$

2.1.2 Definition of Optimism and Pessimism in Economics

As mentioned earlier non-linear transformations of probability weighting functions translate into either optimism or pessimism. In case of optimism, the better an outcome, relative to other outcomes (its rank-ordering) the more decision weight it gets. In other words, worsening the rank of an outcome x_i while holding the probability of x_i constant, decreases the decision weight of x_i. Pessimism works in the exact same manner but in the opposite direction. The worse an outcome relative to the others, the more decision weight it gets for a given probability. The following figure is a graphical representation of probability transformations.

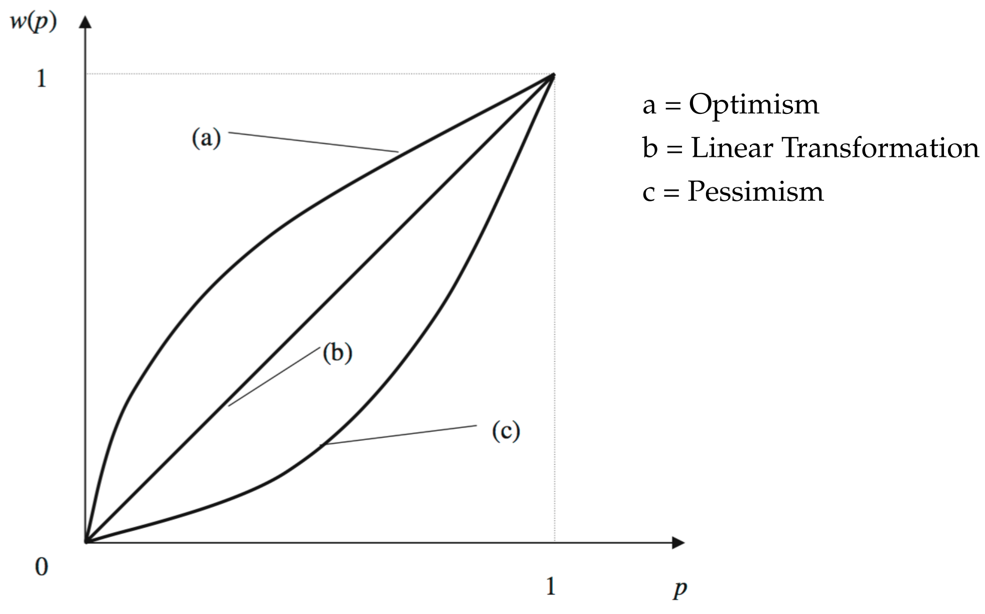

FIGURE 2.1: Probability Transformations

In the figure above, the concave function 'a' corresponds to optimism because for every objective probability p the corresponding subjective probability $w(p)$ is above 45 degree line 'b' which is the linear transformation of each objective probability. The exact opposite reasoning holds for the convex function 'c' which corresponds to pessimism.

In order to better understand of how people assign weights to outcomes, consider the example below consisting of the following prospects:

$$P = 20_{0.25}40_{0.25}60_{0.25}\mathbf{80}$$
$$Q = 40_{0.25}60_{0.25}\mathbf{80}_{0.25}120$$
$$R = 60_{0.25}\mathbf{80}_{0.25}100_{0.25}120$$
$$S = \mathbf{80}_{0.25}100_{0.25}120_{0.25}140$$

As can be seen in bold, the outcome of 80 is present in all four prospects but its ranking differs in each. In prospect P the outcome 80 has the highest ranking and decreases in prospects Q to S. According to RDU a pessimist puts more decision weight to an outcome, the worse the outcome is relative to the other possible outcomes. Hence in prospect P the outcome 80 gets less weight than it does in prospect Q. In prospect Q the outcome 80 gets less weight than in prospect R and so on.

Figure 2.2 is a graphical representation of how a pessimist would assign weights to the outcome of 80 in each of the prospects mentioned above. As it can be seen, prospect S in which its ranking is the worst is assigned the highest weight while in prospect P is it assigned the lowest weight. Note : The objective probability of obtaining outcome 80 is 25% in all four prospects. For an optimist the exact opposite is true. The shape of the probability weighting function is concave and prospect S in which its ranking is the worst is assigned the lowest weight while in prospect P is it assigned the highest weight.

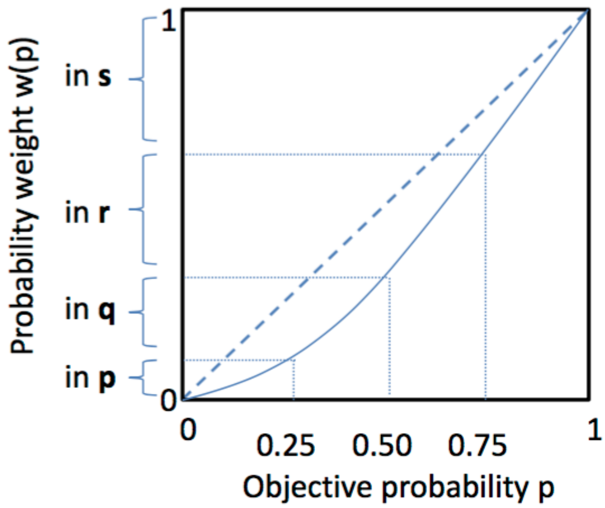

FIGURE 2.2: Pessimism
Figure taken from the course Advanced Behavioural Economics

2.1.3 Social Relevance

A RDU maximiser can be optimistic or pessimistic. In the behavioural finance literature this is referred to as investor sentiment and plenty of research has been done to investigate whether this affects investor behaviour. Not surprisingly investor sentiment does distort investment decisions. This subsection will provide an overview of existing literature that has studied investment distortion as a result of optimism.

Gibbons and Hess (1981) established that average returns on equities vary with days of the week and are consistently negative on Mondays. Similar findings have been reported by Cross (1973) and French (1980). This phenomenon goes against the concept of investor rationality and the market efficiency hypotheses. Even though traditional economics fails to explain the Monday effect, all hope is not lost. There exists a plausible behavioural economics explanation, namely the "Blue-Monday" hypothesis developed by Pettengill (1994). The hypothesis states that investors are affected by systematic mood changes that cause negative price pressures on Monday and positive price pressures on Friday. Consider the acronym TGIF which expresses the delight and optimism people feel on Friday - the end of the work week. Monday on the other hand represents the beginning of the new work week and people feel pessimistic and disutility from having to go back to work.

Investor irrationality can also be observed in a phenomenon called the January effect - a general increase in stock prices during the month of January. This increase once again cannot be explained by theories of rationality. It can however be partially explained by a behavioural framework based on optimistic expectations. Ciccone (2011) argues that the turn of the year is a time of renewed optimism. Some evidence of this can be seen in University of Michigan's Index of Consumer Confidence, which consistently peaks in January. Thus, one of the potential behavioural explanations for the January effect is: optimistic investors bid up the stock prices of firms with higher levels of uncertainty in January.

Furthermore, research by Bolton, Scheinkman, and Xiong (2006) and Burns and Kedia (2006) has shown that CEOs have incentive to misreport earning in times of high investor sentiment. Malmendier and Tate (2005) conclude "that top corporate decision-makers persistently overestimate their own skills relative to others and, as a result, are too optimistic about the outcomes of their decisions". This optimism results in suboptimal investment decisions and loss of welfare. Lastly, Kilka and Weber (2000) and Strong and Xu (2003) suggest that people (individuals and institutions) are more optimistic toward their home markets than they are about international markets and the home bias is driven by this optimism.

Considering the above, it can be said that not only individuals but also institutions suffer from behavioural biases that are affected by optimism and this in turn impacts social welfare. The next section will view optimism from the psychological perspective.

2.2 Optimism in Psychology

Before defining optimism in psychology an important distinction must be drawn between two types of optimism, little versus big optimism (Tiger, 1979). Little optimism involves specific expectations about positive outcomes: for example, "I will win this lottery" Big optimism refers to larger and less specific expectations: for example, "I will be someone successful". The big-versus-little optimism distinction is important because optimism can be described at different levels and optimism may function differently depending on the level at which it is measured.

Carver, Scheier, and Segerstrom (2010) define optimism as "an individual difference variable that reflects the extent to which people hold generalised favourable expectancies about their future". In other words optimists have positive expectations of the future whereas pessimists have negative expectations. The idea that optimists have positive expectations is based on a long tradition of expectancy-value models (Scheier, Carver, and Bridges, 1994). Expectancy-value theories assume people's behaviour reflects the goals that they have. As the name suggests, the theory has two facets, expectancy and value. *Expectancy* is defined as determination that the goal can be achieved. If people suspect that the goal is too difficult and not attainable, they may put in less effort toward achieving it. They may stop before the task is completed, or never even start the task. On the other hand people who believe the goal is attainable will persevere when faced with hardships (Carver, Scheier, and Segerstrom, 2010). The second facet is *value* - The more important a particular goal is to the person, the greater the value attributed to it (Austin and Vancouver, 1996; Carver Charles and Scheier Michael, 1998). Thus, optimists are individuals who are confident and persistent when faced with challenges and pessimists are doubtful and hesitant in the same situations. Optimism as defined by Carver, Scheier, and Segerstrom (2010) corresponds to big optimism and this is the definition used in this thesis.

2.2.1 Theoretical Grounding

There are at least two methods to measure optimism using generalised expectancies. One is to measure generalised expectancies directly, by asking people whether they expect good outcomes or bad outcomes in their lives (Scheier and Carver, 1992). This method is known as the Life Orientation Test (LOT), developed by Scheier and Carver (1985). In order to evaluate the convergent and discriminant validity of the LOT, Scheier and Carver administered this eight-item scale along with a variety of other scales, including measures of hopelessness, depression, and self-esteem, to several samples of undergraduates. They concluded that the LOT satisfies convergent validity because it correlated with conceptually related constructs (hopelessness, depression, etc..). They also maintained that discriminant validity was evident as these same correlations were not so large as to suggest that the LOT is redundant with other scales. However the validity of the LOT was questioned by Smith et al. (1989) who argued that pessimism is simply another facet of neuroticism. They showed that the correlations of the LOT with health and coping measures were mostly eliminated when neuroticism was controlled for and concluded that the LOT is virtually indistinguishable from neuroticism.

Scheier, Carver, and Bridges (1994) replied to this challenge using data from 4,309 subjects showing that the associations between optimism and both depression and coping remained significant after controlling for neuroticism, trait anxiety, self-mastery, and self-esteem. However, while conducting this research they questioned whether or not the items on the LOT scale were measuring what they were intended to measure: generalised expectancies of good versus bad outcomes in life. They identified two problematic items in the original LOT and removed them, this resulted in the Revised Life Orientation Test (LOT-R)

The second approach to measuring optimism is known as the explanatory style. In some cases, the situation itself provides the explanation made by the person. In other cases, the person relies on his or her habitual way of making sense of events that occur, this is called one's explanatory style: how he or she explains the causes of bad events. It is based on the idea that people's expectations of the future are formed based on how they interpret their past (Peterson and Seligman, 1984). Individuals who favour internal ("it is all my fault"), stable ("it is going to last forever"), and global causes ("it is going to undermine everything") are described as pessimistic. On the other hand those who explain bad events in a limited fashion (It is caused because of a particular thing and not a global cause), with external (it is not my all my fault), unstable, and specific causes, are described as optimistic. If an individual attributes past failures to stable causes, then he/she will expect more failures in the future, because the cause is likely to remain unsolved as he/she believes it to be stable. On the other hand, if past failures are seen to be related to unstable causes, the attitude for the future may be more pleasant, because the cause may have been mitigated. Thus according to Peterson and Seligman (1984) within the explanatory style, optimism and pessimism "are assessed as patterns of attributions about the causes of events, and infers that these attributions ultimately yield expectancies".

Although these two measures (LOT-R and the explanatory style) relate to similar constructs research by Ahrens and Haaga (1993) and Peterson and Vaidya (2001) has shown that the two measures cannot be treated interchangeably. This because stable attributions for negative events are only weakly correlated with measures of generalised expectancies. Furthermore, an optimistic expectation according to the LOT-R leads to the belief that goals can be achieved, but it remains neutral with respect to how this will happen. In contrast, the explanatory style measure reflects causality, so it is additionally influenced by people's beliefs about how goals are brought about (Peterson, 2000). According to Carver, Scheier, and Segerstrom (2010) one approach is preferred over the other depending on "whether one views attributions or expectancies as the more fundamental or crucial element". In this work the LOT-R will be used to measure optimism and is explained in detail in section 3.1. I have chosen to use the LOT-R instead of the explanatory style because of its simplicity. To measure optimism using explanatory style a much longer questionnaire needs to be administered (48 questions as opposed to 10) and I expected that subjects would not fill in the answers with care and caution because the subjects were not incentivised with monetary outcome (this will be discussed in more detail in chapter 6).

A final issue that needs to be addressed is whether or not optimism and pessimism are polar opposites on a unidimensional continuum (Herzberg, Glaesmer, and Hoyer, 2006). There is evidence suggesting that the LOT consists of partially independent Optimism and Pessimism factors (Robinson-Whelen et al., 1997) and they are not polar opposites of each other. A number of studies have tried to settle this debate but there is no consensus. Contrary to findings of Herzberg, Glaesmer, and Hoyer (2006), Rauch, Schweizer, and Moosbrugger (2007) argue that a unidimensional view is accurate so optimism and pessimism are indeed polar opposites of each other. For the sake of simplicity, in this thesis I treat optimism and pessimism as polar opposites on a unidimensional continuum.

2.2.2 Social Relevance

As mentioned earlier, optimism is defined as an individual difference variable. Research over the past decades has identified that these individual differences are important. The core processes that shape human behaviour are linked to the this simple difference-anticipating good versus bad (Carver, Scheier, and Segerstrom, 2010). Optimists and pessimists differ from each other in how they face problems; how well they deal with hardships; and also in their social and socioeconomic resources. This subsection will provide an overview of existing literature that studied these differences.

A large number of studies on optimism have been done in the medical context. Scheier et al. (1989) studied the effect of optimism on recovery from coronary artery bypass surgery. They concluded that optimism was an important predictor of coping efforts and of surgical outcomes. Furthermore, they found a strong positive relationship between levels of optimism and post-surgical quality of life 6 months after the surgery. Similar findings have been reported by Allison, Guichard, and Gilain (2000) and Fitzgerald et al. (1993).

There are also studies examining optimism outside of the medical context. Kaniel, Massey, and Robinson (2010) showed that optimistic MBA students experience significantly better job search outcomes than pessimists with similar skills. Two other studies have examined the role of optimism amongst students adjusting to the first semester of higher education and concluded that students with higher levels of optimism experienced less distress at the end of the semester (Aspinwall and Taylor, 1992; Brissette, Scheier, and Carver, 2002).

Considering the above, it can be said that optimism or lack of optimism has far reaching consequences and that makes it a very interesting topic to study.

2.3 Scientific Relevance

Psychologists believe that little and big optimism are correlated however the exact relationship between little and big optimism is not well understood (Peterson, 2000). That being said, contrary findings have also been presented in the literature. Gyurcsik and Brawley (2001) showed that these two forms of optimism are not correlated at all.

There is no consensus as to whether the two distinct forms of optimism are correlated. It is possible to imagine someone who is a little optimist but a big pessimist, or vice versa. Furthermore, it is also possible to imagine situations in which big optimism has desirable consequences but little optimism does not, or vice versa. Consider CEO optimism mentioned in section 2.1.3 which leads to undesirable consequences. Little optimism specific to his belief that he can generate more value in the company leads to investment distortions and suboptimal capital allocations.

I will contribute to the existing literature by measuring little optimism using the economic measure, more specifically the mid-weight method developed by van de Kuilen and Wakker (2011) and analyse whether or not it correlates with big optimism measured using a psychological measure known as the Life-Orientation-Test- Revised (LOT-R) developed by Scheier, Carver, and Bridges (1994). It is well established and agreed upon that the optimism measure of Scheier and Carver (1985) tap big optimism because they ask people to respond to generalisations about the future (Gyurcsik and Brawley, 2001; Peterson, 2000). When it comes to the economic measure it is not as clear cut whether or not it is measuring big optimism or little optimism. Segerstrom and Sephton (2010) write "It is important to distinguish between the effects of situational expectancies (little optimism) and generalised expectancies (big optimism)". Furthermore, Gyurcsik and Brawley (2001) write that little optimism is concerned with specific expectations about specific behaviour or events. As the answers provided by subjects are specific to the prospects which lead to a specific choice I assume that the mid-weight method is measuring little optimism.

It may be that the assumption that the mid-weight method measures little optimism is a very strong one, but even if the midweight method is not measuring little optimism it is still very interesting to see how the economic measure for optimism correlates to the psychological measure for optimism.

Chapter 3

Two Methods of Measuring Optimism

The psychological scale used to measure optimism is the revised Life Orientation Test(LOT-R) developed by (Scheier, Carver, and Bridges, 1994) and the economic measure used is the Midweight Method developed by (Kuilen and Wakker, 2011). This section will describe these methods in detail.

3.1 LOT-R

The LOT-R is a scale measuring optimism defined in terms of generalised outcome expectancies. Outcome expectancies can range from very specific such as "Will I score well on this test?" to very general "Will good things happen to me?". According to Scheier and Carver (1987) "most expectancy-based theories implicitly assume that prediction of an outcome is best when the expectancy in question matches the level of specificity of the outcome". As I am interested in measuring "big" optimism the LOT-R is the best method because it uses generalised outcomes.

This measure of optimism consists of a 10-item questionnaire. Of the 10 items, 3 items measure optimism and are positively worded, 3 items measure pessimism and are negatively worded, the remaining 4 items serve as fillers. It is important to have fillers in the questionnaire to prevent subjects from correctly guessing the trait being measured, i.e. optimism. These fillers help mitigate the experimenter demand effect to some degree. Experimenter demand effect refers to changes in behaviour by experimental subjects in the direction they believe the experimenter wants them to (Zizzo, 2010). The items of the LOT-R are presented below:

1. In uncertain times, I usually expect the best.
2. It's easy for me to relax.
3. If something can go wrong for me, it will. (R)
4. I'm always optimistic about my future.
5. I enjoy my friends a lot.
6. It's important for me to keep busy.
7. I hardly ever expect things to go my way. (R)
8. I don't get upset too easily.
9. I rarely count on good things happening to me. (R)

10. Overall, I expect more good things to happen to me than bad.

Respondents rate each of these item on a 5-point scale described below.

- 4 = Strongly Agree.
- 3 = Agree
- 2 = Neutral
- 1 = Disagree
- 0 = Strongly Disagree

Items 3, 7, and 9 are reverse scored (R). Items 2, 5, 6, and 8 are fillers and should not be scored. The scoring is kept continuous hence the maximum a subject can score is 24 and the minimum is zero. However, there is no benchmark for optimism. Carver, Scheier, and Segerstrom (2010) write "It is common to refer to optimists and pessimists as though they were distinct categories of people, but this is a verbal convenience. Almost never is a line drawn and people placed in one group or the other. People range from very optimistic to very pessimistic, with most being somewhere between."

3.2 Midweight Method

The midweight method is a relatively new method to measure probability weighting functions, both for risk and for ambiguity. Typically to measure RDU one has to measure both the weighting function and the utility function. The key advantage of the midweight method is that it minimises the need to measure utility and focuses on the weighting function. Furthermore, it does not require prior assumption about the form of utility or weighting functions which makes it a suitable model to capture any shape or form.

The midweight method minimises the need to measure utility by requiring that I only find the utility midpoint and not the entire function. The utility midpoint is found using the trade-off method (Wakker and Deneffe, 1996). As the tradeoff method is a fundamental piece of the midweight method, it will be described first.

3.2.1 Tradeoff Method

As people do not transform probabilities linearly, the tradeoff method is advantageous because it is robust to probability weighting. Other methods such as certainty equivalence and probability equivalence are not. The method tradeoff method relies on eliciting indifference between prospects.

The first step is to fix an outcome x_0, two reference outcomes r and R such that R>r, and a probability p. I use this to elicit x_1 by asking the subject for the value of x_1 that makes him/her indifferent between the following prospects:

$$(p : x_1, 1 - p : r) \sim (p : x_0, 1 - p : R) \tag{3.1}$$

Once we know x_1, present the following prospect to elicit x_2.

$$(p : x_2, 1 - p : r) \sim (p : x_1, 1 - p : R) \tag{3.2}$$

The same process can be repeated as many times as necessary. The higher the number of iterations the more accurate the shape of the utility function will be. However, for my purposes (which is to find the utility midpoint) eliciting x_1 and x_2 are sufficient.

Once the outcomes x_0, x_1, and x_2 have been elicited, the preference domain will be restricted to prospects that use only these three outcomes referred to by van de Kuilen and Wakker (2011) as the probability triangle. Considering RDU the two indifference it can be expressed as follow:

$$\pi(u(x_1)) + (1 - \pi)u(r) = \pi(u(x_0)) + (1 - \pi)u(R) \tag{3.3}$$

$$\pi(u(x_2)) + (1 - \pi)u(r) = \pi(u(x_1)) + (1 - \pi)u(R) \tag{3.4}$$

Subtracting equation 3.3 from 3.4 yields:

$$\pi(u(x_2) - u(x_1)) = \pi(u(x_1) - u(x_0)) \tag{3.5}$$

As mentioned earlier, one of the advantages of this method is that it elicits utility independent of probability weighting, as it can be seen in equation 3.5 there is π on both sides of the equation and hence it can be eliminated. Dividing both sides by π yields:

$$u(x_2) - u(x_1) = u(x_1) - u(x_0) \tag{3.6}$$

Equation 3.6 implies that outcomes x_0, x_1 and x_2 are equidistant in terms of utility. Setting x_2 = 1 and x_0 = 0 we see that x_1 = 1/2. In other words x_1 is the utility midpoint between x_2 and x_0. For a more general application of the tradeoff method one can choose any length n of the tradeoff-sequence x_0... x_n and always set u(x_0) = 0 and u(x_n)=1. From this it follows that u(x_i) = i/n.

The tradeoff method is also robust under non-expected utility models, such RDU and cumulative prospect theory models. This is highly relevant as there is consensus in the literature that the EU model is not descriptively valid and non-expected utility models perform better. However, to apply the trade off method to RDU models we need to apply the following constraint: x_0, r and R must be chosen such that

$$x_n....x_2 > x_1 > x_0 > R > r \tag{3.7}$$

This ensures that the ranking of the outcomes corresponding to probability p does not change.

3.2.2 Midweight Method

Once the probability triangle has been established, it is possible to elicit the probability weighting function for subjects using the midweight method.

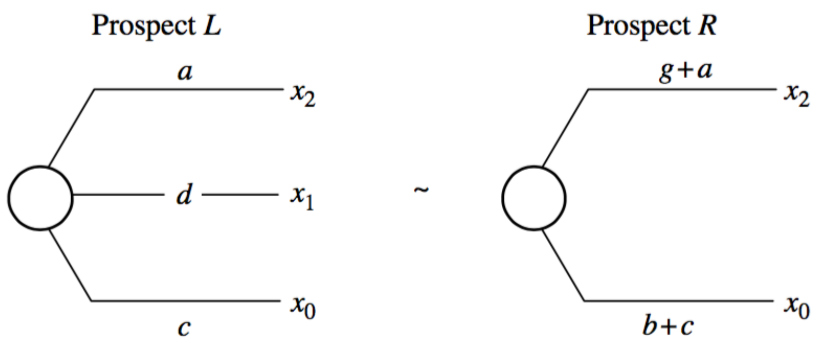

FIGURE 3.1: Distributing d's Weight Evenly over the Upper and Lower Branch
Figure taken from (Kuilen and Wakker, 2011)

Considering figure 3.1: for any probability *a* and larger probability *d+a* (if d > 0), finding their w-midpoint probability *g+a*, with 0 < g < d is the essence of the midweight method. It must be noted that in order for the method to work, the outcome x_0, x_1 and x_2 must satisfy equations (3.6) and (3.7).

Start with the left prospect L = (a:x_2, d:x_1, c:x_0). Here a, d, and c, are the probability masses distributed over x_2, x_1, and x_0 respectively. The probability mass of x_1 is divided equally over the other outcomes to to yield indifference with prospect R. Probability mass of g is moved to the high outcome x_2 and the remainder *b* = *d* - *g* is moved to the lower outcome x_0. The indifference in Figure 3.1 implies:

$$w(g+a) = \frac{w(a) + w(d+a)}{2} \tag{3.8}$$

For proof of equation (3.8) please refer to (Kuilen and Wakker, 2011). Equation (3.8) can be used to directly measure the weighted midpoint between any two probabilities. For example, if I set *a=c=0* and d = 1, I can directly measure $w^{-1}(4/8)$, where $w^{-1}(4/8)$ is the probability corresponding to a weight of 1/2. The same process can be repeated to obtain $w^{-1}(1/8)$, $w^{-1}(2/8)$, $w^{-1}(4/8)$, $w^{-1}(6/8)$, and $w^{-1}(7/8)$. Figure 4.1 lists the indifferences elicited between prospects to obtain the aforementioned probabilities. All left prospects used in the experiment are special cases of prospect L in Figure (3.1) with at least one probability 0, so that at most two branches remain.

Chapter 4

Experimental Design and Data

4.1 Experimental Design

This section describes the experimental design and procedure used to collect data using the two methods described in section 3. This experiment measures optimism within-subjects. To control for learning effects half of the sample was administered the LOT-R first and then the mid-weight method. The other half was administered the mid-weight method followed by the LOT-R.

4.1.1 Subjects

N = 20 students from a wide range of disciplines were asked to fill out my questionnaires at the Erasmus university in Rotterdam. They were selected from the university library and the sports centre. Choosing to sample subjects from just two locations can lead to a selection bias, however as it is a within subject design randomization is not a very severe issue.

4.1.2 Procedure

Data was collected using one on one interviews with the subjects. Although this is time consuming it ensured that subjects understood the choices and minimised erratic answers. To see the instructions and the questionnaire used to measure optimism using the LOT-R please refer to appendix A. To measure optimism using the mid-weight method the first step is to measure the utility midpoint and is described below.

4.1.3 Measuring Utility Midpoint Probability Weighting for Risk

I set x_0 = 60 and obtained values x_1 and x_2 to generate indifferences using the trade-off method described in 3.2.1. Indifference was elicited between the following prospects:

$$(x_{1_{0.25}}30) \sim (60_{0.25}40) \quad \textit{and} \quad (x_{2_{0.25}}30) \sim (x_{1_{0.25}}40) \tag{4.1}$$

If x_1 and x_2 are elicited as above, considering RDU it must be that x_1 is the utility midpoint of x_0 and x_2 (Equation 3.6). The choice of x_0 and the probabilities used in equation above are not arbitrary. They are the same ones used by van de Kuilen and Wakker (2011).

Once the utility midpoint is known I can apply the mid-weight method to elicit the following probabilities: $w^{-1}(1/8)$, $w^{-1}(2/8)$, $w^{-1}(4/8)$, $w^{-1}(6/8)$, and $w^{-1}(7/8)$. The figure below lists the indifferences elicited to obtain these probabilities. The indifferences were elicited using direct matching. The main advantage of using direct matching is that it is extremely easy for subjects to understand the task.

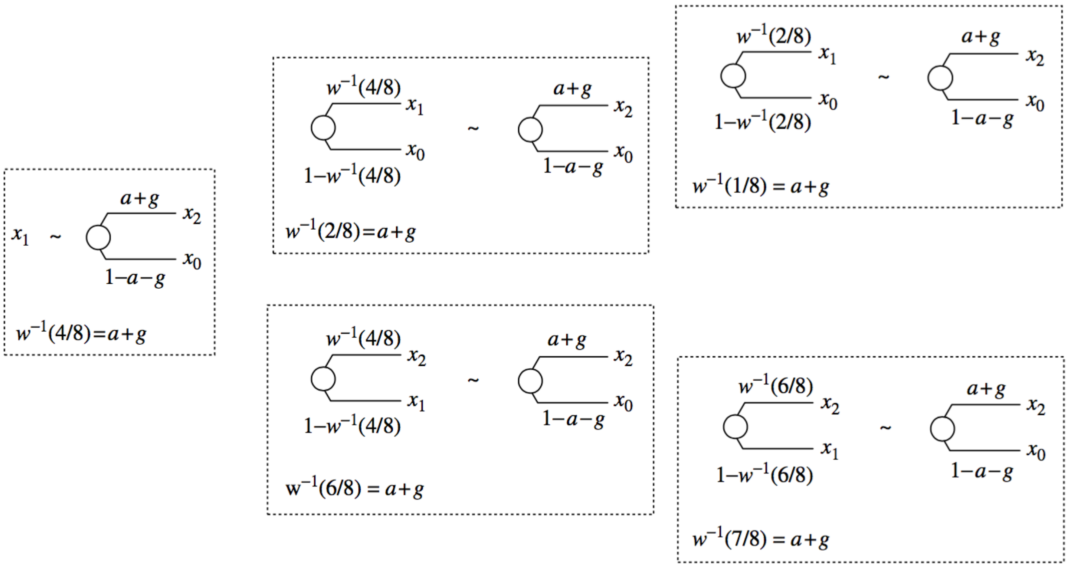

FIGURE 4.1: Indifferences to elicit $w^{-1}(j/8)$
Figure taken from (Kuilen and Wakker, 2011)

Once again, to control for order effects, I split the subjects into two groups, for one group I elicited $w^{-1}(1/8)$ and $w^{-1}(2/8)$, before $w^{-1}(6/8)$, and $w^{-1}(7/8)$, and for the other group I did it the other way around.

4.2 Data Analysis

Measuring optimism using the LOT-R is straight forward and results in an absolute value between 0 and 24.

In order to measure optimism based on the mid-weight method I estimated Prelec's (1998) two-parameter compound invariance weighting function. This is done by minimising the sum of squared residuals of the following equation for every subject:

$$w(p) = e^{-\beta(-lnp)^{\alpha}} \tag{4.2}$$

In the equation above, α captures likelihood insensitivity (i.e., the degree to which behaviour is sensitive toward changes in likelihood), and β captures the degree of optimism or pessimism. Using equation 4.2, I estimated β for each subject separately. This method gives an easily interpretable estimate of optimism and is widely used in the literature (Jullien and Salanié, 2000; Wu and Gonzalez, 1996). Hence I have chosen to apply this method to obtain a parametric estimate of optimism.

Once the β estimates were obtained I used Microsoft excel to plot a scatter diagram with LOT-R scores of each subject on the x-axis and the corresponding β estimates on the y-axis. The smaller the β estimate is the more optimistic a subject is. Hence I expect a negative correlation between LOT-R scores and β estimates. The next section will be used to present the results of my analysis.

Chapter 5

Results

5.1 LOT-R Scores

In my sample of 20 students the LOT-R scores ranged from 7 to 20, with a mean score of 14.75 and a median of 15. As mentioned earlier there is no benchmark for optimism, a line cannot be drawn to place people in one group or the other. "People range from very optimistic to very pessimistic, with most being somewhere in between" (Carver, Scheier, and Segerstrom, 2010). My data follows a similar pattern as can be seen in figure 5.1.

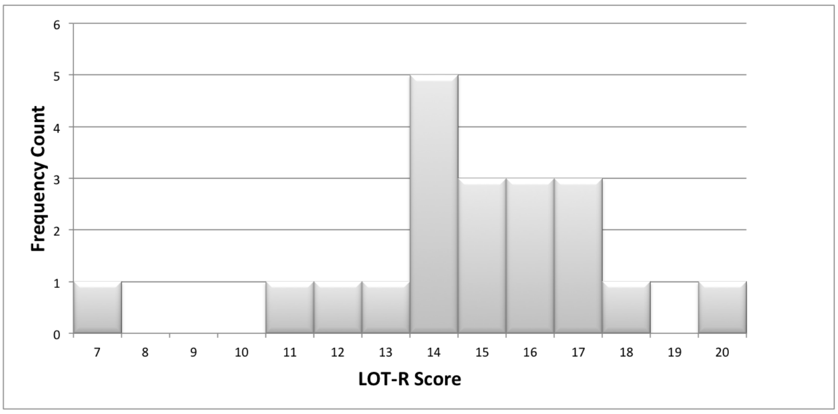

FIGURE 5.1: Frequency count of LOT-R Scores

5.2 Mid-Weight Method

In order to use the mid-weight method to elicit probabilities, the first step was to measure utility mid-points using the trade off method. Hence the results of the trade-off method will be discussed first.

5.2.1 Tradeoff Method

A large number of subjects applied a rule of thumb/heuristic approach when the tradeoff method was applied to elicit x_1 and x_2. The median values of x_1 and x_2 were 70 and 80 respectively. To understand the rule of thumb applied by the subjects we must take a closer look at the following prospect:

$$(x_{1_{0.25}}30) \sim (60_{0.25}40) \tag{5.1}$$

If we assume x_1 = 60 in equation 5.1, the only difference between the prospect on the left and the right is the difference between 30 and 40 as the probability distribution over the two branches is the same for both the prospects. This implies that the prospect on right is strictly better than the prospect on the left. In order to correct for this, subjects took this difference into account and added it to the initially assumed value of x_1 = 60, resulting in the most frequently observed elicited value of x_1 = 70. However, as the probabilities are not distributed evenly over the two branches, when x_1 = 70 the prospect on the right has a higher expected value than the prospect on the left. So, the only way a subject can be indifferent between these two prospects is if he/she transforms probabilities non-linearly. Figure 5.2 below shows the choices made by subjects for x_1.

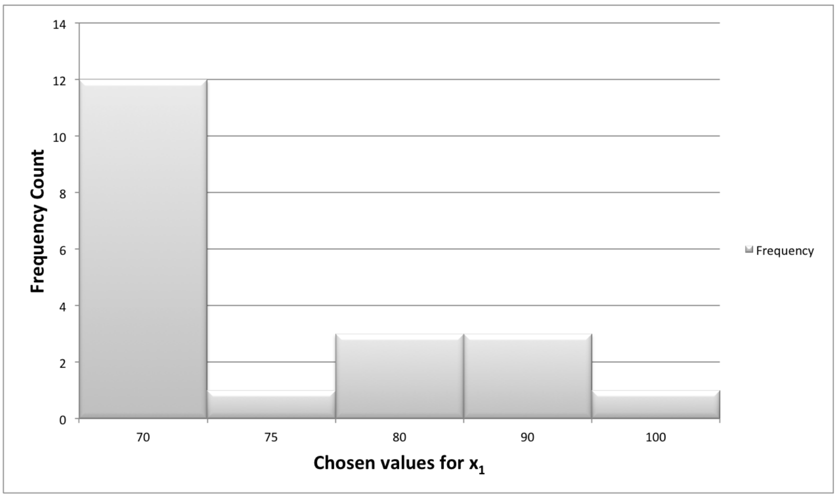

FIGURE 5.2: Frequency count of chosen values for x_1

The same reasoning was applied by the subjects when they elicited x_2 using the following prospect:

$$(x_{2_{0.25}}30) \sim (70_{0.25}40) \tag{5.2}$$

and resulted in the most frequently observed choice among subjects of x_2 = 80.

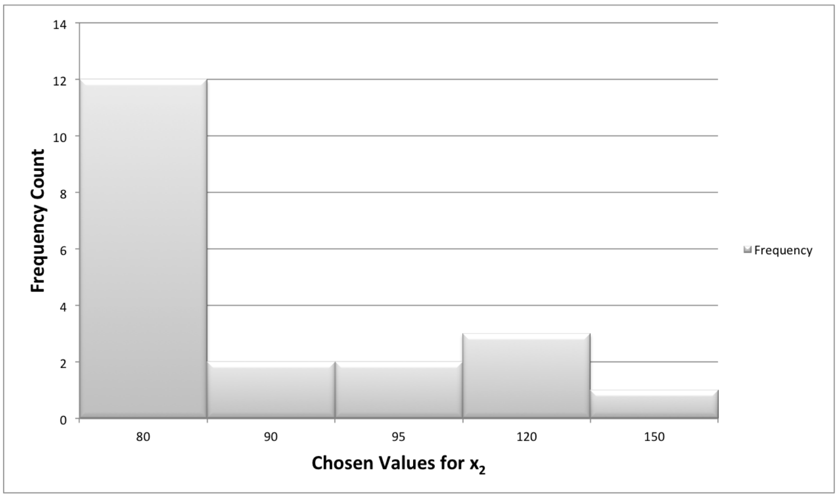

FIGURE 5.3: Frequency count of chosen values for x_2

It can be seen in figures 5.2 and 5.3 that 12 out of 20 subjects (60%) applied a heuristic when choosing the values of x_1 and x_2. Interestingly, the same 12 subjects applied the heuristic in both these cases.

Considering, x_0 = 60 and the median values for x_1 and x_2 are 70 and 80 respectively, suggests a perfectly linear utility function. Although it cannot be assumed that subjects based their answers solely on this heuristic but it nevertheless biased their responses in the direction of a linear utility function. However, it can also be argued that utility is approximately linear for moderate amounts of money (Rabin, 2000).

5.2.2 Mid-Weight Method and Prelec's Function

Applying the mid-weight method resulted in a probability weighting function for each subject. The median probability weighting function is shown in the figure 5.4.

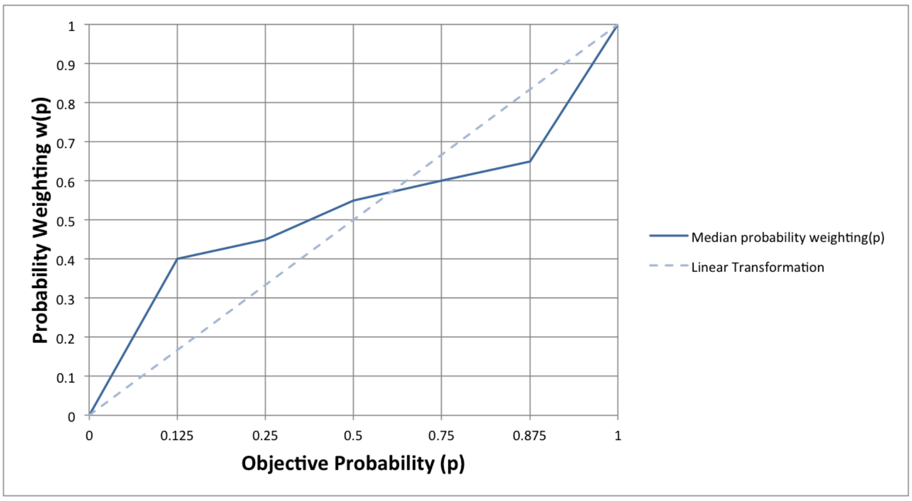

FIGURE 5.4: Median Probability Weighting Function

The median weighting function is inverse-S shaped displaying both lower subadditivity and upper subadditivity and has also been documented in previous empirical studies of the weighting function (Bleichrodt and Pinto, 2000; Wu and Gonzalez, 1996). Lower subadditivity is the phenomenon that a change in probability from impossible to possible has a stronger impact on an individual's decision than an equal change in probability from possible to more possible. This effect is called the possibility effect. Upper subadditivity on the other hand is the phenomenon that a change in probability from possible to certain has more impact than an equal change in probability from possible to more possible. This effect is referred to as the certainty effect (Tversky and Wakker, 1995).

To determine optimism at the individual subject level I used Bleichrodt and Pinto's (2000) classification system of individual weighting functions of subjects. This method measures the slope difference of the probability weighting function between two adjacent probability intervals. A weighting function was classified as exhibiting lower subadditivity if the slope difference on the first two intervals of the weighting function was negative suggesting concavity in this region of the function. Similarly a weighting function was classified as exhibiting upper subadditivity if the slope difference on the last two intervals of the weighting function was positive. If both lower and upper subadditivity was exhibited by the weighting function the subject was classified as having an inverse-S function, concave if the first three slope differences were negative and the subject did not exhibit upper subadditivity, and convex if the first three slope differences were positive and the subject did not exhibit lower subadditivity. Based on this classification, 47% of the subjects exhibited an inverse-s shaped weighting functions, 35% of the weighting functions were concave, 0% was convex and the remaining 18% were unclassified.

As the above analysis is non-parametric it cannot be used to correlate the LOT-R scores of subjects to their optimism measured using the mid-weight method. As mentioned earlier, I used Prelec's (1998) function to estimate β which captures the degree of optimism or pessimism. The median and mean value of β were 2.36 and 3.11 respectively. It must be noted that this mean is calculated using 17 subjects and not 20. Three subjects had to be removed from the data set because their estimates for α were negative and this violates monotonicity. Table 5.1 below shows the LOT-R score and the β estimates for the 17 subjects. This table will be used to visually represent the result in a scatter plot and to calculate the correlation between the two measures.

Subject	LOT-R Score	β Estimates
1	11	11.8
2	20	8.1
3	12	2.3
4	17	2.9
5	17	3.8
6	14	2.8
7	18	0.8
8	14	2.3
9	14	1.8
10	14	0.1
11	16	5.6
12	17	0.7
13	16	0.7
14	14	2.8
15	7	2.9
16	13	2.4
17	16	1.1

TABLE 5.1: Table of LOT-R Scores and β Estimates

5.3 Correlation Between LOT-R score and β Estimates

Now that the LOT-R scores of each subject and their corresponding β estimates have been presented I can address the main issue of interest of this thesis:

How does the economic measure for optimism correlate with to the psychological measure for optimism?

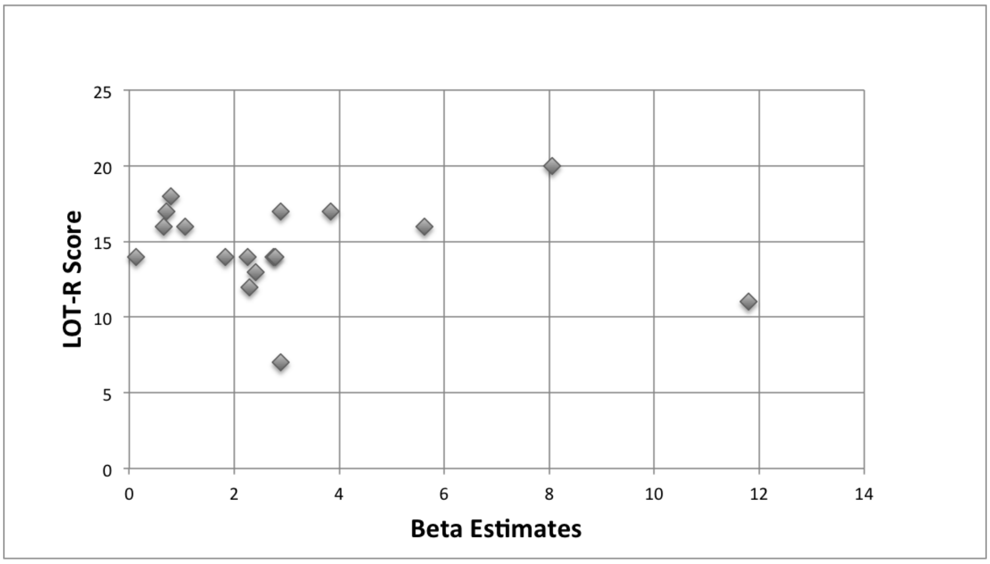

FIGURE 5.5: Correlation Between LOT-R and β Estimates

Figure 5.5 above shows a scatter plot with LOT-R scores on the y-axis and the β estimates on the x-axis. There is no clear pattern in the data and the negative relationship I was expecting to see cannot be observed. The correlation coefficient between the two variables is -0.078 and is statistically insignificant with a t-value of -0.48 which is below the critical value. Hence I cannot reject the null hypothesis of no correlation between LOT-R and the β estimates.

Chapter 6

Discussion

This study demonstrates that there is no significant correlation between optimism measured in psychology and in economics. This finding is not in line with my initial expectation of a negative correlation between the two variables. This section will be used to address why this could be and to recommend direction for future research.

I used personal interviews to obtain my data. This ensured that subjects understood the task and were able to ask questions in case anything was unclear. However, gathering the data in this fashion is very time consuming and led to a small sample size. Furthermore, due to the complexity of the questionnaire I was forced to elicit indifferences using direct matching. This method has the advantage of simplicity but it made it very easy for the subjects to spot the chained nature of the questions in both the trade-off method and the mid-weight method. It might be that chaining questions gives subjects an incentive to not answer truthfully in order to increase their total winnings (Harrison, 1986). Even if subjects have an incentive to lie because they are able to spot that the questions are chained, to exploit this chaining, subjects have to understand the way in which future choices depended on current answers. Empirical studies have concluded that a chained question structure does not have the presumed negative effect that Harrison (1986) predicted (Cerroni, Notaro, Shaw, et al., 2011). Furthermore, chained questions is not a real problem for my design because my survey was not incentivised i.e. the subjects did not receive money based on their choices.

However, the fact that my experiment was not incentivised gives rise to other concerns. Smith (1982) proposed five sufficient conditions for a valid controlled microeconomic experiment and the lack of incentives can potentially violate two of these conditions, namely: saliency, and dominance. Saliency implies that individuals are guaranteed the right to claim a reward which is based on the choices they make in the experiment. Dominance implies that the reward subjects earn are enough to compensate them for their subjective cost of completing the task. While I was interviewing subjects it was clear to me that (some) subjects were frustrated when answering later questions associated with the cognitively challenging task of the mid-weight method and filled in values without exerting much effort. This is a clear violation of Smith's precepts and could explain why I did not observe a negative correlation between the LOT-R and the mid-weight method.

Furthermore, the trade-off method resulted in a perfectly linear utility function for a large number of subjects (60%). As mentioned in section 5.2.1, this is probably caused by a heuristic/rule of thumb applied by subjects and this severely biased my results towards linearity. This result is surprising because Abdellaoui, Barrios, and Wakker (2007) compared the utilities elicited by the trade-off method with utilities elicited using other methods that are less vulnerable to this heuristic and observed no significant differences. Hence it must be that due to violations of Smith's precepts, subjects were more inclined to respond heuristically.

As mentioned in section 3.2, the key advantage of the mid-weight method is that it minimises the need to measure utility and focuses on the weighting function. This is very efficient but from my data it is apparent that this increase in efficiency comes at the cost of data quality. Even in the paper by van de Kuilen and Wakker (2011), that introduced the mid-weight method, linear utility functions were obtained for the median and the mean subject. In the interest of improving the quality of the data it is worthwhile to obtain a detailed measure of utility before measuring the weighting function. Two possible alternative method that are tractable have been presented by Abdellaoui (2000) and Bleichrodt and Pinto (2000). These methods also apply the trade-off method but since they elicit a detailed utility function as opposed to simply measuring the utility mid-point the data is richer.

Another interesting finding worth noting is that, in my study the median probability weighting function was inverse S-shaped while in the study by van de Kuilen and Wakker (2011) the median weighting function was convex. In both my study and theirs the median utility function was linear so the difference between my results and theirs cannot be explained by the heuristic applied by subjects. I cannot explain this discrepancy between my findings and theirs. However, as previous empirical studies have consistently suggested an inverse-S-shaped weighting function (Wu and Gonzalez, 1996) I am confident that findings are valid.

If this experiment were to be repeated I would recommend using a larger sample size, incentivised choices and a different method for eliciting probability weighting functions to check for correlation between the LOT-R and economic measures of optimism.

That said, it must also be acknowledged that perhaps these two methods measure completely different traits and should not be correlated to begin with. According to Peterson (2000) little optimism and big optimism are empirically "no doubt correlated". However, to the best of my knowledge there is no prior literature empirically validating this. So, even if we assume that LOT-R measures big optimism and the mid-weight method measures little optimism (which is a strong assumption) there is no scientific basis to conclude that they should be correlated.

Yet another reason that could cause these two measures to be uncorrelated is dual process theory developed by Kahneman (2011). Dual process theory states that system 1 is fast, automatic and non-conscious, system 2 on the other hand is slow, controlled and conscious. It is possible that when answering questions on the LOT-R subjects used system 1 processes, and used system 2 for the cognitively demanding mid-weight method. Advances in neuroscience makes it possible to study this. Goel et al. (2000) has studied dual process theory and their findings "indicate involvement of two dissociable networks in deductive reasoning" using fMRI machines. In the future this experiment can be repeated with subjects connected to such a machine to observe whether or not dual process theory is a potential explanation for weak the correlation observed between the two measures.

To conclude, from my research I found insignificant correlation between the psychological measure of optimism and the economic measure of optimism. This can be due to methodological issues or simply because the two methods measure different things altogether. Hence future research could take at least two directions, the first is to assume that these two measures are correlated and make improvements to the methodology as discussed above. If using a larger sample size, incentivised experiments and a different method for measuring probability weighting function is applied and the results are still uncorrelated, research must head in the second direction: using neuroscience to determine which cognitive processes are activated while eliciting optimism using the LOT-R versus the chosen economic measure, which ever that may be. If this research highlights that both the methods are using the same cognitive processes we must start to consider that little optimism and big optimism are not correlated or go even further and consider that the psychological measure of optimism is measuring something distinct from the economic measure of optimism.

Appendix A

LOT-R and Trade-off method questionnaire

A.1 LOT-R

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. There are no "correct" or "incorrect" answers. Answer according to your own feelings, rather than how you think "most people" would answer.

Statement	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
In uncertain times, I usually expect the best.					
It's easy for me to relax.					
If something can go wrong for me, it will.					
I'm always optimistic about my future.					
I enjoy my friends a lot.					
It's important for me to keep busy.					
I hardly ever expect things to go my way.					
I don't get upset too easily.					
I rarely count on good things happening to me.					
Overall, I expect more good things to happen to me than bad					

FIGURE A.1: LOT-R questionnaire

A.2 Trade-off Method

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. There are no "correct" or "incorrect" answers. Answer according to your own feelings, rather than how you think "most people" would answer.

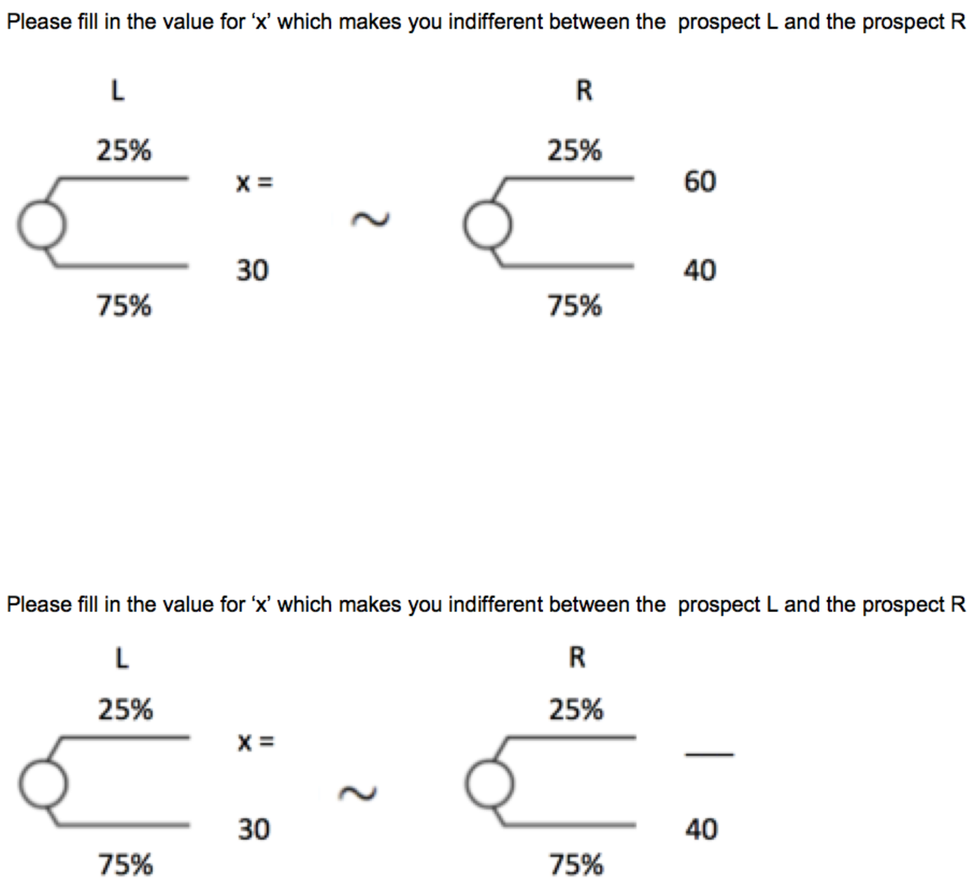

FIGURE A.2: TO-method questionnaire

NOT PART OF QUESTIONNAIRE: The following few lines of text was not part of the questionnaire presented to subjects. As it can be seen on the second choice, the prospect on the right has a blank space. This space was used to fill in the value for x_1 from the previous choice. The questionnaire used to elict probabilities using the mid-weight method followed the same structure as the ones presented here and hence have not been presented separately.

Appendix B

Output of the trade-off method

The table below contains the values of x_1 and x_2 elicited for all subjects.

Subject	x0	x1	x2
1	60	70	80
2	60	80	90
3	60	90	120
4	60	70	80
5	60	70	80
6	60	75	90
7	60	70	80
8	60	100	150
9	60	80	95
10	60	70	80
11	60	70	80
12	60	70	80
13	60	70	80
14	60	90	120
15	60	70	80
16	60	70	80
17	60	70	80
18	60	80	95
19	60	70	80
20	60	90	120

TABLE B.1: Values of x_1 and x_2 elicited using TO-Method

Appendix C

Probabilities elicited using mid-weight method

The table below lists objective probabilities and the corresponding probability transformation for each subject. This data can be used the replicate the probability weighting functions of every subject and to estimate Prelec's function.

Objective Probability	0	0.125	0.25	0.5	0.75	0.875	1
w(p) Subject 1	0	0.5	0.55	0.6	0.65	0.7	1
w(p) Subject 2	0	0.6	0.7	0.8	0.85	0.9	1
w(p) Subject 3	0	0.5	0.6	0.8	0.95	0.99	1
w(p) Subject 4	0	0.4	0.45	0.5	0.6	0.65	1
w(p) Subject 5	0	0.4	0.45	0.5	0.55	0.6	1
w(p) Subject 6	0	0.4	0.5	0.6	0.7	0.8	1
w(p) Subject 7	0	0.28	0.4	0.55	0.45	0.375	1
w(p) Subject 8	0	0.5	0.6	0.75	0.6	0.85	1
w(p) Subject 9	0	0.35	0.4	0.5	0.6	0.65	1
w(p) Subject 10	0	0.15	0.2	0.25	0.3	0.35	1
w(p) Subject 11	0	0.5	0.55	0.6	0.7	0.8	1
w(p) Subject 12	0	0.25	0.4	0.5	0.35	0.4	1
w(p) Subject 13	0	0.125	0.25	0.5	0.33	0.12	1
w(p) Subject 14	0	0.4	0.5	0.6	0.75	0.6	1
w(p) Subject 15	0	0.4	0.45	0.5	0.6	0.65	1
w(p) Subject 16	0	0.4	0.5	0.6	0.75	0.85	1
w(p) Subject 17	0	0.2	0.25	0.5	0.75	0.85	1

TABLE C.1: Elicited probability transformations

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