Three Essays on the Economics of Decision Making under Risk

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A thesis submitted to the University of Kent in fulfilment of the requirements for the degree

of

Doctor of Philosophy in Economics

University of Kent

Janauary 2019

Acknowledgements

First and foremost, I want to thank my supervisor Prof. Iain Fraser. He offered continuous guidance throughout the duration of my PhD studies. His help in the writing process especially was invaluable and his feedback was helpful in quickly overcoming problems I was facing with my research.

I would like also to thank Dr. Edward Cartwright who offered feedback regarding the design and the implementation of all the three laboratory experiments described in this dissertation.

I am indebted to Prof. Kelvin Balcombe from the University of Reading for providing the questions used for the lab experiment described in Chapter 4 of this dissertation.

I gratefully acknowledge also the help of Prof. Iain Fraser and Dr. Alastair Bailey for funding the lab experiment described in Chapter 4.

At last, I want to thank my family. Without their continuous encouragement and support, this PhD journey would have never been completed.

Canterbury, UK
January 2019

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List of acronyms

BDM: Becker-DeGroot-Marschak

CRRA: Constant Relative Risk Aversion

CLT: Construal Level Theory

CPT: Cumulative Prospect Theory

DEU: Discounted Expected Utility

DT: Dual Theory

EG: Eckel and Grossman

EU: Experienced Utility

EUT: Expected Utility Theory

FED: Front End Delay

HL: Holt and Laury

K&T: Kahneman and Tversky

MPL: Multiple Price List

OLS: Ordinary Least Squares

PT: Prospect Theory

PTT: Probability and Time Trade-off

T&K: Tversky and Kahneman

Chapter 1

Introduction

Very often, people have to make decisions where the available options are not certain. In such situations risk becomes an important factor that ought to be seriously considered. It is not difficult to find examples where the importance of handling risky situations properly can be crucial: from simple everyday consumption and savings plans to more complicated future investment plans about stocks, bonds and portfolio optimization. These decisions could be directly related to choices that could generate either gains or losses, or to situations where people have to decide among options where both gains and losses can be present. Furthermore, a number of factors directly related to the decision making can be manipulated and thus, risk preferences could be affected accordingly. The impact of higher stakes and the possibility of intertemporal choices during the decision process constitute two such factors. This dissertation studies the decision making process behind such choices in three different lab experiments which are outlined in Chapters 2, 3, 4.

The analysis of the data collected from all the experiments is based on well-known decision theory models. Expected Utility Theory (EUT) as presented by von Neumann and Morgenstern (1944) is the main model used in Chapter 2 for the analysis of risk preferences, which focuses on observations derived from gain-only questions. In Chapter 3, we complement EUT with Cumulative Prospect Theory (CPT) introduced by Tversky and Kahneman (1992), the most comprehensive decision theory model that can account for sign-dependence in risk preferences. This is a necessary move since the experiment we describe in this Chapter includes questions for gains and losses, too. In Chapter 4, the scope of our experimental design is expanded further by including questions with mixed options, too. In that way, we can focus our analysis on the most crucial tenet of CPT, loss aversion. In Chapter 4, we also make use of the Dual Theory (DT) model, introduced by Yaari (1987); this is a much less used model compared to EUT and CPT, but it offers a different and especially simpler modelling perspective compared to CPT which can be useful to applied research in decision making.

Apart from the above models, a second unifying link among all chapters is the implementation of treatments in all the experiments. The first treatment is the time delay treatment where choices are payable after a specific delay. The employment of such a treatment should not be a surprise since it has been found that time delay tends to direct risk preferences towards an increasingly risk tolerant behavior (Noussair and Wu, 2006).The second treatment is the magnitude treatment where the rewards of the options increase in value. Markowitz (1952) surmised that higher stakes could change risk preferences for both gains and losses through changes in utility curvature. The evidence support an increasingly risk averse behavior when people face choices with higher stakes, at least for gains (Kachelmeier and Shehata, 1992). Chapter 2 describes an experiment with a time delay treatment application, Chapter 3 contains an experiment where both time delay and magnitude treatments are applied and finally, in the experiment in Chapter 4 only a magnitude treatment is implemented. The implementation of treatments enables us not only to check the stability of risk preferences but also to determine if and how the parameters of the decision theory models described above are affected. Ultimately, this will allow us to have a more complete understanding of the patterns of choice under risk.

In the first experiment in Chapter 2, titled “An experimental investigation of the interrelationship between risk and time”, the research question follows the title and it is centred on the potential connection between intertemporal choice and risk attitudes. Recent literature points to such a connection, and most notably to a positive relationship between larger risk aversion and more pronounced levels of impatience (Burks et al., 2009). However, there is little research in the economics literature about the nature of this apparent relationship and especially on its robustness and how it can be affected when experimental treatments like time delay are implemented. This is the idea that motivated the lab experiment of this chapter. Our experimental design required the participants to match a range of rewards that were available at different points in time, that is, smaller rewards were on offer sooner and larger rewards were available after a time delay. Two different time delays were employed, two months and four months. Furthermore, for the risk decision making context, we use the same rewards as previously but now the sooner reward is a certain option while the larger reward is a risky one. In that way, we directly juxtapose the choices of the participants that were indicative of their time and risk preferences (For more details see the instructions in Appendixes A and B in Chapter 2). On top of this matching experimental process, we also make use of the Eckel-Grossman (2008) experimental method, based on choice among different options. The Eckel-Grossman method is a simple and straightforward experimental design for the elicitation of risk preferences which also allows us to compare the robustness of the results of the matching process. This could be an important point because it is not unlikely the procedure invariance of the different experimental designs not to hold and subsequently, the extracted risk preferences of the two experimental designs to diverge (Tversky et al., 1988).

The results of the experiment are consistent with the literature indicating an inverse relationship between risk and time parameters which is represented through a switch towards a more risk tolerant behavior although the change in the levels of patience is limited. On the other hand, the evidence supporting a more patient behavior is rather weak though. We have also found evidence that both risk and time parameters start to level off as time passes. The Eckel-Grossman method reaffirms more categorically the aforementioned findings by also points to unstable risk preferences and an increase in risk tolerance. We do not measure levels of patience with respect to the elicited risk preferences for the Eckel-Grossman method; thus, we are unable to confirm any relationship between risk and time conditional on the Eckel-Grossman method. Note that in our statistical analysis in this chapter we use both parametric and nonparametric techniques and the results we report remain largely unaffected.

In the second experiment of Chapter 3, the research question is expanded since our experiment incorporates options that incur losses. Therefore, the focus is now on risk behavior for both gains and losses. According to CPT, the behavior in the gain domain should mirror the behavior in the loss domain, in the sense that the same options should lead to a risk averse behavior for gains leading to a concave utility segment, while risk seeking behavior prevails in the loss domain (convex utility). This is the reflection effect (Kahneman and Tversky, 1979), the investigation of which was the impetus behind Chapter 3. However, our analysis is not confined to utility curvature only, the role of nonlinear probability weighting for each domain is examined thoroughly. Two experimental treatments are implemented: the magnitude treatment (higher stakes) and a time delay treatment of four months. Our contribution to the literature is twofold: first, we investigate the impact of higher stakes on reflection effect, an issue on which the literature has not really focused despite evidence that higher stakes can challenge theories like CPT (Fehr-Duda et. al, 2010). Second, we also examine temporal risk preferences given the presence of probability weighting. To our knowledge, only Abdellaoui et al. (2011) have attempted a similar investigation but only for gains, whereas we expand the research to the loss domain, too. For the elicitation of risk preferences, we make use of the Holt and Laury (2002) experimental design for both gains and losses. In that way, we generate data that can be used for sign-dependent models and in addition, it can be used for the reflection effect hypothesis testing since the same rewards are employed in either domain. For the simultaneous estimation of the model parameters in either domain, we use the statistical technique of maximum likelihood. Through this technique we estimate the treatment effects for each parameter. Moreover, the calculation of standard errors allows us to perform a number of statistical tests for domain-specific parameters.

The reflection effect hypothesis is confirmed for lower stakes, but when higher stakes are utilized it is statistically rejected, marginally though. Higher stakes also generate probability treatment effects in the loss domain leading to the emergence of risk attitudes that do not comply with reflection effect since a probabilistic risk averse behavior prevails for either domain. Note that this behavior is governed by the elevation parameter of the probability weighting function.The emergence of probability treatment effects points to a violation of separability: A separability condition between outcomes and decision weights means that changes in outcomes are reflected on utility only, whereas changes in probabilities should be reflected on probability weighting only. If changes across outcomes, like offering higher stakes, have also an impact on probability weighting then this condition is violated. We will refer the reader back to this definition throughout this thesis. Moreover, the utility fourfold pattern of Markowitz (1952) is generally satisfied when the sign-dependent EUT model is employed. Regarding the time delay impact, this is found only on probability weighting and only in the gain domain. The result is a more risk tolerant behavior, similar in nature to that of Chapter 2, but now this behavioral change is expressed probabilistically only. Furthermore, the absence of any effects in the loss domain, hints at an asymmetric temporal risk attitude between gains and losses, an attitude that resembles the sign effect in time discounting (Thaler, 1981).

In Chapter 4, the concept of loss aversion constitutes the focal point of our research. Loss aversion, the idea that losses loom larger than equivalent magnitude gains, has found applications in various fields of economics beyond the laboratory. This chapter investigates the volatility of loss aversion for risky choices under higher stakes and has been partly motivated by the conjecture of Kahneman and Tversky (1979) that loss aversion most likely increases with the stake size. A second motivation is that the literature, especially from other fields, has also shown that loss aversion can be unstable and context-dependent, but this has not been investigated for risky choices and by using an analytic econometric specification that allows the simultaneous estimation of all the model parameters of CPT. Even though the focus of our analysis is on loss aversion, we also examine the higher stakes impact on probability weighting and utility curvature as well; the treatment effects on the latter could be especially important since loss aversion manifests itself with respect to utility curvature in the loss domain, thus, disentangling these two parameters could be useful in comprehending the nature of loss aversion. To identify loss aversion in a CPT model, we have included mixed options, that is, options that include both negative and positive rewards. We include options in each domain with up to three rewards, a fact that is rather uncommon in the literature. The statistical technique of maximum likelihood is used in this chapter in order to estimate the model parameters as well as the corresponding treatment effects. Note that we also use of the DT model as well. This model has the advantage that it assumes linear utility and subsequently by employing it, we can fully disentangle loss aversion from utility curvature.

The main result of the experiment of Chapter 4 is the sizeable increase in loss aversion which could double its value under higher stakes, a result that is robust to different treatment effects implementations on the CPT model parameters. Yet, for lower stakes loss neutrality prevails, since the loss aversion parameter always statistically equals one. Furthermore, we found differential domain effects on utility after controlling for any loss aversion change. These effects show little change in the utility for losses but much larger for gains, revealing thus the underlying mechanisms for CPT under higher stakes. Note also that probability treatment effects emerge only when we account for no treatment effects on loss aversion; this contradicts other papers which emphasize the role of probability weighting but without taking into account the presence of loss aversion (Fehr-Duda et al., 2010). This finding in particular should be viewed in conjunction with the analysis of Chapter 3. To conclude, a simple model like DT returns parameter estimates for loss aversion and probability weighting that are not qualitative different from those of CPT. Ultimately, this signals that more parsimonious sign-dependent models than CPT are available and could be considered by researchers.

In Chapter 5, we summarize the conclusions from the experiments outlined in the three previous chapters and we propose some potential topics for future research.

Chapter 2

An experimental investigation of the interrelationship between risk and time

Abstract

The objective of this study is to determine the interrelationship between the reported risk and time preferences of economic agents. We conduct a lab experiment where the participants match two different rewards available at different points in time. Then they match the same rewards but this time one reward is certain and the other is offered under risk. We test for the stability of the results by adopting as treatments varying time horizons of two and four months. We find a consistently negative relationship between risk and time parameters signalling a rising risk tolerant behavior but slight evidence of more patience. However, this relationship appears to be stabilized after four months. To test further the stability of risk preferences, we also use the Eckel-Grossman (2002, 2008) risk elicitation technique, and we vary the time horizon as previously. The main result is that there is a considerable increase in risk loving behavior for half of the participants (49.4%) after four months.

2.1 Introduction

Virtually all economic decisions can be affected significantly by two different factors, risk and time. Therefore, they should be modeled in such a way so that to take into account the effect of both risk and time. For intertemporal choices, that is, the choice among different options taking place at different dates, the impact of time has generally been described by the exponential discounting model which can be dated back at least to Samuelson (1937). Likewise, for the modeling of risk, utility functional forms like the CRRA (Constant Relative Risk Aversion) have been employed in the context of decision theories like Expected Utility Theory (EUT) or more recently Prospect Theory (PT) to characterize the risk behavior of people.

Measuring risk and time preferences separately tends to be easier but from an analytical and holistic point of view is not always satisfactory since risk and time parameters cannot always be separated from each other e.g. the Discounted Expected Utility (DEU) model. In recent years there have been numerous attempts to describe and quantify experimentally peoples' risk and time preferences in the laboratory and in the field (Coller and Williams, 1999; Eckel and Grossman, 2002; Holt and Laury, 2002; Dave et al., 2010; Takeuchi, 2011) as well as some that focus on simultaneously estimating risk and time preferences (Andersen et al., 2008; Ida and Goto, 2009; Tanaka et al., 2010). Although recent research suggests that risk and time could be somehow related (Burks et al., 2009; Dohmen et al., 2010; Benjamin et al., 2013) it is far from clear what lies at the root of this relationship and how it could be affected by manipulating the context of decision making.

Anderhub et al. (2001) was one of the first attempts in the economic literature to examine experimentally how risk and time interact. In a lab experiment, participants were asked to offer a maximum price on buying a risky prospect given an initial endowment and then a minimum price on selling it. The incentives were real and were to be paid by deferred cheques at three different points in time: the present, in four weeks and in eight weeks. They report that greater risk aversion is related to lower levels of patience. Noussair and Wu (2006) also examined the intertemporal decision making. They adopt a Holt and Laury (2002) (hereafter HL) design and focus on testing the stability of risk preferences when the rewards are materialized in the present or in future dates. Noussair and Wu (2006) find that risk preferences tend not to be stable and in particular that risk aversion is falling as lotteries with rewards paid in the distant future are chosen. Anderson and Stafford (2009) also find that risk behavior is generally not stable across time, albeit they don't report how exactly it is altered. Like Anderhub et al. (2001), in their experiment participant's impatience levels are positively related to the levels of risk aversion. Abdellaoui et al. (2011) also report that participants can alter their preferences and become more risk tolerant for delayed lotteries and this conclusion holds even after accounting for non-linear probability weighting. But the literature also offers contradictory results on the risk and time relationship. Van Praag and Booij (2003) using data from a large survey also find that risk and time preferences can be context- and model-dependent but this time greater risk aversion is associated with more patience. Cohen et al. (2011) find no correlation between risk and time attitudes for a student population and only a very mild one for a sample of the French population.

Sagristano et al. (2002) offer a potential explanation regarding temporal instability via the exploitation the Construal Level Theory (CLT) which is based on the concept of psychological distance and more precisely, one of the four dimensions of psychological distance, the temporal distance (Liberman et al., 2007). According to CLT, events which are not present are considered to be in distance from us and thus, they cannot be experienced directly. Consequently, situations which are related to a more distant future could be assigned more extreme values relative to situations of the present, that is, preferences could change because they are considered to be time-dependent (Trope and Liberman, 2000; Liberman et al., 2002). Sagristano et al. (2002) show that gambles at different points in time is possible to be perceived differently since people tend to prefer high probability gambles in the near future and lower probability gambles in the more distant future. In this manner, the probabilities of gambles could well be discounted just like monetary rewards leading to changes of risk preferences across time. Another important insight from the psychology literature is that despite the many notional similarities between delay and probability (Prelec and Loewenstein, 1991), still they should not be viewed as the same decision making processes but rather as cognitively analogous processes that ought to be examined under similar experimental and methodological procedures (see Green and Myerson (2004) for a survey). However, this insight does not address the interactions between risk and time but it treats risk and time as separate dimensions.

In a seminal paper, Keren and Roelofsma (1995) investigated experimentally the effect of risk and time on each other. They conducted an experiment where the rewards were offered at different points in time and simultaneously the probability of realization of the rewards varies. They show that peoples' preferences can be affected by both risk and time and that more risk averse agents discount more steeply compared to less risk averse agents. In addition, the effect of the risk factor on time preferences, through the manipulation of the probabilities of realization, seems to be larger than vice versa. Although the scope of Keren and Roelofsma (1995) is quite broad, their findings imply a tradeoff between time and risk. These results mean that people may equate risk and time, at least partially, and thus, but also offer empirical support for qualitative differences between risk and time beyond the single process idea. The analysis in Keren and Roelofsma (1995) is partly based on the idea that certainty effect of PT can be expanded to include time delay: then, a time delay could change the certainty perception of a reward into a probabilistic one since it may be viewed as adding risk to a non-risky reward, potentially due to risks associated with having to wait for future rewards. As a result, preference reversals may follow. A well-known example of certainty effect is the Allais paradox (Weber and Chapman, 2005).

The assumption that risk and time can be viewed in a similar fashion, has paved the way for a handful of theoretical models on the relationship between risk and time. Two papers are of particular interest: Baucells and Heukamp (2012) propose the Probability and Time Trade-off model (PTT) based on this assumption that risk and time could play the role of quantifiers of psychological distance. The PTT model can combine the probability perception as expressed through a probability weighting function with falling discount rates in the form of hyperbolic-type discount functions and explain preference reversals in the light of time delay (see Baucells and Heukamp (2010) for an application). Furthermore, Halevy (2008) exploits the concept of survival analysis and proposes a model where an agent's utility is dependent on a time discounting factor and on a hazard rate (the probability of consumption up until a specific point in time). Thus, a relationship between time discounting and the probability of survival can be established.

This chapter contributes to the relatively small literature that exploits real incentives for the investigation of the interactions between risk and time preferences (Anderhub, 2001; Noussair and Wu, 2006; Anderson and Stafford, 2009; Baucells and Heukamp, 2010; Abdellaoui et al., 2011). More precisely, we perform an experiment where we delay the availability for both the risky and the intertemporal choices. We use decision questions on time discounting and on probability assessment for time and risk preference respectively. Regarding the probabilities scale, we do not focus solely at its end points but we try to span the whole range of it. This is an advantage compared to Anderson and Stafford (2009) and Baucells and Heukamp (2010) which in combination with the analogous variation in rewards offers a more balanced experimental approach. This is an important point since Lovallo and Kahneman (2000) have shown that tolerance for delay can be affected by the composition (skewness) of the gambles. The risk and time parameters are extracted thrice, at the present and by delaying them by two months and four months, much larger than the delays, up to eight weeks, offered by Anderhub et al. (2001) and Anderson and Stafford (2009) albeit smaller than of Abdellaoui et al. (2011) and Baucells and Heukamp (2010) which can be up to one year. The monetary incentives we employ for both types of questions are always the same, a fact that allows us to contrast directly the risk and time parameters and to track effectively the nature of their relationship. Note that Anderhub et al. (2001) use a similar trick but they do not examine the stability of the risk and time preferences. The experimental results indicate that there is indeed an interaction between risk and time leading to an increasingly risk tolerant behavior. Regarding time preferences, we can only find a small tendency for a more patient behavior for the first two months. In addition, we find some evidence of stabilization for both risk and time preferences. This means that both risk and time indicators display less variability as the time horizon becomes lengthier. This is a finding which to our knowledge has not been reported earlier in the economics literature. We also utilize another experimental approach, the popular Eckel-Grossman (hereafter EG) (2002, 2008) method where risk parameters are derived based on interval estimates of the CRRA utility function. In this manner, we can better determine how risk behavior is affected by two different risk elicitation techniques. The experimental results again indicate, more emphatically, that time delay affects risk behavior since the participants' risk aversion follows a declining pattern when decisions are paid in future dates.

The chapter is organized as follows: In Section 2.2 we discuss the methodology behind the experiment, in Section 2.3 we present the experimental design and in Section 2.4 we present the results. In Section 2.5 we draw some final conclusions.

2.2 Methodology

In this section we describe the methodological approach behind the decision questions of the upcoming experiment. Generally, a discounting process can be described by the formula

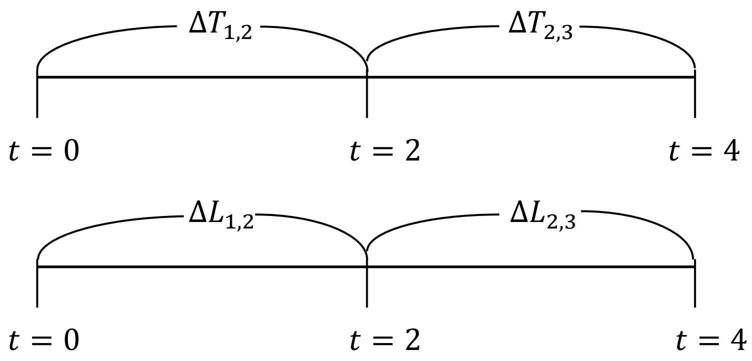
$$V = A * T(t) \qquad (2.1)$$

where V is the subjective value of the delayed reward after delay t, A the value of the same reward undiscounted (the objective value) and $T(t)$ the discount indicator. Assume an individual who is indifferent between two different options timed at different points in time, that is, $(x_1, t_1) \sim (x_2, t_2)$ where $x_1 < x_2$ and $t_1 < t_2$. The individual's indifference implies that the subjective value of the future reward has to be adjusted properly. This adjustment implies a devaluation which is due to the presence of the discount indicator $T(t)$.Then, the subjective value of $x_2$is equal to$x_2 * T(t)$. Thus, being indifferent between the two rewards means that

$$x_1 = x_2 * T(t) \Rightarrow T(t) = x_1/x_2 \qquad (2.2)$$

Therefore, the discount indicator can described by the ratio of the two rewards. Essentially we adopt a nonparametric approach in modeling the discount indicators without assuming any particular functional form for them. Thus, we call it a discount indicator since we are not interested in revealing its precise form and henceforth, for convenience, we drop the argument$t$and we use the simple notation T.

To test the stability of both the risk and time preferences, one can vary the timing of the individual's decision making, called henceforth time horizon. This can be done by moving forward the time horizon from the present to the future, and more specifically in two months' and four months' time after the present. Therefore, by changing the time horizon we are able to check how firm the individual's preferences are and comment on their variations across time. To discern among the time horizons, we introduce an index notation where each time horizon is indexed with a number from 1 to 3. Based on this notation, we define T_1 to be the discount indicator when the time horizon is the present, T_2 and T_3 to be the discount indicators for a time horizon of two months and four months respectively (see Fig. 2.1 below).



Note: The indices t=0, t=2 and t=4, correspond to the present, two and four months respectively.

Fig. 2.1 The time reference frame for discount indicators and loss functions

Next we introduce an indicator for the respondents' risk behavior. Assume that an individual who is indifferent between two different types of rewards, a certain reward and a risky reward which is offered after playing a lottery i.e. $(x_1, 1) \sim (x_2, p)$ where x_1, x_2 $(x_1 < x_2)$ are the certain and risky rewards respectively and $p$the lowest acceptable winning odds for the lottery. In this gamble-related method we contrast a gamble with a certain outcome which plays the role of the certainty equivalent of the gamble. Assuming a behavior consistent with EUT, the expected value of the risky reward should equal the certain reward, that is,

$$x_1 = p * x_2 \Rightarrow p = x_1/x_2 \text{ (2.3)}$$

This implies that the ratio of the two rewards could reveal the individual's probabilistic assessment of the risky reward. In that way we can elicit a probability assessments for a gamble at various levels of rewards.

To characterize better the individual's decisions, we introduce a loss function defined by the equation

$$L = CE - (p * r) \qquad (2.4)$$

where CE the certain reward and r the risky reward of the lottery. This loss function is also indexed with respect to the time horizons i.e. L_t, t =1, 2, 3. The sign of the loss function determines the individual's risk behavior nature. If $L < 0$the individual can be described as risk averse since the certainty equivalent is smaller than the expected value of the lottery. If on the other hand, $L > 0$ the individual can be classified as risk lover since she is willing to take greater risks in the lottery compared to the value of the certainty equivalent and if $L = 0$the individual is risk neutral.

We are also interested in the change of both the discount indicators and the loss function across time periods. Therefore, we employ the following transformations $\Delta T_{t,t+1} = T_{t+1} - T_t$ and $\Delta L_{t,t+1} = L_{t+1} - L_t$. Subsequently, we generate the variables $\Delta T_{1,2} = T_2 - T_1$, $\Delta T_{2,3} = T_3 - T_2$ for the discount indicators and $\Delta L_{1,2} = L_2 - L_1$, $\Delta L_{2,3} = L_3 - L_2$ for the loss functions. These variables represent the change of T_t, L_tacross the two time intervals i.e. from present to two months and from two months to four months as defined by the three different time horizons earlier. To enhance further our analysis, we introduce the concept of time reference frame. Imagine that time is represented by a time line, like the real numbers line, where all the three time horizons are ordered. A time reference frame corresponds to the relative position of $\Delta T_{t,t+1}$ and $\Delta L_{t,t+1}$ on this time line[1]. For example, $\Delta T_{1,2}$ is defined by the present and two months' time horizon while $\Delta T_{2,3}$ is defined by two and four months' time horizons. This means that even if their relative position on the time line is different, since $\Delta T_{2,3}$ has been "pushed" even further into the future by starting two months later, their equal delay difference of two months makes $\Delta T_{1,2}$ and $\Delta T_{2,3}$ directly comparable (see also Fig. 2.1). Evidently, the time reference frame concept holds for both $\Delta L_{1,2}$ and $\Delta L_{2,3}$.

[1]This concept draws an analogy with analytic geometry where vectors are considered equivalent as long as they have the same length even if they are not located at the same points in a vector space. Thus, in our case $\Delta T_{1,2}, \Delta T_{2,3}$ can be considered equivalent and compared directly since they span the same time period, two months, despite being positioned at different points in time. The same rationale holds for $\Delta L_{1,2}, \Delta L_{2,3}$.

Regarding time preferences, we define three different types based on the sign of $\Delta T_{t,t+1}$. If $\Delta T_{t,t+1} = T_{t+1} - T_t < 0$, then the individual is becoming more impatient (or less patient) between periods t and $t+1$ since she chooses not to delay further the payment; we call such a behavior time-increasing impatience. If $\Delta T_{t,t+1} = 0$the level of impatience does not change (time-constant impatience) and if $\Delta T_{t,t+1} > 0$individuals are becoming less impatient (or more patient) by opting for a more distant payment (time-decreasing impatience). Similarly, if $\Delta L_{t,t+1} = L_{t+1} - L_t > 0$, the loss function increases and hence, the individual can sustain larger losses which means that she becomes more risk loving; we call such a behavior time-decreasing risk aversion. If $\Delta L_{t,t+1} < 0$the loss function decreases (time-increasing risk aversion) and the individual becomes more risk averse. Finally, if $\Delta L_{t,t+1} = 0$ the individual's risk preferences don't change (time-constant risk aversion).

2.3 The experiment

Eighty-four students of the University of Kent participated in the experiment. All participants had been notified in advance that a £5 show-up fee would be awarded to each one of them at the end of the experiment irrespective of their answers. They were also informed that they had the opportunity to win up to £50 depending on their answers. The experiment lasted about one hour. The experiment consisted of five parts. The first two parts contained ten questions each and the next two of twenty questions each. The final part contained three questions. In total, all participants had to answer sixty-three questions. Separate instruction and answer sheets were available for the questions of each part of the experiment.

2.3.1 Time discounting and probability assessment

In part1, participants had to match two different rewards available at different points in time. The smaller reward was available immediately whereas the larger reward was available after some delay. They were asked to specify the longest acceptable delay for receiving the late and larger reward according to their preferences so that at the end to be indifferent between the two rewards. More precisely, each respondent had to answer ten questions of the following form[2]:

For me, getting £x today is just as good as getting £y in k,

where k is the longest acceptable time delay the respondent considers appropriate for this intertemporal choice so that to be indifferent between x and y.Time delay k was to be selected from a list with seven available choices ranging from one week to four months. The values of x, y ranged from £10-£50 and were sequentially incremented by £10 and it is always $y > x$.

[2]The experimental design we have adopted for the first four parts follows closely that of Takeuchi (2011) with some modifications. First, we offer specific time delays options e.g. one month, two months, since this is a paper-and-pencil experiment. Moreover, a different probability scale with fewer options is available and a varying time horizon treatment has been implemented for checking the stability of the elicited risk and time preferences. Finally, we offer higher monetary rewards.

In part 2, the questions were on risk preferences and subjective probability assessment. The participants had to match a certain reward with a risky one, the latter being available after playing a lottery. More precisely, they were asked to specify the lowest acceptable odds for winning the lottery according to their likings, so that at the end to be indifferent between the certain reward and the risky reward. The questions were of the form:

For me, getting £x for certain is just as good as getting £y with chance m%,

where m is the lowest acceptable odds level that the respondent considers most appropriate for winning a lottery. The odds level was to be selected from a range of 10%-90% odds levels arranged in a line. The values of x, y are defined as before.

We employ two treatments, both of which aim at testing if and how time discounting and risk preferences are affected by the introduction of an additional time delay. This additional time delay results in the change of time horizon and in the shift of the time reference frame. We have chosen two different values for this additional time delay, two months and four months. This is a useful feature because it is far from easy to collect data from the same participants at different points in time to examine the long-term consistency of peoples' preferences[3].The decision questions for part 3 with a time horizon of two and four months were of the form:

Imagine yourself t months from now. Then,

For me, getting £x, is just as good as getting £y in k,

where the time delay k and the rewards x and $y$are define as previously.Obviously, t takes two different values here: two months and four months. Likewise, the decision questions on the winning odds for part 4 were of the form:

Imagine yourself t months from now. Then,

For me, getting £x for certain is just as good as getting £y with chance m%

where x, y, m, t are defined as before[4].In Table 2.1 that follows, we offer a succinct summary of the experimental methods and the treatments that were applied in the experiment. To put it briefly, two risk elicitation methods are used (the aforementioned probability assessment and the EG method that follows) and the time discounting method. For every method the same treatments are applied.

[3]A similar technique called FED (Front End Delay) has become popular in economics after being introduced by Coller and Williams (1999). By using FED, that is, offering money after a specific time delay, one can mitigate the immediacy effect (i.e. peoples' tendency to prefer immediate rewards over more distant outcomes), an effect considered to be the main reason behaving hyperbolic-type discounting (Prelec and Loewenstein, 1991; Myerson and Green, 1995). In that way, one estimates lower discount rates which are better interpretable for policy purposes.

[4]Note that care has been taken to avoid order effects by randomizing the distribution of the risk and time related questions. We do not observe significant order effects either for discount indicators or for loss functions, apart from the p-value of the t-test for the discount indicator T_1 which is 0.011. However, when we use the sign test, because of the discrete data of the discount indicators, these order effects are eliminated (p-values are above 0.088).

Table 2.1 Description of the experiment

	Risk elicitation methods		Time elicitation method
Treatments (time delay in months)	Subjective probability assessment	EG method	Nonparametric time discounting method
0 (Present)	✓	✓	✓
2	✓	✓	✓
4	✓	✓	✓

2.3.2 The Eckel-Grossman method

Lastly, a version of the Eckel and Grossman (2002, 2008) (EG) method is adopted. This simple and easy to implement method allows us to estimate the risk parameters of a participant after assuming that her utility is of CRRA functional form. More importantly, it offers us an alternative way to estimate risk preferences based on objective probability estimates this time in contrast to the subjective probability-based techniques. In this method, each participant is presented with six different gambles and is asked to choose only one of them. Each gamble is comprised of two rewards of different magnitude, one smaller and one larger. Both rewards are equally likely to be realized, 50% winning chance for each. Note that the gambles are presented in such an order so that the expected value and the variance of the gambles to increase as the participants move from the first to the final gamble[5] (see Table 2.2). Then, based on the participant's choice, we can deduce the range of the values the CRRA coefficient can assume. The EG method has also been employed with the same varying time horizons of two and four months as the other four parts. In that way, we can cast an alternative look on the stability of the risk parameters even though under the EG method we are not able to track any possible tradeoff between risk and time since the time dimension is not investigated in this part.

Table 2.2 Reward matrix for the EG method

	Low reward	High reward	Expected Value	Standard deviation	CRRA range
Gamble 1	14	14	14	0	$3.46< r$
Gamble 2	12	18	15	3	$1.16< r <3.46$
Gamble 3	10	22	16	6	$0.71< r <1.16$
Gamble 4	8	26	17	9	$0.5< r <0.71$
Gamble 5	6	30	18	12	$0< r <0.5$
Gamble 6	1	35	18	17	$r <0$

[5]Notice that the first gamble has zero variance (zero variability in rewards) implying a sure reward of £14. Moreover, gambles 5 and 6 have the same expected value but gamble 6 is riskier since it has larger variance. As the difference of rewards increases, the variance also increases and the gambles become more risky. The participants were not shown the last three columns of Table 2.2, they were shown only the rewards.

2.3.3 Payment procedure

The Becker-DeGroot-Marschak (BDM) (1964) mechanism was utilized so that the responses to be as truthful as possible[6].At the end of each session, one participant and then one decision question were randomly selected. If that decision question was on time, then the respondent's time delay answer to that question was compared to a random number representing the range of the time delays, measured in days, from 7 to 120. If the random number was larger or equal to the participant's answer, then she would receive the sooner reward. Otherwise, she would receive the larger reward after the delay she has opted for. In contrast, if the chosen question was on probability assessment, then the respondent's choice was compared with a random number ranging from 10 to 90. If the random number was smaller than her answer then she would receive immediately the certain reward, otherwise she would play the lottery and her odds of winning the lottery were equal to that random number. Subsequently, a new random number ranging between 0 and 100 would be generated; if the sum of the two random numbers was equal or larger to 100, then the participant would receive the larger reward. Otherwise, she would receive 25% of the certain reward. Finally, if the chosen question was on the EG method, then a random number from 0 to 100 was generated; if that number was smaller than 50, the participant would receive the lower reward of her chosen gamble, otherwise she would receive the higher reward. The payment process was exactly the same when the treatments were introduced. The only difference now is that the payment is deferred by a period equal to the time horizon. (The instructions of the experiment and a sample of the questions are in the Appendices).

For those questions where the payment had to be deferred, it is important the participant to be fully convinced that she would receive the money for certain, otherwise she may not select her truly preferred option. This is a critical point which could have an impact on time-related questions especially and should be confronted effectively. Therefore, in order the incentive scheme to be as reliable as possible, we offer the future rewards in the form of guaranteed post-dated cheque (Andreoni and Sprenger, 2012). In that way we eliminate whatever kind of risk can be associated with the credibility of a future payment. In that way, we are able to remove potentially nuisance factors that exist in real world and could jeopardize the quality of our data. In essence, we isolate the effect of the time delay treatments only on the discounting of preferences. This is an advantage of the lab experiments compared to real world settings where such control is very difficult.

In our study we have followed the paradigm of experimental economics and we have opted for real incentives to be awarded to participants. In a sense, we adopt the popular in experimental economics concept of saliency advocated by Smith (1982) which implies that the incentives

[6]The BDM mechanism is obviously the first option since it has been used widely as a preference elicitation mechanism in economic experiments. Other options like the quadratic and linear scoring rules do exist and have been used before in economic experiments (e.g. Andersen et al.(2014)) but we believe that BDM is the simplest and most easily understood option for our experiment. Note also that BDM implicitly assumes that agents are EUT maximizers, an assumption which we basically adopt in our analysis for the risk parameter determination (Keller et al., 1993).

should be real so that to directly impact the actions taken by the participants[7].This was done with the hope that our results would carry a greater degree of validity and credibility. Nonetheless, in psychology and other social sciences, the use of hypothetical incentives is not uncommon at all; the differences actually between different types of incentives may not be particularly significant (e.g. Johnson and Bickel, 2002; Camerer, 1995). Interestingly, one can find cases where some economists have defended hypothetical payment procedures. Loewenstein and Thaler (1989) for example stress that hypothetical incentives allow for larger stakes and larger delays to be used in the experimental process. This is indeed a valid argument which could possibly affect the experimental results because it does not offer us full control over two crucial factors, the magnitude of the incentives and the length of the time horizon[8].

2.4 Results

In Section 2.4.1 we present the results of time discounting and probability assessment initially and then in Section 2.4.2 the results of the EG method. To enrich the conclusions, the statistical analysis is both parametric and nonparametric. At first, we examine the risk and time parameters relationship and then its implications, the increasing risk tolerance and the apparent stabilization for the risk and time parameters. Note that henceforth we will use the terms loss function and risk interchangeably, and likewise the same holds for the words discount indicator and time.

2.4.1 The T-L analysis

At first, we examine the relationship between the discount indicator and the loss function. Table 2.3 gives the results of three different methods used in examining this relationship: the classic Pearson correlation coefficient, the non-parametric Spearman rank correlation coefficient and the OLS estimator. The Stata 15 software package has been used for the econometric and statistical analysis in this chapter. For the two correlation coefficients the results are negative, quite close in value and statistically significant at 1% although they are relatively weak since none of them is above 0.224 in absolute value[9]. This signals an inverse relationship between discount indicator and loss function hinting at a more risk tolerant behavior accompanied by decreasing patience. This conclusion is also confirmed after using an OLS estimator where the risk and time relationship remains negative and statistically significant. It is also unaffected if we use gender and age as explanatory variables[10]. Another point that we can easily see in Table 2.3, where the correlations between T and L and the estimates from a regression of T on L are presented, is that the value for both coefficients and the OLS estimator declines, in absolute value, after two months. Beyond this time period it seems that a stabilization process starts with little-changing values between two and four months. It is likely that this is an indication that the negative relationship between risk and time is initially falling and then reaches a plateau when decision

[7]The other major preconditions for a valid microeconomic experiment according to Smith (1982) (i.e. nonsatiation and monotonicity of the utility function) can safely assumed to be satisfied given that we offer monetary rewards of significant amount for students.
[8]See also Bardsley et al. (2010), Chapter 6, for a further discussion about the necessity of real incentives and the differences regarding incentives between economics and psychology.
[9]Another non-parametric coefficient, Kendall's tau correlation coefficient returns similar qualitative results.
[10] We have used the White-Huber estimator of robust standard errors for the OLS estimator.

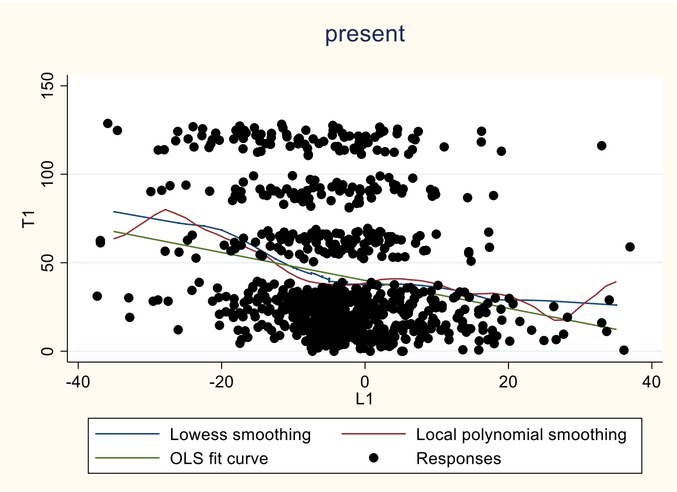
making is made further in the future. We suspect that this could be due to a declining variation for both the risk and time indicators as time horizon shifts. We present below in Fig. 2.2 three different estimators that have been plotted together for all the time horizons: OLS, a locally weighted regression (Cleveland, 1979) and the local polynomial estimator. The negative association of $T_t - L_t$ is graphically verified by all plots. However, to offer a precise interpretation for this relationship in terms of risk and time preferences we have to analyze separately the loss functions and the discount indicators.

Table 2.3 Correlation coefficients and OLS estimator between T and L[11]

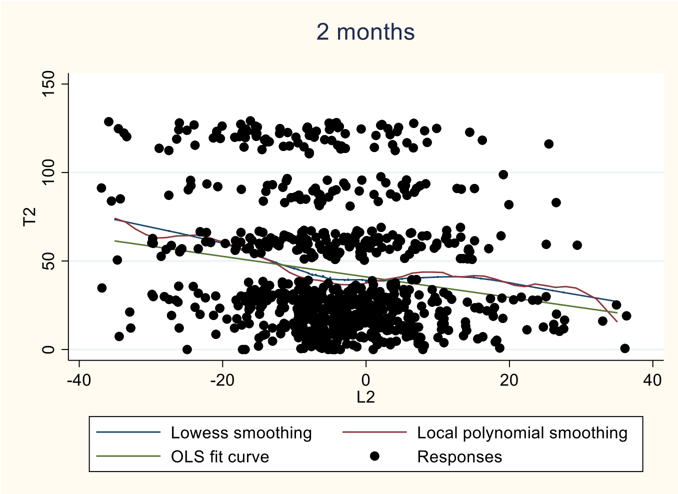
	Pearson correlation coefficient	Spearman coefficient	OLS regression
$T_1 - L_1$	$\rho =$ -0.222***	$\rho =$ -0.224***	-0.789***
$T_2 - L_2$	$\rho =$ -0.186***	$\rho =$ -0.165***	-0.579***
$T_3 - L_3$	$\rho =$ -0.186***	$\rho =$ -0.173***	-0.594***
N	84	84	84
T	10	10	10

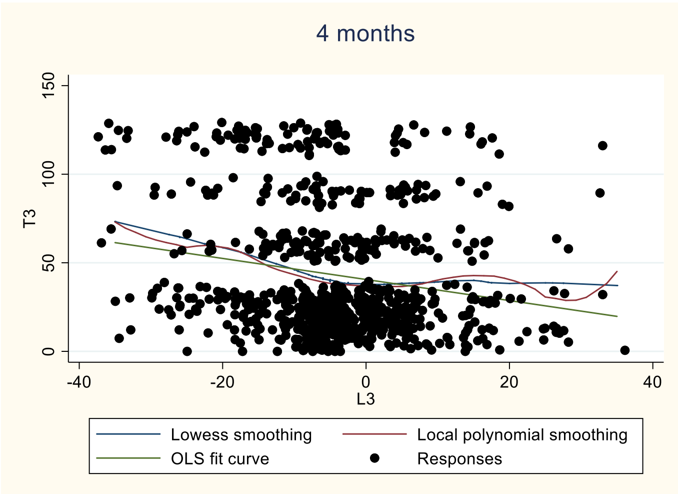
Statistical significance: *p<0.1; **p<0.05; ***p<0.01

Fig. 2.2 Loss function and discount indicator plots per time horizon



[11]The number of participants in the experiment were $N = 84$ and the number of tasks per treatment were $T = 10$. Note that 12 questions were unanswered and were dropped from the data. So, instead of 840 observations, 828 observations were used for the data analysis of Section 2.4.1.





We turn our attention to the loss functions now. Table 2.4 reports the loss functions results for all the time horizons. Risk aversion is the dominant behavior in every horizon followed by risk loving behavior and then risk neutrality. However, since the probability scale of the experiment includes a limited range of winning odds options, we do not really concentrate on the pure categorization of risk preferences but rather, on the direction and the magnitude of the loss function change. One can discern a specific albeit weak pattern in our data: there is a small tendency towards an increasing risk loving behavior, around 2.3 percentage points after two months. This change is attributable almost exclusively to a constantly falling risk neutrality. Notice that risk aversion does not participate in this tradeoff since it fluctuates very little. When the time horizon shifts to four months, this tendency towards a more risk loving behavior is practically unaffected. So, the shift of the time horizon by an additional two months does not impact risk attitudes, a fact that reflects the stabilization of risk preferences after a four months' time period. In addition, there is practically no change regarding the risk behavior classification between L_2, L_3; actually between these two loss functions the classification of only five questions changes.

Table 2.4 Risk behavior classification based on loss function

	Risk loving	Risk aversion	Risk neutrality
L_1	218 (26.33%)	528 (63.77%)	82 (9.9%)
L_2	237 (28.62%)	524 (63.28%)	67 (8.1%)
L_3	237(28.62%)	529 (63.9%)	62 (7.48%)

Number of questions and corresponding percentage rates in parentheses

For the statistical testing of the loss functionsL_1, L_2, L_3 we use both parametric and non-parametric tests. As we can see in Table2.5, the Wilcoxon signed-rank test clearly shows that loss functions do change when the time horizon varies. The p-values of 0.051 and 0.045 show that in general the distribution of the loss functions L_2, L_3 should not be considered the same as that of L_1. On the other hand, the p-value of 0.841 for the distributional hypothesis $L_2 = L_3$shows that after two months the loss functions distributions can be safely considered as indistinguishable. We can also see here that the p-values for the parametric t-test are close to those of the signed-rank test and qualitatively do not alter our conclusions. Actually the t-tests show that it is even easier to distinguish between L_1, L_2 where ($p = 0.021$). All in all, these tests suggest that the differences between the loss functions are eliminated when the time horizon moves beyond two months. This constitutes a statistical confirmation of the stabilization process but from the angle of the risk dimension only[12].

We now turn our attention on how the risk and time attitudes of the participants vary over the time reference frames. Therefore, we make use of the already specified variables $\Delta T_{1,2}, \Delta T_{2,3}$ and $\Delta \mathrm{L}_{1,2}, \Delta \mathrm{L}_{2,3}$[13]. For the time discount indicators (see Table 2.6), the change in time reference frame generates a tradeoff between time-decreasing impatience and time-constant impatience, that is, around 13% rise in constant levels of impatience and simultaneously an equivalent decline in rising patience. This noteworthy tradeoff is conditional on a virtually unaffected time-increasing impatience behavior (29.6% vs. 29.95%). The obvious conclusion here is that there is

Table 2.5 Tests for the loss functions

	Wilcoxon signed-rank test	T-test
$L_1 = L_2$	$p = 0.051$	$p = 0.021$
$L_1 = L_3$	$p = 0.045$	$p = 0.062$
$L_2 = L_3$	$p = 0.841$	$p = 0.777$

[12]The statistical analysis of the discount indicators T_1, T_2, T_3does not produce any meaningful results. Note though that the amount of zeros between T_2, T_3 is much larger than of the other two pairs implying a kind of stabilization for the time dimension as well.

[13]We have avoided using the variable $\Delta T_{1,3}$ and $\Delta L_{1,3}$ because the time interval between the two periods is four months and not two months.

a trend towards stabilization of the discounting process which seems to be intensified in the time reference frame between two and four months[14]. Yet, for the first two months our data shows a slight prevalence of a more patient behavior compared to a less one (32.48 vs. 29.6%, see Table 2.6). But then, this increase in patience is associated with a rising risk loving behavior for the same time interval (Table 2.4). So, for the first two months we can detect a slight co-movement of more patience and more risk tolerance. In any case, t-test cannot statistically confirm any switch in preferences between the two time reference frames (the bootstrap t-test with 2000 replications returns confidence intervals for the mean [-1.8, 3.9]), an indication that the stabilization process for the time indicator amplifies after the first two months.

Table 2.6 Change in time preferences based on time reference frame

	Time-decreasing impatience	Time-increasing impatience	Time-constant impatience
$\Delta T_{1,2}$	269 (32.48%)	245 (29.6%)	314 (37.92%)
$\Delta T_{2,3}$	159 (19.2%)	248 (29.95%)	421 (50.85%)

Number of questions and corresponding percentage rates in parentheses

Regarding the loss function now (Table 2.7), we observe that time-increasing risk aversion is falling, around 5.7 percentage points, and there is also a very small decline in decreasing risk aversion by 1.2 percentage points. In turn, these changes are reflected in a rise of around 6.8 percentage points of a time-constant risk aversion behavior due to the time reference frame change. Hence, this implies a tradeoff mostly between the falling level of a rising risk averse behavior and increasing risk neutrality across time intervals, in the same spirit as the tradeoff between risk loving and risk neutrality earlier (see Table 2.4). Although this trend seems to be relatively weak since the variation of the loss functions is not that large, a one-sided t-test returns $p = 0.048$ favoring the alternative hypothesis $\Delta L_{2,3} > \Delta L_{1,2}$ which means that moving the time reference frame forward can still lead to a more risk tolerant behavior.

Table 2.7 Change in risk behavior based on time reference frame

	Time-decreasing risk aversion	Time-increasing risk aversion	Time-constant risk aversion
$\Delta L_{1,2}$	214 (25.84%)	253 (30.55%)	361 (43.6%)
$\Delta L_{2,3}$	204 (24.63%)	206 (24.88%)	418 (50.48%)

Number of questions and corresponding percentage rates in parentheses

Finally, let's look at Fig. 2.3 which depicts the box plots for $\Delta T_{1,2}, \Delta T_{2,3}, \Delta L_{1,2}, \Delta L_{2,3}$. As you can see the variation for all these variables declines steadily across time irrespective of the time

[14]We shun talking about concepts like hyperbolic discounting or exponential discounting. The methodologies we have employed for determining the nature of discounting based on Takeuchi (2011) and Anderhub et al. (2001), fail to offer a clear picture.

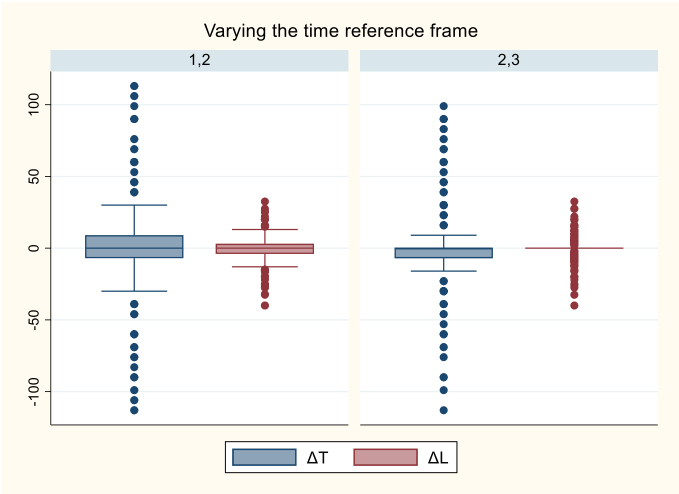
reference frame and an increasing numbers of severe outliers are observed (Table 2.8). We have tested for the equality of variances for the pairs $\Delta T_{1,2}, \Delta T_{2,3}$ and $\Delta L_{1,2}, \Delta L_{2,3}$ using Levene's robust test statistic. The p-values this test returns are 0.000 and 0.01 for the first and the second pair respectively confirming that we can confidently reject the null hypothesis of equal variances for both pairs, $\Delta T_{1,2}, \Delta T_{2,3}$ and $\Delta L_{1,2}, \Delta L_{2,3}$. This decline in variation, which is much more evident for the time than the risk indicators, may prompt one to assume that for these variables, as time horizon increases, they will all start converging towards zero and past a specific time horizon, one should expect that they will be zero. This would imply that we may reach a point where both T_t, L_t would reach a specific value, a kind of steady-state value so that $T_t = T$ and $L_t = L$. Thus, a stabilization of preferences could follow. This may be due to an increasing difficulty to distinguish between different rewards for probabilistic or intertemporal choices. But in any case, we want to avoid rushing into hasty conclusions since we were unable to make use of multiple and lengthier time horizons.

To summarize the above analysis, we keep the following basic conclusions: an inverse relationship between risk and time parameters (i.e. rising risk tolerance and more patience) is established for all time horizons but it is relatively small, a result close to Abdellaoui et al. (2013) who found $\rho =$ -0.23. Importantly, this relationship weakens and then apparently becomes stable after four months. This inverse relationship is translated to a more risk tolerant behavior or equivalently a falling risk averse behavior with the passage of time, a position that the literature broadly supports (Noussair and Wu, 2006; Abdellaoui et al., 2011; Savadori and Mittone, 2015). We find some weak evidence of an apparently more patient behavior but only for the first two months. This blurred picture we get is part of the mixed results that appear in the literature on the interaction between risk and time (van Praag and Booij, 2003; Cohen et al., 2011). Note here that contrary to the evidence for a more patient behavior, the change in attitude towards an increasing risk loving behavior can be viewed more clearly. Perhaps an explanation for this result is that the impact of time delay is not particularly severe as Keren and Roelofsma (1995) have already shown. Finally, we report some evidence for a stabilization process for both risk and time. We are unaware of a similar finding in the literature, but it is likely that CLT can offer some insight here: Liberman et al. (2002) mention that future events tend to be more extreme in value and at the same time to exhibit less variability. By incorporating time delay into a risky choice, participants not only become more risk lovers, a more extreme behavior, but also their risk behavior becomes less variable after some time. Thus, this last finding can be fully supported by the CLT theory.

Table 2.8 Standard deviations and severe outliers, low and high bounds[15]

	$\Delta T_{1,2}$	$\Delta T_{2,3}$	$\Delta L_{1,2}$	$\Delta L_{2,3}$
St. deviation	29.16	22.79	7.41	6.58
Severe outliers (low-high)	5.31%-4.83%	13.04%-12.2%	1.21%-0.48%	24.88%-24.64%

Fig. 2.3 Box plots for $\Delta T, \Delta L$



2.4.2 The Eckel-Grossman method results

The last part of the experiment is the EG (2002, 2008) technique. This technique allows us to contrast the results on risk preferences elicited under experimental designs of different nature. EG is an experimental technique where participants can choose the gamble they prefer whereas in the previous parts we have implemented a matching procedure where the participants would match their subjective estimates of winning odds with a certain reward. Thus, by using the EG technique, we implicitly contrast two different experimental procedures regarding risk preferences. A potential advantage of EG is its simplicity since there is only one probability (50%) for all gambles which is more intuitive to the participants. Of course, given the simple design of EG, we focus only on the change of the risk aversion coefficients across time and not on the relationship between risk and time indicators[16].

Following the previous notation, we index the gambles which the participants choose and correspond to the three different time horizons, the present, two months and four months as G_1, G_2 and G_3respectively. In every horizon, and for the whole sample of observations, risk aversion is the dominant behavior (Table 2.9). Notice that for G_3, the risk loving behavior

[15]Severe outliers are defined to be the observations outside the range, that is, $Q(25) - 3IQR$, $Q(75) + 3IQR$, where $Q(25), Q(75), IQR$ the 25th percentile, the 75th percentile and the interquartile range respectively. These expressions constitute the low and high bounds of the severe outliers.

[16]We consider observations for 81, not 84 participants because three participants didn't fully answer the questions for the EG method.

increases evidently compared to a constant risk loving behavior for G_1 and G_2. Nonetheless, because in EG method only the last gamble corresponds to a risk loving behavior, this perspective is probably insufficient to show a clear tendency in participants' preferences[17]. Therefore, we focus on the stability of risk preferences across time instead.

Table 2.9 Risk behavior classification for each time horizon for the EG method

Participants classification	G_1	G_2	G_3
Risk-loving	9 (11.11%)	9 (11.11%)	15 (18.51%)
Risk-averse	72 (88.88%)	72 (88.88%)	66 (81.48%)

Number of participants and corresponding percentage rates in parentheses

In Table 2.10, we report three different categories of time changing risk behavior for all the pairs of gambles: time-decreasing risk aversion (the CRRA coefficient decreases), time-increasing risk aversion (the CRRA coefficient increases) and time constant risk aversion behavior where participants report no change in their risk preferences. Regarding the comparison between $G_1\&G_2$, 33.33% of the participants report a falling risk aversion coefficient, 22.22% report an increasing risk aversion coefficient and 44.44% a constant risk aversion coefficient. That is, more than half of the participants change their risk preferences after a change of two months in the time horizon. Subsequently, 60% of these participants who do change their risk preferences prefer to adopt a more risk loving behavior.

Table 2.10 Risk behavior change for the EG method

Pairs of gambles	Time-decreasing risk aversion	Time-increasing risk aversion	Time-constant risk aversion
$G_1\&G_2$	27 (33.33%)	18 (22.22%)	36 (44.44%)
$G_1\&G_3$	40 (49.38%)	16 (19.8%)	25 (30.8%)
$G_2\&G_3$	32 (39.5%)	11 (13.5%)	38 (46.9%)

Number of participants and corresponding percentage rates in parentheses

For the pair $G_1\&G_3$, the change in time horizon for two additional months (four months in total now) has resulted in an additional fall in risk aversion where now half of the participants report lower risk aversion coefficients, that is, about 16% of the participants adopt a more risk tolerant behavior. This change can be attributed mostly to a decline in time-constant risk aversion behavior, around 13.6 percentage points even though we can also detect a small fall in time-increasing risk aversion, around 2.4 percentage points. Now notice the results for the pair $G_2\&G_3$. The time interval for this pair is exactly the same (two months) as for the pair $G_1\&G_2$but the time

[17]Remember also that in the EG method there is no way we can actually measure risk neutrality since the CRRA coefficient is never actually equal to zero (see Table 2.2).

reference frame is different since it has been moved forward by two months for $G_2\&G_3$. For the latter pair of gambles we report a rise in time-decreasing risk aversion compared to $G_1\&G_2$(5 participants, 6.2%) and a fall in time-increasing risk aversion (8.7% of the participants). Finally, there is little fluctuation on the number of participants whose risk behavior remains unaffected, where just two more participants opt for the same gambles. So, even for equally spaced time intervals, a change in the time reference frame is capable of changing the reported risk behavior and more precisely to change it pointing to a more risk tolerant behavior. Furthermore, the time reference frame shift seems to slow the change of risk preferences, that is, the change in risk preferences between the gambles $G_1\&G_2$is relatively close to that of the gambles $G_2\&G_3$. This could serve as a signal that risk behavior becomes more stable and is probably related to the minimal change in time-constant risk behavior.

All in all, through the comparison of the different pairs of gambles, we can clearly see two patterns: a constantly falling time-increasing risk aversion coupled with a rising time-decreasing risk aversion. These facts seem to be in the same direction as the results from the first experimental design but now the numbers reveal a much larger risk aversion decline. Moreover, there is always a significant percentage of participants, up to 46.9%, who choose not to change their risk preferences despite the variations in time horizons. This fact is in accord with the results reported earlier, where also a large proportion of participants, up to 50% don't change their risk preferences at all (see Table 2.7). On the whole, there is clear evidence of a declining risk aversion when the time horizon or the time reference frame is altered. Note that although there are no discount indicators to contrast with the risk coefficients derived from EG so that to confirm a statistical relationship, still a relationship between risk and time is revealed since the impact of timedelay leads to a decline in risk aversion, exactly as is reported previously in Section 2.4.1.

Note that in the above analysis about the EG method we have assumed that choosing the same gamble in each treatment implies constant risk preferences. This is a simplification since we only have an interval estimate of the risk aversion coefficient, not its precise value. In other words, choosing the same gamble may still imply a shift in risk attitudes, but this shift is not adequate to lead to a different choice of gamble. An interval regression approach where an upper and a lower bound estimate for each gamble are available could offer a different perspective. However, it may be problematic that the upper and lower bounds for Gambles 1 and 6 respectively are not available (due to the nature of the EG design) and there is also variation in the length of the intervals of the risk coefficient. Nonetheless, we have implemented this method by using treatment dummies as explanatory variables, denoting the change in time horizon and time reference frame. Although the sign of the dummy variables is always negative, indicating a switch towards a more risk tolerant behaviour in accord with the aforementioned results, it is statistically insignificant; thus, this approach cannot confirm a meaningful switch in risk attitudes.

So, qualitatively there is an agreement between the results of the two different experimental methods. But the evidence is mixed for the preferences stabilization. It is difficult to talk about any stabilization process here since the EG method is not as dense, especially regarding the probability scale, as the matching-type questions of the previous parts. Given the differences in the experimental designs, it is likely that different lengths of time delay could have been required so that the EG method to exhibit that stabilization process. There is no guarantee however that the two approaches would necessarily return similar results (Bostic et al., 1990).

We can also have a look at the EG results from a purely statistical perspective. For each gamble the participant chooses, we derive the average based on the interval bounds of the risk aversion coefficients described in Table 2.2. For Gambles 1 and 6 where the risk coefficients lie in half-closed intervals, we use as risk estimates the numbers 3.46 and -0.5 respectively[18]. These numbers serve as indices for the six different risk levels observed in the EG design. We have used the Wilcoxon signed-rank test and the Kornbrot's rank difference test for comparing the distributions between the three gambles[19]. The results, p-values, presented in Table 2.11 indicate that there is a statistical difference between the pairs $G_1\&G_3$ and $G_2\&G_3$. This means that the statistical difference is detected only after we move the time horizon by four months. This is in accord with the results reported earlier (Table 2.10) where the trend towards a more risk tolerant behavior becomes clearer after four months. Still, these tests fail to capture any statistical shift in risk preferences after two months. Note however that these tests compare the distributions of the gambles but they do not offer any indication on the direction of the change.

Table 2.11 Nonparametric tests (p-values) for the EG method

Pairs of gambles	Wilcoxon sign rank test	Kornbrot test
$G_1\&G_2$	0.291	0.148
$G_1\&G_3$	0.0029	0.0012
$G_2\&G_3$	0.0024	0.0011

For this reason, we use the sign test to compare the medians of the pairs of gambles. We denote the median of each gamble G_1, G_2, G_3 as $M_{G_1}, M_{G_2}, M_{G_3}$ respectively. In Table 2.12 we report the results of these tests (the null hypothesis always states that the medians of each pair are equal). As we can see, the medians of the gambles realized earlier in time are larger than the medians of the gambles realized later in time for the same pair of gambles as previously, $G_1\&G_3$ and $G_2\&G_3$. This implies that earlier realized gambles correspond to a higher degree of risk aversion compared to later gambles. This conclusion offers the statistical confirmation of the tendency towards risk preferences instability which tends to be in favor of a more risk tolerant behavior[20]. Finally, a graphical representation of this tendency is presented in Fig. 2.4 where the histograms for all the EG gambles are depicted. One can see that the probability mass of the gambles starts to move leftwards as time passes, indicative of a lower risk aversion coefficient. But this shift is more evident the longer the time horizon, a fact seen when one compares the pair of gambles $G_1\&G_3$.

[18]The number 3.46 is the lower bound for the CRRA coefficient of Gamble 1. For Gamble 6, we use the number -0.5 which is slightly smaller than its upper bound which equals zero.

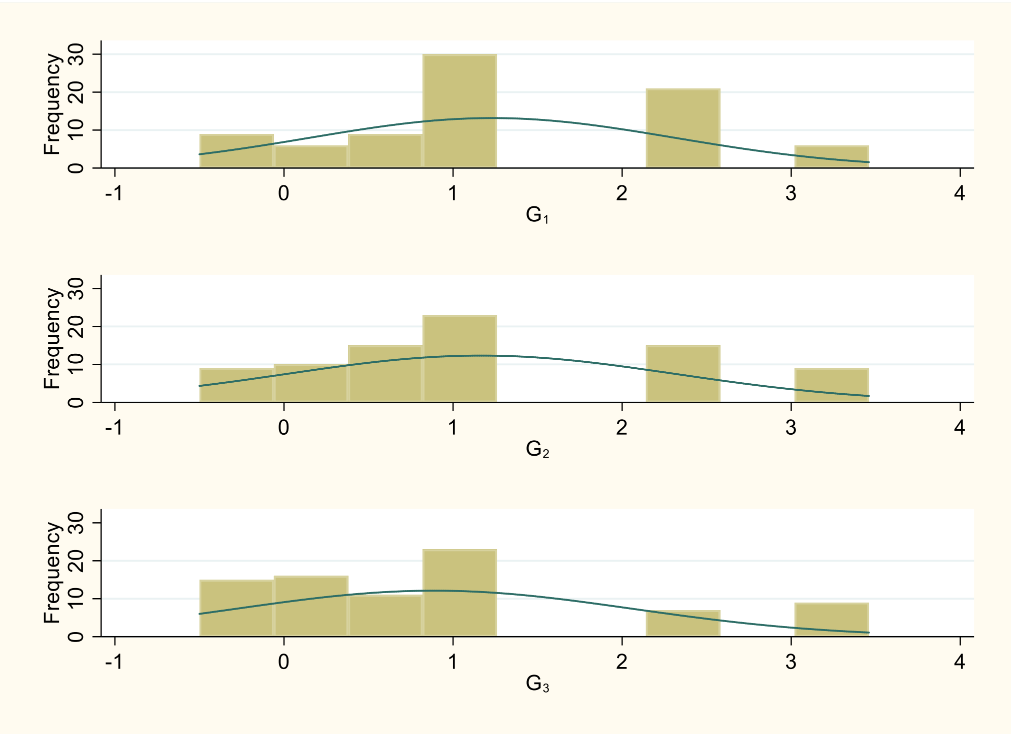
[19] Kornbrot's rank difference test is a version of the Wilcoxon-signed rank test for ordinal data. Given the indexation of the risk coefficients, the Kornbrot test should be the preferred option, although the results of the other two tests are not different.

[20] Note that this conclusion is not affected if we had used the conventional t-test and we were to compare means and not medians. Given the ordering nature of the data, we believe that a non-parametric approach is more suitable here. Moreover, the Jonckheere-Terpstra test also reveals a decreasing trend in the medians of these gambles with respect to the horizon ($p = 0.0044$), confirming thus the sign test.

Table 2.12 The sign test on the equality of the medians

Alternative hypotheses	Sign test
$H_1: M_{G_1} > M_{G_2}$	0.116
$H_1: M_{G_1} > M_{G_3}$	0.0009
$H_1: M_{G_2} > M_{G_3}$	0.001

Fig. 2.4 Probability densities per horizon for the EG method gambles



2.5 Conclusions

In this chapter, we conducted an experiment using real incentives to verify the relationship between risk and time and how this relationship evolves when the time dimension is altered. The first important observation is that we detect an inverse relationship between the risk parameter as defined by the loss function and the discount indicator, but this association is small to establish any firm conclusion about the nature of their connection, that is, that more risk tolerance is associated with more patience. We also find evidence of a more risk tolerant behavior regarding risk preferences and at the same time of a slightly more patient behavior between the present and two months' time. Overall, we fail to establish any specific relationship between risk attitudes and time patience in the same way as some papers in the literature have done (Anderhub et al., 2001; Anderson and Stafford, 2009). Perhaps this may be due to the limited available options the participants had to indicate their willingness to wait. On the other hand, the switch in risk preferences towards risk tolerance is more tangible. This could imply that the immediacy effect has comparatively a smaller impact than the certainty effect conditional on the same time delay, so a parallelism of them may not always be fully functional (Keren and Roelofsma, 1995; Weber and Chapman, 2005). From a theoretical point of view, the PTT model of Baucells and Heukamp (2012) seems to be quite generic and flexible enough to accommodate our findings on time and risk parameters and the subsequent increasing risk tolerance over the time horizons. However, PTT assumes a linear tradeoff between risk and time indicators, an assumption which can be quite restrictive for our experiment.

We have complemented our experiment with the EG method which returns much stronger evidence on the rise of risk tolerant behavior. We believe that the main reason for that is the higher degree of experimental control this method offers. In the EG method, a specific interval estimate of the risk parameter is achieved whereas in the probability assessment decision questions, the loss function is estimated based on the lower bound of winning odds for each gamble. In that way, it is more likely that the EG method will come up with more intensely varied risk parameters across time. On the other hand, perhaps it is due to this feature that the EG method fails to offer any signs which would imply a stabilization of the risk preferences similar to that of the probability assessment decision questions. The EG results are consistent with the already reported literature (Keren and Roelofsma 1995; Anderhub et al., 2001; Noussair and Wu, 2006; Anderson and Stafford, 2009). Noussair and Wu (2006) in particular report that 38.6% of the participants exhibit an increasing risk loving behavior when the payment of the gambles is delayed. Their result is close to our findings regarding the time-decreasing risk aversion behavior (33.33%, 49.38% and 39.5%). Note however, that they have used a HL design compared to the EG of our experiment and the time delay is up to three months.

One additional interesting result, which to our knowledge has received no attention in the economics literature, is the noticeable tendency towards an equilibrium position for both the risk and the time parameters. This can be seen through the declining relationship between risk and time parameters as well as the declining variability of the discount indicators and the loss functions via the time reference frame. CLT can explain this behavioral pattern since it allows initially for a changing behavior, as expressed through risk tolerance, which subsequently becomes a more stable and abstract behavioral feature (Liberman and Trope, 1998; Liberman et al., 2002). Still however, we cannot rush to any strong conclusions given that we have utilized only two time horizons in our experiment. Most importantly, it is really difficult to postulate a quantitative relationship between the risk and time parameters which would allow a solid comparison of time and risk factors to take place (see Yi et al. (2006) for an application how probabilities can be transformed into delays). Note also that this equilibrium convergence may represent learning process, in the sense that participants could adjust their answers conditional on the answers in the previous time horizons (Erev and Roth, 1998). Since risk and time are seemingly closely intertwined, viewing them as a joint learning process may be an idea that merits further experimental research. In any case, a simple statistical relationship between risk and time indicators may be not enough to firmly validate the existence of this tradeoff. A more comprehensive way to quantify this process based on a firm theoretical justification would be necessary.

Real-world applications of our results can be found in the field of finance where van Binsbergen et al. (2012) show that the price of risk in the short term is larger than the price of risk in the long term. In other words, risk aversion as described from the price of risk is inversely related with time and thus, it declines across time. There are also some attempts to explicitly model these results, for example, Eisenbach and Schmalz (2016) who offer an application in the insurance markets by using a time-dependent risk aversion model and Guo (2015) who proposes models which incorporate the risk and time connection we have found. Moreover, some authors have been able to find evidence supporting our last observation of declining variability. They have shown that it is possible to predict stock returns in the long run, a fact that also implies that the variability of stocks decreases with the time horizon (Siegel, 1998; Barberis, 2000; Campbell and Viceira, 2005). Obviously, this is an ongoing and a relatively recent literature and further research is needed to see how robust this relationship between risk and time really is. Nonetheless, it indicates a very interesting area where the questions we have set and tried to answer in this chapter could find wide applicability.

Although our experiment has taken place in the controlled environment of the laboratory where multiple dimensions of real world are not present and this does enhances the quality of our data, there are some limitations the experimental design is imposing on our results. For example, we could have used multiple time delays as well as lengthier time delays where one would be able to get a better view of the robustness of the results. This would be especially useful in tracking more effectively the apparent stabilization process of the risk aversion and discount indicator parameters. The aforementioned constraints prevented us from achieving a broader view regarding the interrelationship between risk and time. Additional treatments and the inclusion of more experimental factors e.g. the magnitude of the incentives, might have been helpful in the confirmation of hypotheses like the magnitude effect or the detection of other interesting patterns. The above constitute some issues that future experimental studies could tackle to fathom the true structure of the relationship between risk and time.

Appendix A: Experimental Instructions

Welcome! You are going to participate in an economic experiment. Please put in silent mode or turn off your mobile phones. All your decisions will be anonymous and the data generated will be ***treated confidentially.***

Procedure: This experiment has 5 parts.

In part 1, you will be asked to report the *longest acceptable delay* you consider appropriate so that to equally prefer two different monetary rewards, one smaller reward occurring now and another larger one occurring in the future. In part 2, you will be asked to report the *lowest acceptable odd* you consider appropriate so that to equally prefer two different rewards, one certain and one uncertain.

In parts 3 and 4 you will be asked to report *longest acceptable delays* and *lowest acceptable odds* for similar questions as in parts 1 and 2, but this time the decision questions are set and paid in future dates (e.g. in 2 months from now). For parts 3 and 4 this process will take place twice for two different future dates. Finally, in Part 5 you will be asked to choose between 6 different gambles which are payable in future dates.

For each part, you will be given an instructions sheet explaining the decision questions and the payment procedure. Attached you will find the decision questions. Lastly, you will complete a questionnaire on some socio-demographic questions.

The Payoffs: The payments will take place at the end of the experiment. Each one of you will receive a participation fee of **£5**.In addition, one participant will have the opportunity to win up to **£50**. All participants have an equal chance of winning. The payment process will be as follows:

One participant will be randomly selected by picking a number out of a hat. Then, a random number will be drawn from 1 to 63 corresponding to the 63 decision questions of the experiment. The decision question with numbering equal to the random number will be chosen for the payment process.

Some questions could result in receiving late rewards offered after a specific time delay. These late rewards will be awarded in the form of a post-dated cheque. Note that this is a fully funded experiment and the future payment will be guaranteed by Prof. Iain Fraser.

Simple examples of the payment procedures for each part of the experiment are provided with the instruction sheets which you will be given shortly.

Given the experimental procedures we follow, it can be shown you can get the maximum amount of money by being truthful during the reporting procedure. Over-reporting or under-reporting in any part of the experiment can make you worse-off. It is in your self-interest to truthfully answer all the decision questions.

Remember: There are no correct or wrong answers. Just give the answers you consider that most closely describes your preferences.

Sample questions:

For me, getting £10 today is just as good as getting £30 in _

1 week   2 weeks   3 weeks   1 month   2 months   3 months   4 months

For me, getting £20 for certain is just as good as winning £30 with chance _%

10% chance   50% chance   90% chance

10%   25%   35%   50%   65%   75%   90%

Appendix B: The EG method

Below you can see ***6*** different gambles. Each gamble has two potential outcomes, one lower and one higher. Both outcomes are offered with the same probability level (50%). That is, they are both equally likely to occur. ***You can choose one and only one*** of these***6*** different gambles.

To indicate your choice, tick the box next to your preferred gamble.

	Payoffs	**Chances**	**Your choice** **Choose only one gamble**
Gamble 1	**£14**	50%	
	£14	50%	
Gamble 2	**£12**	50%	
	£18	50%	
Gamble 3	**£10**	50%	
	£22	50%	
Gamble 4	**£8**	50%	
	£26	50%	
Gamble 5	**£6**	50%	
	£30	50%	
Gamble 6	**£1**	50%	
	£35	50%	

The payment procedure: Assume that you have selected the Gamble 4, where you have 50% chances of winning £26 and 50% chances of winning £8. Then a random number between 0-100 will be drawn. If the random number is above 50, you will be paid the high payoff, £26 at the end of the experiment. Otherwise, you will receive the low payoff, £8.

Chapter 3

An experimental investigation of risk behavior for gains and losses: The effect of higher stakes and time delay

Abstract

We investigate in a lab experiment the nature of risk preferences in the gain and loss domain. A simple experimental design is utilized with the same choices both in the gain and loss domain. We use Expected Utility Theory (EUT) and Cumulative Prospect Theory (CPT) to account not only for utility curvature but also for probability weighting and we examine the effect of higher stakes as well as the effect of delayed lotteries. Higher stakes weaken the reflection effect hypothesis and their impact is evident at both the utility and the probability parameters indicating the importance of the latter in the modelling process. Evidence for a clear asymmetry in probabilistic behavior between gains and losses under higher stakes is presented. Under time delay, only probability weighting for gains is affected, resulting in greater risk tolerance. This is indicative of an asymmetric behavior between gains and losses which is also featured probabilistically.

3.1 Introduction

Risk affects all aspects of our life and many economic decisions are intertwined with risk. These risky economic decisions could result in generating profits (gains) or incurring debts (losses). Examples include the trading of stocks and bonds, the management of a business, the investment plans of a company, the purchase of insurance contract etc. Such decision making could be affected by a number of contextual factors with varying impulse. Two crucial factors are the size of the monetary payoffs and the time factor when one faces intertemporal choices, choices that are made available in future dates.

The most popular of decision theory models, Expected Utility Theory (EUT), does not explicitly discern between the domains of gains and losses. Fishburn and Kochenberger (1979) attempted to address this deficiency of EUT by introducing a utility function reflecting changes in wealth from a reference point so that to accommodate both gains and losses, a sign-dependent EUT. In that way they were adopting reference dependence, implying that preferences are shaped based on changes of wealth and not on the final value of the outcomes at stake. This is one of the tenets of Prospect Theory (PT) introduced by Kahneman and Tversky (1979) (hereafter K&T (1979)), later expanded to Cumulative Prospect Theory (CPT) by Tversky and Kahneman (1992) (hereafter T&K (1992)) to account for violations of stochastic dominance in probability weighting.

To describe risk behavior in either domain, CPT stipulates a phenomenon called the reflection effect, according to which an individual's choices in the gain domain should be reversed in the loss domain as long as the same prospects are used for risk elicitation. This effect implies a very similar pattern of behavior in both domains, concave utility (risk aversion) for gains and convex utility (risk seeking) for losses. The reflection effect follows directly from the invariance assumption of choice theory which states that preferences should not change when the same options are framed as gains or losses. Significant differences in the behavior in the two domains point out to violations of a normative decision making process as described by CPT and subsequently imply the existence of framing effects (Tversky and Kahneman, 1986; Birnbaum, 2006). In general, the literature offers empirical support for the reflection effect (Fishburn and Kochenberger, 1979; Budescu and Weiss, 1987; T&K, 1992) although other authors report conflicting evidence (Cohen et al. 1987; Hershey and Schoemaker, 1980). One reason for these conflicting findings is that there are references in the literature about concave or linear utilities for losses (Fennema and van Assen, 1999; Abdellaoui et al., 2007). To account for all these, Wakker et al. (2007) introduced the partial reflection effect hypothesis where the utility curvature for losses can be slightly convex and close to being a dichotomous line[21]. This new version of reflection effect allows for some differentiation in the parameters of the utility curvatures but it is not clear if it allows for statistical equality of these parameters.

The discussion about reflection effect is limited to the shape and the degree of curvature of the utility function for gains and losses, yet is not limited by the type of model e.g. Fishburn and

[21] Partial reflection effect is also related with the evolution of reflection effect itself. K&T (1979, p. 268) state: "… the preference between negative prospects is the mirror image of the preference between positive prospects. Thus, the reflection of prospects around 0 reverses the preference order". But they appear to soften their position later when they state (T&K, 1992, p.306): "… prospect theory does not imply perfect reflection in the sense that the preference between any two positive prospects is reversed when gains are replaced by losses".

Kochenberger (1979) have tested reflection effect in a EUT reference dependent model. But another element of CPT, the nonlinear probability weighting, can also describe risk preferences in each domain and therefore it should be taken into account. The fourfold pattern that produces an inverse S-shaped weighting function where people overweight small probabilities and underweight high probabilities is well-known (Starmer, 2000). Another example is the principle of diminishing sensitivity, in a probabilistic context, which implies that changes near the end of the probability scale can be ignored or over-weighted and thus, they can affect probability weighing more acutely than changes close to the middle of scale (K&T, 1979). Hence, behavior could be equally affected by both probability and outcome size and thus, utility alone could be unlikely to explain accurately peoples' behavior. Therefore, CPT can complement EUT by eliminating the confounding between utility and probability weighting and allowing the researcher to obtain a broader picture on risk preferences. Across the two domains, the probability weighting function used by T&K (1992) allows for limited distinction between gains and losses but still produces similar inverse S-shape functions. Prelec (1998) also assumed equivalence across domains for the curvature of his own probability weighting function but he allowed room for differentiation for the other parameters. Albeit empirical evidence in the literature tends to support the inverse S-shape pattern in either domain (Etchart-Vincent and l'Haridon, 2011), these patterns may not necessarily be identical (Abdellaoui, 2000). A sizeable deviation between the probability parameters in each domain could also be indicative of the existence of framing effects for probability weighting, too.

A factor that could impact risk attitude is the change of the outcome values used during the elicitation process. Markowitz (1952), incorporated first this insight into his proposed utility function and provided a link between the stakes size and the domain. His utility function was initially convex and then concave for small and larger gains respectively, but on the other hand it was concave and then convex for small and larger losses respectively. But CPT remains silent about the higher stakes impact on the utility curvature and the reflection effect. Since then, a number of studies have examined the higher stakes impact either in the lab (Holt and Laury, 2002; Fehr-Duda et al., 2010; Drichoutis and Lusk, 2016) or in the field (Binswanger, 1980; Sillers, 1980). The general conclusion that follows from these papers is that higher stakes change risk attitudes towards an increasingly risk averse behavior, for gains at least (Harrison et al. (2007) report an exception). Nonetheless, there is little research on the impact of higher stakes in the loss domain and the results are not always clear. Hogarth and Einhorn (1990) reported larger variations for risk preferences for gains and almost no difference between medium and high stakes for losses and likewise Fehr-Duda et al. (2010) found little change in preferences in the loss domain utility parameters when higher stakes are utilized whereas Vieider (2012) reported differences mostly for utility parameters and only for larger stakes probability weighting may be affected. To our knowledge, Laury and Holt (2008) is the only paper that examines reflection effect under higher stakes; they found that reflection effect can be affected negatively from higher stakes but their analysis is of descriptive nature and lacks any solid statistical confirmation.

By using higher stakes we also have the opportunity to check how the shapes of utility and probability weighting functions are going to be affected. It is normally expected that a separability with respect to outcomes and probabilities should hold, that is, changes in outcomes indicate analogous changes in the utility function while changes in probabilities are related to probability adjustments (we refer the reader back to the separability definition given in p. 3). However, this claim could be invalid due to possible interactions between utility and probability and thus, higher stakes could impact the probability weighting functions parameters as well. This has been confirmed by Fehr-Duda et al. (2010) for both gains and losses and Bouchouicha and Vieider (2017) for gains-only models. Finally, the investigation of the impact of higher stakes makes sense in the light of the EUT criticism by Rabin (2000) who claimed that a utility curvature change is upper and lower bounded and is conditional on the wealth level. So, one should be careful into drawing safe conclusions over different ranges of outcome values by using only EUT because the concavity could be minimal and the utility could be close to being linear.

Another factor that could affect risk preferences is time delay. Originating with Thaler (1981), many studies have found evidence of a sign effect, that is, there is a different mechanism between gain and loss discounting, and in particular that gains are discounted more heavily than losses when they are both offered with a time delay (Benzion et al., 1989; Frederick et al., 2002; but see Shelley (1994) for the opposite result). In addition, it has been documented in the literature that the discounting of future prospects, in the gain domain, leads to an increasingly risk tolerant behavior indicated by peoples' preference switch from safe to riskier prospects (Noussair and Wu, 2006; Savadori and Mittone, 2015). To our knowledge, it seems that only Abdellaoui et al. (2011) have investigated the impact of delayed lotteries on risk preferences, by attempting to discriminate between utility and probability weighting. They found a more risk-loving behavior for delayed lotteries displayed primarily on probability weighting function than on utility curvature. Apart from the importance of probability, this finding also indicates a potential trade-off relationship between risk preferences and time delay, a fact supported by an affect-based reasoning (Rottenstreich and Hsee, 2001; Loewenstein et al., 2001) which states that future choices are related to weaker emotional reactions and thus, they are susceptible to change. We are unaware of any investigation of these findings in the context of sign-dependent models like CPT.

Time delay does not affect directly either of the two components of a lottery, the outcomes and the probabilities. This is important because it makes time less tangible than monetary outcomes and it may imply that the mechanisms behind time delay may be more demanding cognitively and of different nature qualitatively than these behind monetary outcomes. These distinct properties between the dimensions of time and money have been highlighted before in the literature and could impact mental accounting and could result in different investment decisions (Leclerc et al., 1995; Soster et al., 2010). For example, including time delay in decision making changes the environment where the decisions are made and this affects the decision process by resulting in a less narrow framing than when higher stakes are used, in the sense that the choice of lotteries and the time delay impact could be considered separately and not simultaneously (Kahneman, 2003; see also Öncüler and Onay (2009)).Note that in the papers cited previously, time preferences are not elicited and discount rates are not derived. This is a path we follow in the upcoming analysis given the difficulties in implementing it in the loss domain.

In this chapter, we attempt to examine further the nature of risk attitudes in the gain and loss domain. Our experiment incorporates the following contributions to the relevant literature of decision making. First, it is one of the very first attempts that extends the popular Holt and Laury

(HL) (2002) experimental design in the loss domain so that sign-dependent models can be implemented straightforwardly. Despite the popularity of the HL design, we are aware of only a handful of papers who have embedded losses in the HL design (Laury and Holt, 2008; Gazda et al., 2011; Brink and Rankin, 2013; Schipper, 2014). Second, we make use of the maximum likelihood technique in order to examine statistically treatment effects in either domain, a technique not employed up until now for sign-dependent models with the HL design. Third, our chapter is one of the few in the economic literature that uses a sign-dependent version of EUT along with the CPT model. The sign-dependent EUT model has been far less used in the literature than CPT, in fact, we are aware of only a few applications of it (Gaudecker et al., 2011; Bocquèho et al., 2014; Andersson et al., 2016; Bouchouicha and Vieider, 2017); even then however, the research questions put forward do not always focus on both domains or examine the impact of treatments. Fourth, we use two treatments for both gains and losses, the magnitude treatment and the time delay treatment. In the magnitude treatment all outcomes increase by a factor of four and in the time delay treatment all outcomes are available after four months. Although the usage of higher stakes in economic experiments is not uncommon, the usage of time delay is not so. Abdellaoui et al. (2011) is apparently the only attempt so far examining delayed lotteries conditional on probability weighting but their analysis is confined to gains only without comparing different sign-dependent models.

The main results of our experiment are summarized as follows: Although for low stakes the reflection effect holds, under higher stakes it weakens and it can be marginally rejected. Separability issues in the loss domain arise where the higher stakes impact is absorbed by the probability weighting function, yielding a dissimilarity between gains and losses featured beyond the utility curvature and which is incompatible with a probabilistic interpretation of the reflection effect hypothesis. Furthermore, the probabilistic behavior in either domain is driven exclusively by the elevation parameter indicating risk aversion for both gains and losses. Note that Markowitz's (1952) utility-based fourfold pattern is also largely confirmed when probability weighting is assumed to be linear under EUT. As for time delay, its impact is detected on probability weighting for gains and not on utility curvature. We detect no effect in the loss domain. Subsequently, a probabilistically more risk tolerant behavior for gains emerges together with an asymmetric risk attitude between gains and losses with respect to time delay. Although we do not elicit time preferences in this chapter, this asymmetric risk attitude is reminiscent of the sign effect in intertemporal choices. The reflection effect hypothesis holds and it's unaffected by the impact of time delay.

The chapter is organized as follows: In Section 3.2 we present the experimental design and in Section 3.3 we discuss the econometric approach. In Section 3.4 we present the results and in Section 3.5thefinal conclusions.

3.2 The Experiment

This section discusses the experimental design as well as the procedures behind the experiment. A description of the experimental treatments and their implementation follows.

3.2.1 The experimental design

Eighty students, from the University of Kent (at Canterbury campus) participated in the experiment. The students were either undergraduate or postgraduate and were members from various Departments of the University. In total, six experimental sessions took place and each student participated in only one session which lasted around 50 minutes. All participants had been notified beforehand that a £5 show-up fee would be awarded to each one of them at the end of the experiment. In addition, the participants were explicitly informed that they would be given the opportunity to win additional money, up to £46.2 depending on their answers. The participants were initially given analytical instructions which included examples and a detailed description of the payment process; then separate answer sheets were distributed for the questions of the experiment.

For the elicitation of risk preferences we have used the Multiple Price List (MPL) format first proposed by Holt and Laury (HL) (2002). HL is a very popular experimental design which has been applied extensively in laboratory as well as field experiments (Andersen et al., 2006; Coble and Lusk, 2010; Dave et al., 2010). In the HL experimental design, the participants face ten separate decision questions each of which is comprised of two options, Lottery A and Lottery B (see Table 3.1). Each one of these two lotteries consists of two different outcomes, one larger and one smaller which remain constant throughout the ten decision questions and are offered at varying probabilities. In particular, the two pairs of outcomes for Lottery A and Lottery B are £6, £4.8 and £11.55, £0.3 respectively. For both lotteries, as we move down the HL design, the probabilities for each outcome always change by the same amount, 0.1. For the larger outcomes (£6, £11.55) of each lottery, the probability of winning increases constantly by 0.1 and subsequently for the smaller outcomes (£4.8, £0.3) the probability of winning declines continuously by 0.1.

Table 3.1 Choices in the experiment

Lottery A (Safe option)	Lottery B (Risky option)	Difference (£)	Range of CRRA parameter
1/10 of £6 & 9/10 of £4.8	1/10 of £11.55 & 9/10 of £0.3	3.50	$r<-1.71$
2/10 of £6 & 8/10 of £4.8	2/10 of £11.55 & 8/10 of £0.3	2.49	$-1.71<r<-0.95$
3/10 of £6 & 7/10 of £4.8	3/10 of £11.55 & 7/10 of £0.3	1.49	$-0.95<r<-0.49$
4/10 of £6 & 6/10 of £4.8	4/10 of £11.55 & 6/10 of £0.3	0.48	$-0.49<r<-0.15$
5/10 of £6 & 5/10 of £4.8	5/10 of £11.55 & 5/10 of £0.3	-0.53	$-0.15<r<0.15$
6/10 of £6 & 4/10 of £4.8	6/10 of £11.55 & 4/10 of £0.3	-1.53	$0.15<r<0.41$
7/10 of £6 & 3/10 of £4.8	7/10 of £11.55 & 3/10 of £0.3	-2.54	$0.41<r<0.68$
8/10 of £6 & 2/10 of £4.8	8/10 of £11.55 & 2/10 of £0.3	-3.54	$0.68<r<0.97$
9/10 of £6 & 1/10 of £4.8	9/10 of £11.55 & 1/10 of £0.3	-4.55	$0.97<r<1.37$
10/10 of £6 &0/10 of £4.8	10/10 of £11.55&0/10 of £0.3	-5.55	$r>1.37$

Participants' choices in the HL experimental design are indicative of their risk attitudes. In the first four decision questions (see Table 3.1 for details), the difference in the expected payments is positive and favours Lottery A whereas in the last six decision questions the difference in the expected payments is negative and favors Lottery B. This difference presented in the third column of Table 3.1 is the difference in the expected values between Lottery A and Lottery B. Typically, participants start by choosing Lottery A in the first decision question and then at some point they switch to Lottery B. The decision question at which this switch takes place indicates the interval where a participant's risk preferences lie (i.e. the last column of Table 3.1) when a Constant Relative Risk Aversion (CRRA) utility function is utilized[22]. This means that if one switches in one of the first four questions she is considered to be risk-seeking while if one switches in one of the last five decision questions she is classified as risk-averse. Lastly, a switch at the fifth decision question points to a risk-neutral participant.

The same HL design was also used for the decision questions in the loss domain. Of course all outcomes now are losses and subsequently they are represented by negative numbers, but still they are same numbers in absolute value as previously (-£6, -£4.8 for Lottery A and -£11.55, -£0.3 for Lottery B). There is also one subtle difference in the HL design between the two domains: Lotteries A and B are reversed and thus, participants now start from Lottery B and at some point switch to Lottery A. This is necessary in order to ensure the "mirror image" between gains and losses as predicted from CPT (Laury and Holt, 2008). In the same spirit, the classification of risk preferences also changes to manifest the gains-losses mirror image. So, a switch in the first four decision questions reveals risk aversion and a switch in one of the last five decision questions reveals a risk loving behavior.

3.2.2 The treatments

As mentioned earlier, we employ a treatment factor which has three levels: the baseline treatment which offers the lower stakes(£4.8, £6 for Lottery A and £0.3, £11.55 for Lottery B) as described in Table 3.1, the magnitude treatment which offers higher stakes and in particular four times higher than those of the baseline treatment (£19.2, £24 for Lottery A and £1.2, £46.2 for Lottery B)[23] and the time delay treatment which offers the lower stakes of the baseline treatment but payable after a time delay of four months. The same decision questions were presented to the participants in the loss domain for each one of the treatments. In essence, we performed a 2x3within subject experiment where the same HL experimental design was used in two domains (gains and losses) with three treatments (baseline, magnitude and time delay) in each domain. A summary of the experimental methods and the treatments used can be found in Table 3.2.

A concern with within-subject experimental designs is the potential existence of order effects i.e. a participant's answers in one question could be affected by her answers in the previous question. This is an issue that appears when an experimenter elicits multiple observations per treatment from the same subject and has been documented previously in the literature of experimental economics (Harrison et al., 2005; Lusk and Shogren, 2007). To account for this phenomenon, we do not adopt the monotonic switching approach and instead we opt to re-

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[22] The last column refers to the lower and upper bounds of the coefficient of a CRRA utility function when a participant switches in a particular decision question. Such values could be useful if one wanted to determine risk behavior based only on the switching point between the lotteries. In the upcoming analysis, we will not use them because all the questions, in every domain and in every treatment, have been randomised. Note that no information about the last two columns of Table 3.1 was presented to the participants.

[23] The hourly wage rate in UK for 2016 was £5.55 for the ages 18-20 and 6.95 for the ages 21-24. Given that over 90% of the participants belong to either one of these two age groups, the offer of £46.2 implies that participants were given the opportunity to earn 8.32 or 6.64 times higher their hourly wage in just 50'.

arrange and present in a random order all the questions in every treatment and for both domains. Thus, we control satisfactorily for the presence of order effects (Charness et al., 2012).

During the experiment we have presented the questions to subjects with a fixed order with respect to each treatment and each domain, that is, first the questions for the baseline, then for the magnitude and at the end for the time delay treatment. Likewise, within each treatment we first presented the questions for gains and afterwards the questions for losses. We have adopted this approach in order the whole process to be less cognitively demanding for the participants. Mixing questions of various treatments could have been cognitively challenging for the participants and this could have an impact on the quality of our data. We are not aware of any attempt in the literature to test for order effects with respect to treatments and domains.

Table 3.2 Description of the treatments in the experiment

	HL experimental design	
Treatments	Gain domain	Loss domain
Baseline	✓	✓
Magnitude: (x4) stakes	✓	✓
Time delay: 4 months	✓	✓

Due to budget constraints, we were forced to pay a subset of the participants, at least 10%, in each session[24]. For the questions in the loss domain, the payment took place from a fixed endowment conditional on a loss domain decision question chosen for payment. This fixed endowment was equal to the largest possible loss they could incur, that is, for the baseline and the time delay treatment the fixed endowment was £11.55 and for the magnitude treatment the fixed endowment was £46.2[25]. At the end of each session one question was randomly selected as the binding question for payment. Then, the participants were paid according to their answer to that question (See the Appendix A of this chapter which includes the experimental instructions and sample questions). In total, 80 participants participated in three treatments and in two domains. Since each participant answered 10 questions 80*6*10=4800 observations extracted, where 6 is the product of the domains (2) and the treatments (3). However there was one missing value due to one unanswered question, so in total, 4799 observation were used in the experiment.

[24] There is no evidence that paying a subset of the participants affects negatively the effectiveness of the random lottery incentive in the context of simple MPLs. Charness et al. (2016) review a number of studies on different payment procedures in economic experiments and they conclude that paying a subset of the participants (Harrison et al., 2007; Brokesova et al., 2015; see also Beaud and Willinger (2015) who examine the impact of significant amount of losses) or even paying only one of them does not seem to have an adverse effect on the participants' behavior and motivation. Charness et al. (2016) report that some concerns may be raised regarding experiments in a dynamic choice context but this is irrelevant in our case.

[25] Offering an initial endowment is practically the default option in economic experiments containing potential losses (Harrison and Rutström, 2009; Vieider et al., 2015; Baillon and Bleichrodt, 2015), otherwise, participants may lose real money. Yet, Etchart-Vincent and l'Haridon (2011) examined the experimental procedures in the loss domain and found no difference between losses from an endowment and hypothetical losses.

Inevitably when the time delay treatment was applicable the payments had to be awarded after the time delay of four months. At that point, we had to assure the participants that they would not be deceived and they would receive their money, otherwise they may not reveal their true preferences. For that reason, a guaranteed post-dated cheque was given to the students if a question under the time delay treatment was binding for payment at the end of the experiment. This is a technique that has been used before in the elicitation of time preferences or of delayed risk preferences (Coble and Lusk, 2010; Andreoni and Sprenger, 2012). Although this type of payment eliminates the possibility of deception, it may still result in the elicitation of distorted preferences since the payment remains secured, though delayed. In other words, the guaranteed post-dated cheque could inadvertently result in insufficient variation of risk preferences in both the gain and loss domain and subsequently the time delay treatment may be less effective than we would like it to be.

3.3 Methodology

This section first describes how the basic model specifications, EUT and CPT have been constructed. Then we describe the econometric modelling of both models. We consider EUT assign-dependent in the same fashion and around the same reference point as CPT.

3.3.1 The model specifications

To be able to introduce a reference-dependent EUT, we need a function which would account for different curvature parameters for each domain. Such a function under the terminology of CPT is called value function which is in essence a utility function based on the deviations from a reference point. Henceforth, for simplicity we will use the simpler term utility instead of value function to describe these deviations. The dominant functional form in the literature is the piece-wise power function with different specifications for gains and losses which returns the usual S-shaped graph reported by K&T (1979), that is,

$$u(x) = \begin{cases} x^{\alpha} & if\ x \geq 0 \\ -(-x)^{\beta} & if\ x < 0 \end{cases} \qquad (3.1)$$

The exponents α, β $(\alpha > 0, \beta > 0)$represent the utility curvature parameters for the gain and loss domain respectively.Then the utility for choosing one of the two lotteries comprised of two outcomes,$x_1$and x_2 is

$$V = p_1 u(x_1) + p_2 u(x_2) \qquad (3.2)$$

where p_1, p_2 and $u(x_1), u(x_2)$ are the probabilities and the values of the two outcomes of each lottery.

Now, we define the other model we use, the CPT model. CPT satisfies not only sign-dependence but also eliminates potential confounding effects by allowing us to control separately for utility curvature and non-linear probability weighting. Under CPT, the utility for choosing one of the two lotteries comprised of two outcomes, $x_1$and x_2 is

$$V = w(p_1) u(x_1) + w(p_2) u(x_2) \qquad (3.3)$$

where $w(p_1), w(p_2)$ and $u(x_1), u(x_2)$are the decision weights and the values respectively that a participant assigns to each lottery. To model the non-linear probability weighting, we use the probability weighting function introduced by Prelec (1998)

$$w(p) = e^{-\delta(-lnp)^{\gamma}}, 0 \leq p \leq 1, \gamma > 0, \delta > 0 \qquad (3.4)$$

The parameter γdescribes the curvature of the probability weighting function: small values of γ $(\gamma < 1)$ indicate an inverse S-shape graph and larger values of γ $(\gamma > 1)$indicate an S-shaped probability weighting function graph. The other parameter, δ, can be viewed as an indicator of the elevation of the weighting function; small values of δ lead to a more elevated curve and thus, higher weights on probability. In the special case where $\gamma = \delta = 1$, the Prelec probability weighting function collapses to linear probability since it becomes $w(p) = p$and then EUT and CPT are indistinguishable. Since in our econometric analysis we discriminate between gains and losses regarding the probability weighting function, its parameters can assume different values that separately describe risk behavior in the gain domain (γ^+, δ^+) and in the loss domain (γ^-, δ^-):

$$w(p) = \begin{cases} w^+(p) = e^{-\delta^+(-lnp)^{\gamma^+}}, x \geq 0 \\ w^-(p) = e^{-\delta^-(-lnp)^{\gamma^-}}, x < 0 \end{cases} \qquad (3.5)$$

In CPT the outcomes are ranked in each domain where it is $|x_1| < |x_2|$ so that the decision weights to sum up to 1, that is:

$$w(p_2) = e^{-\delta(-lnp_2)^{\gamma}}$$

$$w(p_1) = w(p_1 + p_2) - w(p_2) = 1 - w(p_2)(3.6)$$

Essentially, the process of ranking is the same for both domains with the difference that outcomes are ranked from best to worst for gains and from worse to best for losses in order the “mirror image” around the reference point between gains and losses to be preserved. As for the utility function for CPT we use the same functional form specification as for EUT, the power function. In that way, equation (3.3) is analogous to equation (3.2) apart from probability weighting and rank-dependence.

As it is evident from the above, in this chapter we use the CPT of T&K (1992) and not the original version of prospect theory of K&T (1979). The major difference is that CPT, by exploiting the Rank Dependent Utility of Quiggin (1982), requires not just the weighting of the probabilities but also the ranking of the outcomes, so that the elicited preferences to be both sign-dependent and rank-dependent. This is necessary in order for violations of stochastic dominance with respect to probability weighting to be avoided. As mentioned earlier, in our experimental design we don’t have mixed gambles, we only have gambles in either the gain or the loss domain only. Without mixed gambles, the loss aversion parameter λlacks any interpretation in the context of decision theory models like ours and therefore we ignore it by assuming a loss neutral behavior i.e. $\lambda = 1$.

3.3.2 Econometric modelling

To model econometrically the choices of the participants, we adopt the random utility approach as in Andersen et al. (2008) and Coble and Lusk (2010). Then, we assume that the utility $U_{ij,K}$ of a participant j for a decision question$i$ and after opting for either Lottery A or Lottery B indexed by $K = A, B$ is

$$U_{ij,K} = V_{ij,K} + \varepsilon_{ij,K} \qquad (3.7)$$

where $\varepsilon_{ij,K}$ is a stochastic specification for the error term. Note here that $\varepsilon_{ij,K}$, also carries an experimental interpretation in the sense that it accounts for the all the kind of errors people are making in the decision making process due to negligence, fatigue etc. The utility of an individual for choosing either Lottery A or Lottery B in a decision question is

$$V_{i,K} = w(p_{1,i,K})u(x_{1,i,K}) + w(p_{2,i,K})u(x_{2,i,K}) \qquad (3.8)$$

Then the probability of choosing Lottery A over Lottery B implies that

$$U_{ij,A} > U_{ij,B} \Rightarrow (V_{ij,A} - V_{ij,B}) + (\varepsilon_{ij,A} - \varepsilon_{ij,B}) > 0$$

and it's equal to

$$\Pr(A) = \Phi\left(\frac{V_{ij,A} - V_{ij,B}}{\sigma}\right) \qquad (3.9)$$

Note that is assumed that the error terms $\varepsilon_{ij,A}$ and $\varepsilon_{ij,B}$ are assumed to be independent and identically distributed according to the cumulative distribution function $\Phi(\cdot)$ which corresponds to the normal distribution with mean 0 and standard deviation σ[26]. Thus, we maximize the following likelihood function in a probit model specification:

$$\arg\max_{\theta} \log\mathrm{L} = \sum_{i=1}^{I}\sum_{j=1}^{J}[y_{ij}(\ln(\Pr(A))\,|\theta) + (1 - y_{ij})(\ln(1 - \Pr(A))\,|\theta)] \; (3.10)$$

where y_{ij} =1 if Lottery A is chosen as most preferable and y_{ij} =0 if Lottery B is the preferred choice[27] and θ is the vector of parameters to be estimated.

The question now is how to estimate the vector θ that includes the treatment effects due to higher stakes and time delay. To address this issue we adopt the approach by Fehr-Duda et al. (2010) where each model parameter is constructed as a linear function of the higher stakes and of the time delay. For example, for the treatment effect on the parameter γ^- we have $\gamma^- = \gamma_0^- + \gamma_t^- * treat$ where $treat$ is a dummy variable representing either the higher stakes or the time delay and $\gamma_0^-$is the parameter that represents the baseline treatment. If there is indeed a treatment effect onγ^-, then we should expect the treatment coefficient $\gamma_t^-$to be statistically significant. The sign of the treatment coefficient denotes the direction of the treatment effect.

[26] To be more precise, the standard deviation of the difference in the error terms is $\sqrt{2}\sigma$, since the difference of two normally distributed variables, $N(0, \sigma^2)$, follows also a normal distribution with variance equal to $2\sigma^2$.
[27] The econometric modelling is exactly the same for EUT. The only difference is that for EUT the decision weights collapse to the probabilities assigned to the outcomes of each lottery.

The same rationale applies for the other model parameters, too. So, under EUT and CPT we estimate the following respective vectors:

$$\theta = (\alpha_0, \alpha_t, \beta_0, \beta_t, \sigma)'$$

$$\theta = (\alpha_0, \alpha_t, \beta_0, \beta_t, \gamma_0^-, \gamma_t^-, \gamma_0^+, \gamma_t^+, \delta_0^-, \delta_t^-, \delta_0^+, \delta_t^+, \sigma)'$$

For all models we account for potential correlation among the responses reported from the same participant by using clustered standard errors in the maximum likelihood estimation. This is a plausible concern because the observations within each cluster could be correlated with each other since all of them have been generated by the same participant. In that way we avoid any potential efficiency questions that may arise for the variance-covariance matrix of the maximum likelihood estimator. The Stata 15 software package has been used for programming the maximum likelihood and the simulation of the graphs. In Appendix B of this chapter, a sample code for the sign-dependent EUT model has been included.

After having identified the different types of models, the question of selecting the best model comes next. For this selection the Likelihood Ratio test will be used. The test statistic is given by the formula $LR = -2 * (ln(L_1) - \ln(L_2))$ where L_1, L_2 are the likelihoods of the two models, EUT and CPT respectively. The test statistic follows a X^2 distribution under the null hypothesis which favours the simpler model, the EUT. This test allows for selection between two different nested models as the decision theoretical models of our experiment, since EUT can be derived from CPT if we restrict the probability parameters γ, δ of the latter to be equal to one.

Our structural modelling approach assumes that risk preferences for all participants can be described by either EUT or CPT, in other words, we imply a homogeneity of preferences for all participants. Obviously this can be a quite restrictive assumption since not all participants need to behave in a similar way. Thus, heterogeneity in risk attitudes could be present. That heterogeneity could be present in our data in three different ways: first, it could be observed heterogeneity, in the sense that utility and probability parameters could depend on demographic characteristics of each individual (see Harrison and Rutström (2009) for an application). Unfortunately, we have collected little demographic data and our sample is a quite homogeneous student population in order to offer any valuable information. Second, heterogeneity could be present in the form of unobserved heterogeneity, that is, some participants' risk preferences may be better described by EUT while for the rest a CPT model may be more suitable. Then, an econometric approach based on finite mixture models could be plausible (see Conte et al. (2011) for an application). But our data is not rich enough (the same pair of gambles is used for all choices in the HL design) to allow for the estimation of such computationally intensive models. A third level of heterogeneity could be present at the individual level, that is, each model parameter could be dependent on each participant, so a between-subject variation could emerge. In section 3.4.1 below, we have attempted to sketch graphically how the switching point varies per treatment and per domain. This variability is not included in our econometric model since in this case a large number of parameters would have to be estimated.

Since we use exactly the same lotteries for both the gain and the loss domain, and in addition we fully cover the largest possible losses that the participants could possibly incur, implicitly we assume that the reference point is zero. Thus, the starting point from which participants tend to define their wealth for both gains and losses is zero and so the changes in wealth are analogous for either domain. This has been assumed for the simplicity of the econometric analysis but also because it is implied by K&T (1979). However, it is possible that reference point may not necessarily be fixed, but rather to be considered as a function of the recent beliefs the participant may hold or more generally of the expectations people may harbour (Abeler et al., 2011; Kőszegi and Rabin, 2006; Kőszegi and Rabin, 2007) or even to be dependent on previous experiences or even not to be unique (Frederick and Loewenstein, 1999). This is a difficult point and is not examined further in this chapter.

3.4 Results

In this section we present the main results of the econometric analysis. At first we discuss and we represent graphically the choices of the participants across domains for all treatments. Then, we comment on the estimated parameters of EUT and CPT under the magnitude and time delay treatments. Note that we will henceforth use the phrases higher stakes and magnitude treatment interchangeably.

3.4.1 Description of the choices

Fig. 3.1 offers a first look at the choices of the participants. They depict the percentage of participants choosing the safe option per domain. We consider as safe option the gambles of Lottery A since they exhibit lower variability compared to the corresponding gambles of Lottery B. Since the same gambles are used for both gains and losses (only the sign of the gambles changes), the switching point indicating risk neutrality, and after assuming EUT preferences and a CRRA utility functional form, was always the same, the fifth gamble[28].

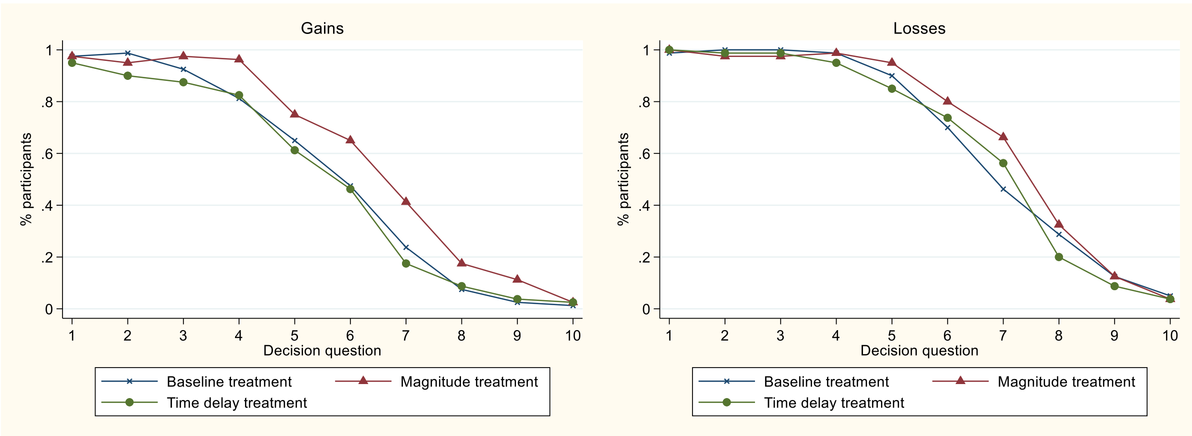
In the gain domain, the participants' preferences in the baseline and time delay treatments are close enough, signalling that the effect of the time delay treatment may be relatively small. On the other hand, the magnitude treatment clearly seems to influence participants' preferences since its line is always above the lines of the other two treatments (e.g. for the magnitude treatment, participants practically start switching from question 5 and onwards whereas for the baseline and time delay treatments already almost 20% of the participants have switched up until question 4). This could mean that higher stakes result in switching later and thus, a higher degree of risk aversion is to be expected.

In the loss domain on the other hand, the picture is much more imprecise and we cannot clearly distinguish any effect of the magnitude and the time delay treatment. It seems however that the magnitude treatment still has a small effect given that its corresponding line is slightly above the lines of the other two treatments. Another observation is that the pattern of choices is very

[28] Recall the reversal here for the loss domain: in the gain domain, participants switch from Lottery A to Lottery B, whereas in the loss domain participants switch from Lottery B to Lottery A. This reversal is necessary in order to ensure the hypothesized reflection effect between gains and losses.

similar irrespective of the treatment. Note also that the majority of participants switch in the last five questions, an indication of risk loving behavior as the reflection effect stipulates. Finally, note the smooth downward sloping lines of both graphs reflecting a consistent pattern of choice. It is also worth mentioning that we get this clear pattern without imposing monotonic switching or having to remove any individual from our data due to possible fears of violating monotonicity i.e. switching back and forth more than once.

Fig. 3.1 Switching patterns per domain



However, the above do not tell us anything about individual behavior. It worth exploring how each participant behaves in the absence of monotonic switching. Table 3.3 below shows this behavior per domain and per treatment. As we can see the majority of the participants switch only once i.e. they behave as if monotonic switching had been imposed 411 out of 480 times (85%). In addition, in 7 cases there is no switch at all. But for the rest, their preferences could be imprecise since they switch more than once. The number of multiple switches can take different values ranging from 2 to 7. Note that we also document an even number of multiple switches (2 or 4), albeit very small, just 13 (2.7%). Generally, this happens because participants choose the same lottery in their first and last questions or because they start their choices in a reverse order than expected, that is, choosing the right lottery (Lottery B) for gains and the left lottery (Lottery A) for losses. All in all, multiple switching does exist (around 15% of the cases). These findings confirm the validity of our approach not to impose monotonic switching and to include an error term in the econometric analysis so that to account for variability in choice.

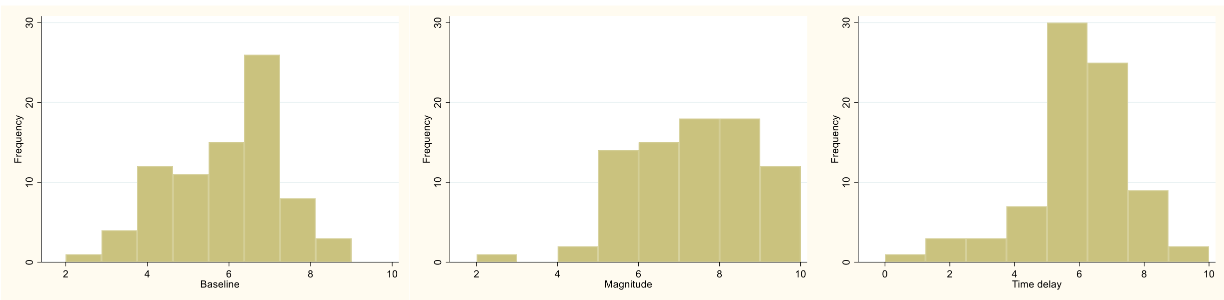
Another issue in describing individual choices is the variability of the switching point. Note that the Figures 3.1 represent an aggregate picture and cannot fully reveal the exact switching point of each individual. In Fig. 3.2a and 3.2b below we present in the form of histograms the variation in switching points per domain and per treatment. Such a variation could hint at a degree of individual heterogeneity in risk attitudes, a fact that our structural modelling approach based on EUT and CPT cannot capture since in essence it generates mean estimates. Note that in the case of multiple switches and in order to make the comparisons meaningful, we define a single switching point, approximately at the mid-point of the multiple switches interval.

Table 3.3 Multiple switches per domain and treatment

	Gain domain			Loss domain			Total switches
Number of switches	Baseline	Magnitude	Time delay	Baseline	Magnitude	Time delay	
0	-	-	1	3	2	1	7
1	63	69	70	66	69	74	411
2	1	1	2	-	1	1	6
3	12	9	5	8	6	3	43
4	2	1	1	2	-	1	7
5	1	-	1	1	2	-	5
7	1	-	-	-	-	-	1
	80	80	80	80	80	80	480

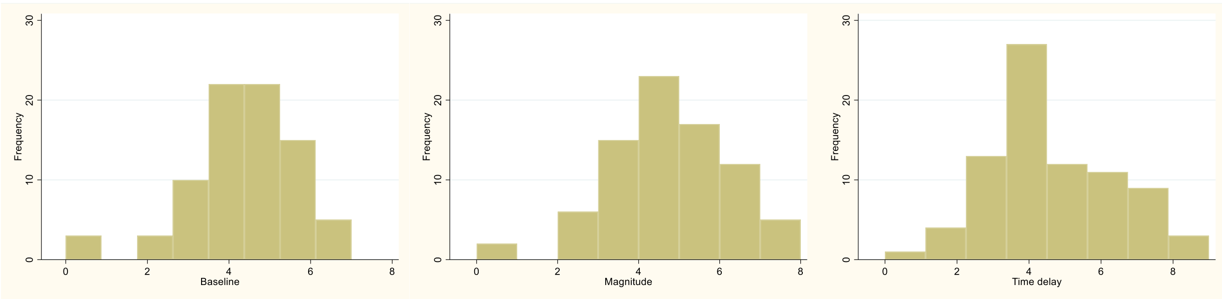
For gains first, in the baseline treatment we can see that switching at questions 7 and 6 are the two dominant options, then followed by questions 4 and 5; in total, switching at these four questions represent 80% of the participants. In the magnitude treatment, the switching point starts moving to the right and the questions 5, 6, 7 and 8 are the dominant switching points. This reveals that the magnitude treatment seems to be strong enough to induce change in risk attitudes and it is an indication of higher levels of risk aversion. It also shows that very few switches happen in the first four questions. As for time delay, questions 5, 6 and 7 represent around 69% of the switching points. This is quite close to the baseline treatment (where questions 5, 6 and 7 represent 65% of the switching points) revealing a potentially limited influence of the time delay treatment.

Fig. 3.2a Switching points variation in the gain domain



Moving to the loss domain now, for the baseline treatment first, switching at questions 4 and 5 accounts for slightly more than half of the participants (55%) followed by questions 6 and 3. In total all the participants have switched by question 8. For the magnitude treatment, we have a similar picture where a switch at questions 4 and 5 represents exactly half of the participants (50%), followed by a switch at questions 3 and 6. Again, there are very few switches at the two first and two last questions. For the time delay treatment, the overall picture is again similar with 49% of the participants switching at questions 4 or 5 and 30% either at questions 3 or 6. These switches are accompanied by very few switches in the two first and two last questions. Note that these findings for the loss domain are generally in accord with the aggregate pattern of choices in Fig. 3.1 where there is limited choice differentiation across the three treatments.

Fig. 3.2b Switching points variation in the loss domain



3.4.2 EUT under higher stakes

We start the investigation for magnitude treatment effects by focusing first on the EUT model (see Table 3.4 below).For either domain, the treatment effect is statistically significant and negative in value, -0.309 and -0.385 for gains and losses respectively, signalling steeper utility curvatures and leading to a more risk averse behavior for gains and a more risk seeking behavior for losses. The reflection effect hypothesis for the baseline treatment is firmly rejected since for the equality $\alpha_0 = \beta_0$, the p-value is $p = 0.000$, indicating an asymmetry between gains and losses. We can also detect a small differential domain effect i.e. $\alpha_t = \beta_t$ ($p = 0.048$) which means that the treatment effect is considered to be slightly larger statistically for losses than for gains. To test for the reflection effect under higher stakes, one has to add up the baseline coefficients and the treatment effects, that is, we test $\alpha_0 + \beta_t = \beta_0 + \beta_t$. For this test it is$p = 0.0003$, thus, the reflection effect hypothesis is rejected under higher stakes, too. Furthermore, the utility curvature for gains for the baseline treatment can be considered linear since $\alpha_0 = 1, p = 0.848$, but for losses it is concave since $\beta_0 = 1, p = 0.000$. However, under the impact of higher stakes, utility for gains becomes concave ($\alpha_0 + \alpha_t = 1$, $p = 0.000$) whereas for losses it becomes convex ($\beta_0 + \beta_t = 1$, $p = 0.0001$). Hence, higher stakes can reverse risk attitudes in both domains. Note that these changes in risk attitudes are in accord with the changes in preferences proposed by Markowitz (1952) where for larger outcomes people become more risk averse for gains and more risk seeking for losses from an initial risk aversion position; however, the convex segment (risk seeking) for gains for the baseline treatment of Markowitz's utility function is replicated only numerically ($\alpha_0 = 1.007$) but not statistically as shown earlier.

Table 3.4 Model parameters for the magnitude treatment[29]
(Standard errors in parentheses, 3199 observations)

	EUT		CPT				
		Utility parameters		Probability parameters			
α_0	1.007*** (0.036)	α_0	1.106*** (0.115)	γ_0^+	1.213*** (0.174)	δ_0^+	1.868*** (0.231)
α_t	-0.309*** (0.02)	α_t	-0.421*** (0.06)	γ_t^+	0.137 (0.278)	δ_t^+	-0.028 (0.335)
β_0	1.205*** (0.045)	β_0	1.144*** (0.09)	γ_0^-	1.363*** (0.302)	δ_0^-	1.031*** (0.115)
β_t	-0.385*** (0.035)	β_t	-0.379*** (0.067)	γ_t^-	0.103 (0.372)	δ_t^-	-0.454*** (0.087)
σ	3.113*** (0.422)	σ	3.028*** (0.689)				
N	80	80					
T	60	60					
$logL$	-1206.49	-1009.41					

Statistical significance: ***p<0.01, **p<0.05, *p<0.1

3.4.3 Utility in CPT and the reflection effect under higher stakes

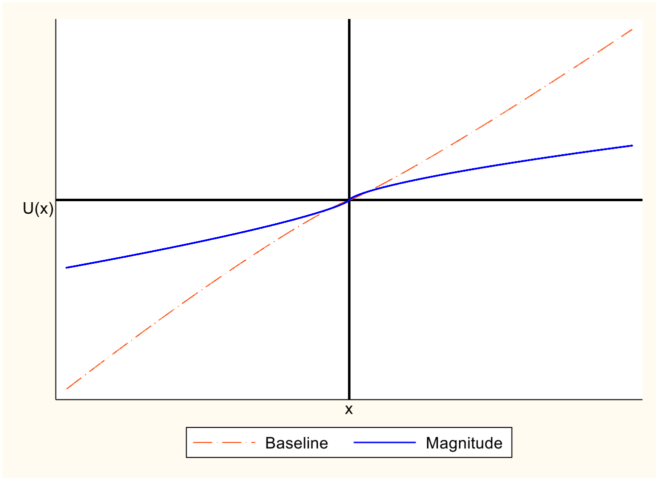
Now, we move to the other decision theory model, the CPT. Starting with the utility curvature, we observe treatment effects which are statistically significant, quite large and negative in value, -0.421 and -0.379 for the gain and loss domains respectively. The reflection effect hypothesis for the baseline treatment, $\alpha_0 = \beta_0$, is not rejected now since Wald test returns $p = 0.66$. Furthermore, there is no differential domain effect since the equality, $\alpha_t = \beta_t$ is comfortably satisfied ($p = 0.568$). This absence of differential domain effect leads to the weakening of reflection effect under higher stakes, which now can be marginally rejected given that for $\alpha_0 + \alpha_t = \beta_0 + \beta_t$, it is $p = 0.046$. Thus, CPT offers a very different picture on reflection effect (see Fig. 3.3a), which initially holds for the baseline treatment but when higher stakes kick in, it is possible this effect to be reversed. There is also another way to view this reversal of the reflection effect: statistically, both utility curvatures for the baseline treatment are linear since it is $\alpha_0 = 1$, $p = 0.357$ and $\beta_0 = 1$, $p = 0.11$. But after taking into account the treatment effects, the linear utility assumption collapses for the magnitude treatment ($\alpha_0 + \alpha_t = 1, p = 0.000$ and $\beta_0 + \beta_t = 1, p = 0.000$).

Although under higher stakes we have ended up with steeper utility curvature for either domain (Fig. 3.3a), we have avoided labelling this behavioral change as rising risk aversion for gains and rising risk seeking for losses because the presence of probability weighting under CPT invalidates

[29] Recall that the number of observation in our data should have been equal to $N * T = 4800$ (the number of participants times the number of questions for both domains and for all treatments), but instead it is 4799 since there was one missing value. Here 3199 observations are used for the econometric analysis.

the direct relationship between utility curvature and risk aversion put forward under EUT (Chateauneuf and Cohen, 1994). Note also that we have ended up with linear utility in the baseline treatment, a finding that can be attributed to the relatively small amounts on offer (Wakker and Deneffe, 1996). It is also a confirmation of the partial reflection effect, at least for the loss domain (Wakker et al., 2007).

Fig. 3.3a Value function graph for CPT (Magnitude treatment)



3.4.4 Probability weighting in CPT under higher stakes

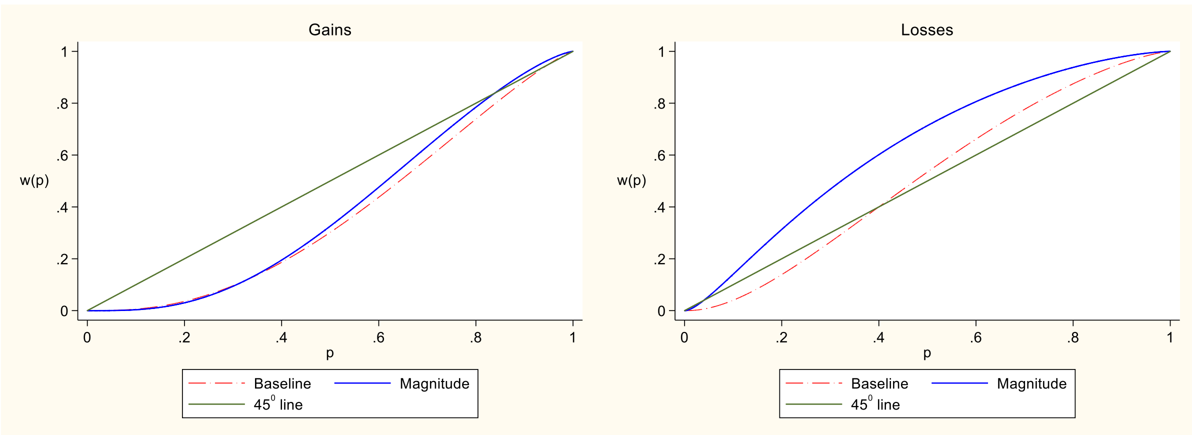
We start the investigation of the probability factor by focusing first on the curvature parameter, γ. That curvature can be considered linear in the baseline treatment for either domain ($\gamma_0^- = 1, p = 0.229$ and $\gamma_0^+ = 1$, $p = 0.221$). This linearity in curvature is present even when higher stakes are employed since it is $\gamma_0^- + \gamma_t^- = 1, p = 0.086$ and $\gamma_0^+ + \gamma_t^+ = 1, p = 0.149$. This is not surprising since both treatment effects, γ_t^+, γ_t^-, are close in value and statistically insignificant, so that to be $\gamma_t^+ = \gamma_t^-, p = 0.94$. Thus, all the curvatures of the probability weighting functions can be thought as practically linear. In addition, a non-linear test (based on the delta method)to detect any probability curvature divergence between gains and losses under the magnitude treatment, shows that for the equality$(\gamma_0^+ + \gamma_t^+)/(\gamma_0^- + \gamma_t^-) = 1$, it is$p = 0.736$, so we can be comfortable that the probability curvature linearity remains unaffected. Ultimately, this reveals the limited role of probability curvature in the HL design with varying stakes.

Regarding the other probability parameter, the elevation parameter δ, it can only be considered linear in the baseline treatment for losses ($\delta_0^- = 1, p = 0.782$), but this linearity collapses under higher stakes, where the treatment effect δ_t^- is almost half the value of δ_0^- and statistically significant ($\delta_0^- + \delta_t^- = 1, p = 0.000$). This strong treatment effect shrinks the value of δ and leads to a more elevated probability graph (see right panel of Fig. 3.2b). For the gain domain on the other hand, the treatment effect $\delta_t^+$is negligible and does not affect the already large value of δ_0^+ which reveals probabilistic pessimism and a graph below the dichotomous line (see left panel of Fig. 3.2b). Note finally, that δ is the factor that drives a wedge between the two domains since the equality $(\delta_0^+ + \delta_t^+)/(\delta_0^- + \delta_t^-) = 2.1$ can be marginally accepted at 10% ($p = 0.107$).

The above findings imply that for both domains, δ departs considerably from linearity contrary to the tendency exhibited by γ, and it is this parameter that governs the formation of the probability shapes.

The next step is to determine if there is any meaningful impact of higher stakes on probability weighting. The existence of two probability parameters complicates things and makes necessary the treatment effects on both parameters to be taken into account. Therefore, we use a t-test with 2000 bootstrap replications, which is performed upon the difference between the baseline and the magnitude treatment for the two probability weighting curves in each domain (see Fehr-Duda et al. (2010)). The null hypothesis of the t-test states that that difference is considered statistically to be zero, and thus, no probability treatment effects are present and subsequently no separability exists[30](the definition of separability is given in p. 3). For gains, the test returns a bootstrap test statistic $z =$ -1.29 along with 95% confidence intervals that contain zero i.e. [-0.047, 0.0096]; this illustrates that no probability treatment effects (i.e. separability) exist in this domain. For losses, a different picture emerges: the test statistic equals $z =$ -8.48, a sufficiently small value so that the 95% confidence intervals not to contain zero i.e. [-0.149, -0.093], signalling that a statistically significant difference in probability weighting exists in the presence of higher stakes. We stress that the existence of separability in this domain should be attributed almost exclusively to the treatment effect on the elevation and not on the curvature parameter due to the linearity of the latter as shown earlier.

Fig. 3.3b Probability weighting graphs per domain (Magnitude treatment)



We look now at how probability forms risk attitudes. The probability-driven behavior for gains, always indicates risk aversion since the large values of the elevation parameter δ for either treatment (δ_0^+ and $\delta_0^+ + \delta_t^+$), yield a pessimistic attitude leading to a convex probability weighting function. This means that risk aversion is prevalent with respect to probability. This is important because it complements the linear utility of the baseline treatment revealing that it is

[30]This is a simple t-test of unpaired data. Note that we explicitly control for unequal variances of the samples derived out of the treatments.

probability weighting that drives risk attitudes in the baseline treatment[31]. It could also follow from the HL design which has been shown to provide better estimates of probability weighting than estimates of utility curvature (Drichoutis and Lusk, 2016). But in the magnitude treatment, the whole impact of higher stakes is absorbed in the utility curvature only, as the absence of separability shows. On the other hand, the probability graph for losses goes from being linear ($\gamma_0^- = 1$, δ_0^- =1, returns $p = 0.4706$) in the baseline treatment to a concave graph under higher stakes which also illustrates probabilistic risk aversion[32]. One could claim that this contradicts the reflection effect hypothesis in principle, but the reflection effect says nothing about equality of the probability parameters, either. Moreover, it seems likely that the existence of separability for losses diverts some of the higher stakes impact away from utility, contributing to the weakening of the reflection effect hypothesis. To summarize, we observe different reactions of probability parameters in each domain under higher stakes which exposes more potential asymmetries between gains and losses, beyond the weakening of the reflection effect. This probabilistic asymmetry seems to contradict most of the literature (Fehr-Duda et al., 2010; Vieider, 2012), albeit the research question and the methodological approaches are not the same as ours. However, Abdellaoui (2000) does find that reflection effect is not conveyed to probability weighting but under a two-step experimental design while Pachur and Kellen (2013) find such a probabilistic asymmetry but conditional on the presence of loss aversion. From another point of view, it is in accord with findings about how the human brain responds to the framing of outcomes (Gehring and Willoughby, 2002; Gonzalez et al., 2005) and the interpretation of losses as a threat that could lead to probabilistic risk aversion (Lejarraga et al., 2012).

At this point we comment further on the prominence of the elevation parameter δin probability weighting. We suspect that the primary explanation for this result lies with the psychological interpretation attributed to the two probability parameters: γ refers to how people discriminate among different probabilities whereas δ refers to how probability is over/under-weighted (see Gonzalez and Wu (1999) for a discussion). Because the participants are literate students, they can easily understand the small, and constant, probability variations (of 0.1), and this in turn can lead to near-linear curvature ($\gamma \approx 1$). Thus, it is the elevation parameter δ that in essence defines probabilistic behavior through over/under-weighting of probabilities. Note that despite the rather scarce empirical studies on losses, the critical role of elevation in probability weighting has been mentioned before (Abdellaoui, 2000) and it has also been directly related to the presence of larger outcomes (Etchart-Vincent, 2004).The importance of elevation is also probably related to the HL design itself, since it varies probabilities but keeps the monetary outcomes unchanged (Drichoutis and Lusk, 2016). Hence, the employment of a two-parameter Prelec weighting function, which clearly separates curvature from elevation, could paint a better, more complete picture for probability weighting. Ultimately, this is a finding that highlights the complicated nature of probability weighting and could bring into question the employment of a single parameter weighting function which is typically the default option for the HL design.

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[31] Recall that Fig. 3.1 clearly shows that in the gain domain and for the magnitude treatment, risk averse behavior is dominant since the majority of the participants switch after the fifth question.

[32] Due to the duality between gains and losses, concavity in the loss domain is equated to convexity in the gain domain.

The well-known fourfold pattern of K&T (1992) that produces inverse S-shaped probability weighting functions is not confirmed by our data(this finding re-appears in the time delay treatment we will see later). Violations of the fourfold pattern have been reported before in the literature (Harbaugh et al., 2002) along with the existence of S-shape, concave or convex probability patterns (Balcombe and Fraser, 2015). It is likely that varying degrees of unobserved heterogeneity in each domain are the main culprits for this finding. In addition, and as explained earlier, such probability patterns may be a feature of a two-parameter Prelec weighting function for the HL design.

As for the model selection process, we use the Likelihood Ratio test. This test shows that our data emphatically favours CPT over EUT since the test statistic is very large (394.16). The obvious reason for this is the presence of larger number of parameters in CPT that captures the probabilistic behavior of the participants as reflected in the HL design. Therefore, the richer conclusions drawn from CPT ought to be taken into account since it is the CPT model that describes best the data.

3.4.5 EUT under time delay

For time delay treatment and the EUT model first, there is very limited impact on utility since the coefficients are both very small and statistically insignificant (see Table 3.5). These utility treatment effects are very close in absolute value, equal to -0.01, and obviously there is no statistical difference between them given that the test $\alpha_t = \beta_t$ returns p-value equal to 0.973. Hence, no differential domain effects exist for time delay. The reflection effect hypothesis of $\alpha_0 = \beta_0$ is firmly rejected ($p = 0.000$) indicating an uneven relation between the two domains. This unevenness is noticeable via tests for the linearity of the utility where $\alpha_0 = 1$ returns $p = 0.000$ while for $\beta_0 = 1$ it is $p = 0.264$ i.e. utility is linear for losses only. Delaying the lotteries, also invalidates reflection effect given that the p-value for $\alpha_0 + \alpha_t = \beta_0 + \beta_t$ equals 0.0001. Hence, as with the magnitude treatment, we find no evidence of support for reflection effect under EUT. The collapse of the reflection effect is also depicted to the values the utility parameters for each domain can assume: for gains, the utility curvature is always concave whereas for losses it is statistically a linear utility ($\alpha_0 + \alpha_t = 1, p = 0.000$ and $\beta_0 + \beta_t = 1, p = 0.466$). Note that these findings on utility curvature confirm the partial reflection effect hypothesis put forward by Wakker et al. (2007, p. 207), but statistically this is not translated to a confirmation of the curvature equality between gains and losses, as the reflection effect stipulates (K&T, 1979).

Table 3.5 Model parameters for the time delay treatment
(Standard errors in parentheses, 3199 observations)

EUT		CPT					
		Utility parameters		Probability parameters			
α_0	0.852***	α_0	1.061***	γ_0^+	1.213***	δ_0^+	1.781***
	(0.029)		(0.102)		(0.172)		(0.219)
α_t	-0.011	α_t	-0.075	γ_t^+	0.205	δ_t^+	-0.074
	(0.022)		(0.048)		(0.303)		(0.302)
β_0	1.041***	β_0	1.106***	γ_0^-	1.322***	δ_0^-	0.989***
	(0.036)		(0.08)		(0.304)		(0.1)
β_t	- 0.013	β_t	-0.035	γ_t^-	0.165	δ_t^-	0.012
	(0.04)		(0.075)		(0.393)		(0.09)
σ	1.656***	σ	2.695***				
	(0.149)		(0.53)				
N	80	80					
T	60	60					
$logL$	-1093.77	-1046.05					

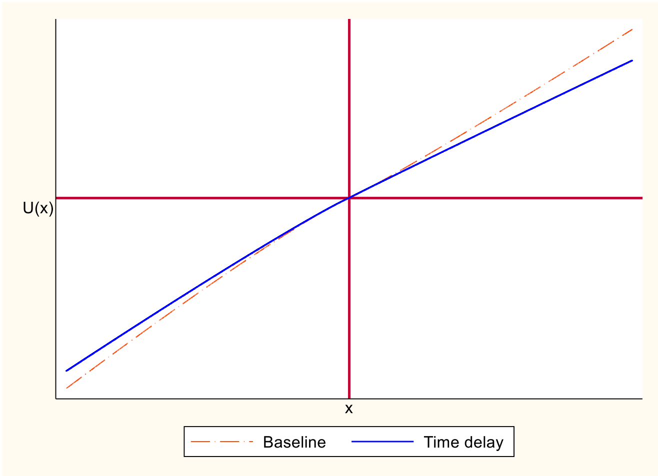
Statistical significance: ***p<0.01, **p<0.05, *p<0.1

3.4.6 Utility in CPT and the reflection effect under time delay

Turning our attention to CPT model now, where as we can see in Table 3.5, the utility treatment effects are both very small numbers and are also statistically insignificant at 1%, a finding that leads to the absence of any differential domain effect ($\alpha_t = \beta_t$, $p = 0.658$). Reflection effect again holds for the baseline treatment comfortably ($\alpha_0 = \beta_0, p = 0.594$) and remains unaffected when the lotteries are delayed ($\alpha_0 + \alpha_t = \beta_0 + \beta_t$, $p = 0.208$). Moreover, utility curvature is linear for either domain ($\alpha_0 = 1, p =0.55$ and $\beta_0 = 1, p = 0.183$) even after the implementation of the time delay treatment ($\alpha_0 + \alpha_t = 1, p = 0.871$ and $\beta_0 + \beta_t = 1, p = 0.383$). Hence, a first conclusion is that after accounting for probability weighting, reflection effect becomes a solid feature of a CPT model with delayed lotteries (see Fig. 3.4a).

Note that this comes contrary to our findings on higher stakes where reflection effect hypothesis weakens and can be rejected. The linear utility specification is also present under time delay, confirming again the partial reflection effect hypothesis in the loss domain (Wakker et al., 2007) as well as the almost linear utility over small values of outcomes (Wakker and Deneffe, 1996). We stress that the linearity of utility is not affected at all by the delayed lotteries, something which is in contrast to magnitude treatment, where the linearity of utility collapses when that treatment is applied. Our results here are in line with Abdellaoui et al. (2011) who find no impact of time delay on utility curvature irrespective of the length of the delay and with Abdellaoui and Kemel (2014) who report larger utility curvature for money than for time but under a quite different experimental approach. Finally, the confirmation of reflection effect in a timedominated framework has also been reported by Leclerc et al. (1995), without utilizing however an explicit equation modeling approach as does this chapter.

Fig. 3.4a Value function graph for CPT (Time delay treatment)



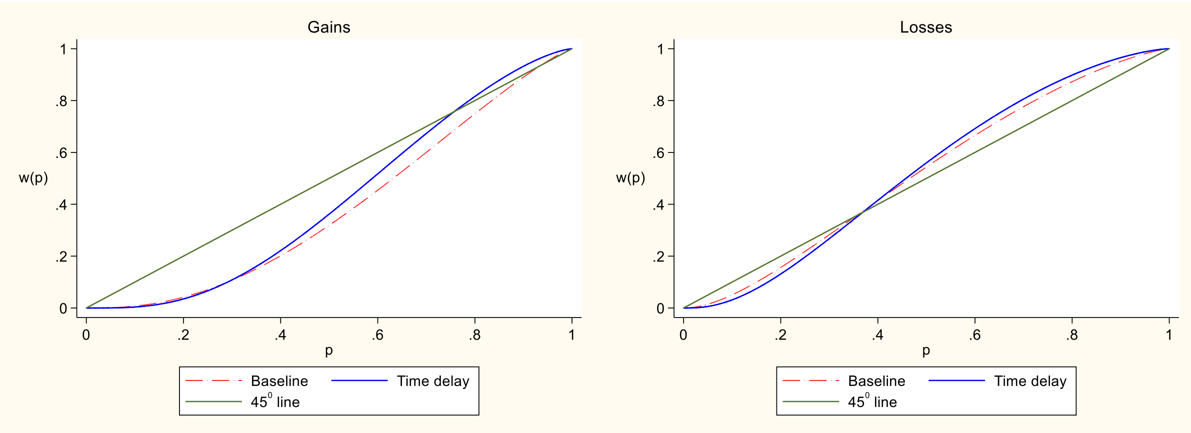
3.4.7 Probability weighting in CPT under time delay

The probability curvature parameter γ is statistically considered linear for the baseline treatment and for both gains and losses ($\gamma_0^- = 1, p = 0.289$ and $\gamma_0^+ = 1,\ p = 0.218$), a result that is of course in line with what reported earlier in Section 3.4.4. The statistical insignificance of the probability curvature treatment effects (γ_t^-, γ_t^+), turns out not to have any meaningful impact on the probability curvatures, since the statistical linearity of the latter is unchanged ($\gamma_0^- + \gamma_t^- = 1, p = 0.123$ and $\gamma_0^+ + \gamma_t^+ = 1, p = 0.114$). We also perform a non-linear test on the existence of a wedge that time delay might put between the two domains: for the test $(\gamma_0^+ + \gamma_t^+)/(\gamma_0^- + \gamma_t^-) = 1$,it is $p = 0.846$. All in all, probability curvature remains statistically linear with no obvious differentiation between the two domains. Recall that this finding for the time delay treatment is in complete accord with that for the magnitude treatment. So, it follows naturally that probability curvature alone does not really affect probabilistic risk behavior in either domain and for either treatment.

As for the elevation parameter δ, its value for losses is linear for the baseline treatment ($\delta_0^- = 1$, $p = 0.912$) and remains such when the time delay treatment kicks in ($\delta_0^- + \delta_t^- = 1, p = 0.994$). On the other hand for gains, the large value of δ_0^+ indicates very clearly a pessimistic behavior, depicted through a convex probability weighting graph and which remains largely unaffected after time delay is implemented (see the left panel of Fig. 3.4b). Note also that there is limited differentiation between the two domains since for the non-linear test $(\delta_0^+ + \delta_t^+)/(\delta_0^- + \delta_t^-) = 1.11$, we get $p = 0.103$. We can infer from the above that it is the elevation parameter that seems to drive a slight wedge between gains and losses, but this wedge is definitely smaller compared to that of the magnitude treatment. In addition, the probabilistic impact of time delay on the loss domain appears to be rather weak.

To draw more accurate conclusions about the probability weighting impact, we have to test if the difference of the weighting curves representing the treatments is statistically significant or not. Using the same bootstrap t-test as in Section 3.4.4, we find that for the gain domain, the test statistic is $z =$ -2.06, a sufficient value so that the 95% confidence intervals not to contain zero i.e. [-0.059, -0.0014], a result that confirms statistically the presence of probability treatment effects for gains. As for losses, the test statistic is $z =$ -0.34, and the resulting confidence intervals [-0.0342, 0.024] indicate no probability treatment effects and no separability (the definition of separability is given in p. 3).

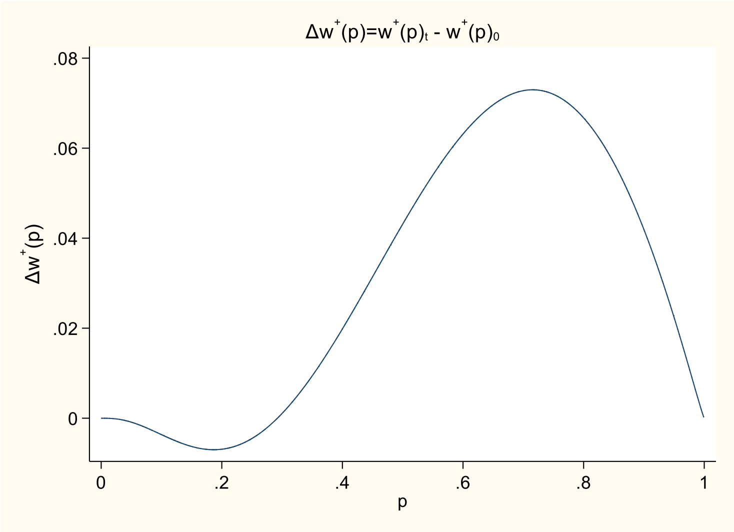
Fig. 3.4b Probability weighting graphs per domain (Time delay treatment)



We now examine more closely the time delay impact on probability weighting. In the left panel of Fig. 3.4b depicting the gain domain, the probability weighting curve for time delay is initially indistinguishable from the curve of the baseline treatment, but after some point it starts lifting up faster. We suspect that behind this uplifting is the elevation parameter since its treatment effect is negative ($\delta_t^+ =$ -0.074), generating a more optimistic behavior, that is, the decision weights for time delay increase, and simultaneously the probability curvature remains linear for either treatments as we have shown earlier. Inevitably, this rise in optimism leads to a higher risk tolerance, with respect to probability only, for lotteries that are payable in the future[33]. In Fig. 3.3c, the difference between the probability curves for the baseline and the time delay treatments ($\Delta w^+(p) = w^+(p)_t$-$w^+(p)_0$) have been plotted for the gain domain. Note that the time delay curve is above the baseline curve after a specific value of probability, around 0.29. This implies that it is the larger probabilities of the HL design that contribute to the rising risk tolerant behavior. This is a finding which is strikingly close to what Abdellaoui et al. (2011) state about "an increase in optimism for probabilities larger than 1/3" (p. 985). In terms of objective probability, represented by the dichotomous line, probabilities are over-weighted towards the end of the scale, after a value of around 0.76.

[33] We emphasize that this finding is due to the comparison between the curves of the two treatments. We ignore the fact that both curves are largely below the dichotomous line, which is how convex weighting usually described.

Fig. 3.4c Difference of probability weighting curves (Time delay treatment)



Observing a rising risk tolerant behavior when lotteries are delayed is a finding that has been reported before in the relevant literature about the interaction between risk and time (Noussair and Wu, 2006; Baucells and Heukamp, 2010; Savadori and Mittone, 2015). Yet, with the notable exception of Abdellaoui et al. (2011), we are unaware of any other work that has reported a similar result by explicitly accounting for the role of probability weighting. The question that arises here is how one can explain that shift in probability weighting. We believe that an affect-based reasoning offers a solid explanatory framework: Rottenstreich and Hsee (2001) proposed that affect-poor outcomes may give rise to a greater insensitivity to probabilities and ultimately in a more linear probabilistic perception (see also Loewenstein et al. (2001)). Given this rationale, we can claim that delayed lotteries could have resulted in a decline of the anticipated affective reactions and thus, to a more risk tolerant behavior. Although this is an appealing hypothesis, if we accept it, we struggle to find a reason why under time delay lotteries are becoming less vivid options. Perhaps an explanation could be the offering of guaranteed post-dated cheques for the payment of the delayed lotteries. It is not unlikely that securing future payments could have led to declining affect for future lotteries because the risk in future payments could have been decreased, or even eliminated. However, this is a standard practice in experiments on intertemporal choice (Andreoni and Sprenger, 2012), which is also unavoidable if we want to refrain from using hypothetical rewards and satisfy salience in economic experiments (Smith, 1982).

As for probability weighting in the loss domain (see right panel, Fig. 3.4b), we stress that these curves are linear in the baseline treatment ($\gamma_0^- = 1, \delta_0^- = 1$ returns $p =$ 0.567) as well as under time delay ($\gamma_0^- + \gamma_t^- = 1, \delta_0^- + \delta_t^- = 1$ returns $p =$ 0.282). Thus, time delay has no effect at all on probability weighting in the loss domain, which coupled with the absence of any effect on utility, reveals a complete insensitivity of risk preferences for losses when the lotteries are delayed. So, this result linked with the increasing risk tolerance in the gain domain, implies a clear asymmetry between gains and losses, which is represented only on probability weighting and not on utility where reflection effect is satisfied. Note that the affect-based reasoning should not be discarded as a hypothesis since Rottenstreich and Hsee (2001) claim that their theory is transferable to losses, too. Nonetheless, the absence of probability treatment effects in the loss domain in our experiment cannot confirm this claim. Still, we are not knowledgeable of any attempt to confirm Rottenstreich and Hsee (2001) in the context of sign-dependent models like CPT. But this affect-based reasoning is a warning against ignoring the role of probability weighting in the elicitation of time-related preferences, as quite often happens in the literature.

Up to this point from our analysis on time delay treatment, two main conclusions follow: first, we can see a distinction between the dimensions of time and money, represented by the time delay and the magnitude treatment respectively, the latter having an impact not only on probability weighting but on utility, too, by invalidating the reflection effect hypothesis: this confirms the different paths of mental accounting between money and time that have been reported in the literature (Leclerc et al., 1995; Soman, 2001) and which are depicted in the lower degree of transferability (fungibility) of time compared to money and the difficulties in properly aggregating time periods and evaluating future decisions (Thaler, 1999). We caution though that we reach this conclusion by capturing the impact of time by both probability weighting and utility, but we have not included a time discount factor.

Second, this probabilistic asymmetry between gains and losses under time delay is a novel finding, which to the best of our knowledge has not been reported before in the literature (recall that the analysis if Abdellaoui et al. (2011) is for gains only). An obvious interpretation is that the rising risk tolerance in the gain domain exists because of the discounting of future lotteries: then, discounting causes a lower present value for future lotteries and thus, participants switch their preferences towards a more risk tolerant behavior. But for losses, the discounting is apparently very small or practically zero due to the absence of probability treatment effects. This asymmetry in discounting hints at the sign effect, a classic finding in the study of intertemporal choice which states that gains are discounted more than losses (Thaler, 1981; Loewenstein and Prelec, 1992; Estle et al., 2006). The existence of practically no discounting for losses may look surprising at first, but it is something that has been reported before (Hardisty et al., 2013) and it is probably related to the apparent aversive behavior shown for delayed lotteries and can lead to an insensitivity in delay discounting for losses (Myerson et al., 2017). In any case, in this chapter we don’t elicit time preferences, so we cannot estimate actual discount rates for gains and losses. Therefore, this discussion is inevitably confined to reporting an asymmetry in risk preferences between gains and losses for delayed lotteries, which is featured in probability weighting only, and not about an actual sign effect.

Finally, regarding the selection of the preferred model, the Likelihood Ratio test again indicates a clear preference for CPT over EUT, since the test statistic is also large (95.44). Thus, again the statistical conclusions for time delay are similar to those from the magnitude treatment and confirm that the more complete CPT model fit better than the simpler EUT model.

3.5 Conclusions

In this chapter we have investigated experimentally risk behavior and how it is affected under two treatments: when higher stakes are offered (magnitude treatment) and when lotteries are offered after a delay (time delay treatment). We find that the reflection effect hypothesis of CPT is dependent on the magnitude of the stakes, since it is present for lower stakes due to the linearity of the utility in either domain, but it can be rejected when higher stakes are utilized, a result in accord with Laury and Holt (2008). This statistical adjustment is due to the strong treatment effects that cause the collapse of the linear utilities making curvatures concave and convex for gains and losses respectively. This hints at the utility-based fourfold pattern of Markowitz (1952), a precursor-model of CPT, which after using the EUT model and controlling for a linear probability perception, it can be largely confirmed (apart from the risk seeking condition for gains in the baseline treatment).

The role of probability weighting turns out to be essential into revealing another level of asymmetry between gains and losses. Higher stakes have no impact on probability weighting function in the gain domain, where probability weighting remains convex marking a probabilistic risk averse behavior; but there is a clear statistically detectable impact for losses transforming the initially linear weighing function to a concave one which also marks a risk averse behavior. In other words, a kind of reflection effect is not confirmed for probabilities, thus the aforementioned utility-based gain-loss asymmetry under higher stakes is transferable to probabilistic behavior, too, a point that has not been emphasized by the literature (Abdellaoui, 2000). We stress that the asymmetry between gains and losses for both the baseline and the magnitude treatment should be ascribed to the elevation parameters only since the curvature parameters are statistically linear in either domain. Elevation has not always been included in probability modelling and is definitely absent from empirical analyses based on the HL design (Drichoutis and Lusk, 2016). The inclusion of two probability parameters has as a side-effect the collapse of the fourfold pattern for the probability weighting function (T&K, 1992). Apart from being a design-related finding, it could hint at the existence of unobserved heterogeneity in our data which would require more elaborate econometric techniques to be tackled. However, the literature has shown that other than inverse-S shape probability patterns should not be ruled out (Balcombe and Fraser, 2015). Note finally, that the importance of probability weighting is also confirmed statistically through the Likelihood Ratio tests that overwhelmingly favour the CPT model over EUT.

Contrary to higher stakes, time delay is found to have no impact on utility curvature. In fact, the treatment effects are so weak that the linearity of the utility parameters in either domain is satisfied and therefore reflection effect holds comfortably. It is probability weighting that comes forth as the carrier of the time delay impact on risk preferences. Two basic conclusions are drawn: in the gain domain, the behavior becomes more risk tolerant, a result that can be better explained by an affect-based reasoning (Rottenstreich and Hsee, 2001) where time delay can lead to less affective reactions for lotteries, and thus, change how people weight probabilities. This probabilistic change is consistent with the switch towards riskier options that have been reported in the literature (e.g. Noussair and Wu (2006)). But for losses, the impact on probability is insignificant, generating a probabilistic asymmetry between the two domains. This asymmetry implies that gains are viewed as less attractive as time passes but this is not happening for losses, a fact that is very much reminiscent of the sign effect in delay discounting (Thaler, 1981; Loewenstein and Prelec, 1992) even though in our experimental design we have not controlled for time discount rates.

Of course, we acknowledge that there are some limitations derived from the experimental design itself as well as from the nature of the lab experiments. Firstly, the popular HL method (2002) uses two pairs of outcomes in each lottery for the utility parameters derivation and this number of outcomes may not be enough to capture all segments of the utility curvature, although by using higher stakes the number of outcomes increases and thus it partly mitigates this deficiency. Regarding the time delay treatment, the deferred cheques we have employed in order to secure the delayed payments could have as a side effect the under-reporting of risk preferences since the participants face no threat in receiving their money. Unfortunately, this is an almost unavoidable obstacle since if we fail to offer a secure future payment implicitly we deceive the participants and hence, we would have violated one of the tenets of the economic experimental protocol, the saliency principle, which requires the decisions of the participants to be directly related to their payoffs (see Plott (1979) and Smith (1982)). Consequently, some caution is necessary before drawing safe conclusions about the impact of time delay on risk preferences.

Another limitation is the non-inclusion of mixed gambles in our experimental design. The inclusion of such gambles would have allowed the identification of loss aversion which complements the reference dependence structure of the gain-loss relationship. K&T (1979) hinted at a possible impact of higher stakes on the loss aversion parameter but it is difficult to have strong prior beliefs about the magnitude of change given the limited attention this question has received in the literature in the context of risky choices. Furthermore, research so far has not clearly identified the exact nature of loss aversion which could range from being an emotional reaction to a judgement mistake (Camerer, 2005). It would also be interesting to see how this affects utility and nonlinear probability weighting and the separability issues which might emerge. This is a question that merits further research.

An interesting direction for future research would be to combine the magnitude and the time delay treatments in a single treatment where larger stakes would be offered in future dates. The adoption of such a treatment could be motivated by the clear indications on the existence of a magnitude effect in the discounting process as well, that is, larger stakes are less heavily discounted than lower stakes (see Frederick et al. (2002) for a survey). This treatment could be put in a wider framework and coupled with the elicitation of time preferences to lead to the investigation of discounted utility-type models beyond the Discounted Expected Utility (DEU) model which empirically has been found to exhibit a number of anomalies (Frederick et al., 2002; Coble and Lusk, 2010). In this way, one can also have a much more comprehensive look at the difference in discounting between gains and losses.

Finally, it may be worthwhile to explore some other decision theory models e.g. Disappointment Aversion, Regret Theory and Weighted Expected Utility. These models could either stand on their own as candidate models beyond EUT and CPT for the interpretation of the data (see Hey and Orme (1994)). It may also be worthwhile to control for unobserved heterogeneity in our analysis by incorporating in a single model EUT and CPT, the latter being components of a finite mixture model (Conte et al., 2011). This last type of models is relatively new in the economics literature although it has a long history in statistics (Newcomb, 1886). It would be interesting to estimate to estimate finite mixture models where the components are not just EUT, CPT or Rank Dependent Utility but other less known decision theory models like those mentioned previously. We are not aware of any such attempt in the literature. Affective measures of utility like Experienced Utility (EU) (Kahneman et al., 1997) are attractive and promising for future research albeit it is difficult to be used in an econometric analysis similar to the one outlined in this chapter. The above constitute some potentially fruitful lines for future research on risk behavior for gains and losses.

Appendix A: Experimental Instructions

Welcome! You are going to participate in an economic experiment. Please put in silent mode or deactivate your mobile phones. Do not show your decision to or discuss your decision with anyone else. All your decisions will be anonymous and ***the data generated will be treated strictly confidentially.***

This is an experiment about the economics of decision making under uncertainty. The experiment is consisted 6 parts. In all parts you will answer questions on choices between different types of lotteries. For each part, you will be given an instructions sheet explaining the decision questions and the payment procedure. Attached you will find the decision questions.

At the end of the experiment each one of you will receive £5 as a participation fee. In addition, two participants will be randomly chosen by picking a number out of a hat and will be given the opportunity to receive rewards up to £46.2, based on their answers in a randomly selected decision question. All rewards are in cash.

It is possible that some questions could result in receiving late rewards offered after a specific time delay. In case you are entitled to a future reward, a payment certificate will be given to you so that to ensure that you will properly receive all the money. Be sure to bring that certificate in order to receive the money. Note that this is a fully funded experiment and the future payment will be guaranteed by Prof. Iain Fraser.

For statistical needs, please answer all the questions. There are no correct or wrong answers. Which lotteries you prefer is a matter of personal taste. Please work in silence and make your choices by thinking carefully about all decision questions.

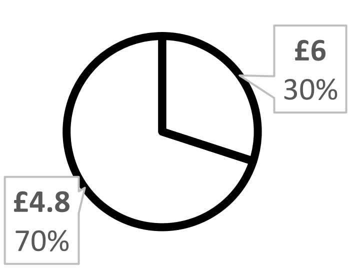
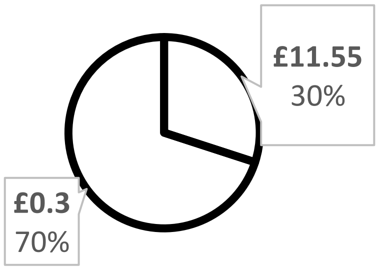
Sample questions:

You will face a series of choices between two different lotteries, Lottery Left and Lottery Right. Each lottery is comprised of two different rewards being offered at varying chances of winning.

The lotteries are presented in the form of pie charts (see below). The monetary rewards are presented as regions of the pie chart and the size of each region is proportional to the probability of the reward. Next to each region you will see labels which specify the exact reward and its associated probability. Both lotteries always contain the same rewards, £6 and £4.8 for Lottery left and £11.55 and £0.3 for Lottery Right. In the example below, Lottery Left consists of £6 at 30% and £4.8 at 70% chance of winning and Lottery Right consists of £0.3 at 70% and £11.55 at 30% chance of winning.

You are asked to indicate which of the two lotteries, Left or Right, you prefer to buy. To indicate your choice, please circle Left or Right in the last column next to the lotteries.

Example:

	Lottery Left	Lottery Right	
0			**Left** **Right**

Payment process:

Assume that the above decision question has been randomly selected for payment at the end of the experiment and you have chosen Lottery Left.

A ten-sided dice will be drawn. If the number turns out to be between 0-2 (0, 1, 2, that is 30%) you receive £6.If the number of the dice turns out to be between 3-9 (3, 4, 5, 6, 7, 8, 9 that is 70%) you receive £4.8 at the end of the experiment.

Any question?

Appendix B: Sample code for EUT model

```
capture program drop CPT_sep_prelec1_noi
program define CPT_sep_prelec1_noi
args lnf alpha beta gamma_plus gamma_minus noise

tempvar prob1l prob2l prob1r prob2r m1 m2 m3 m4 y1left y2left y1right y2right euL euR euDiff
tempvar dw_prob1l_ga  dw_prob1l_lo dw_prob2l_ga  dw_prob2l_lo  dw_prob1r_ga  dw_prob1r_lo
tempvar dw_prob2r_ga   dw_prob2r_lo
tempvar dw_prob1l  dw_prob2l  dw_prob1r  dw_prob2r

quietly {

generate double `prob1l' = $ML_y2
generate double `prob2l' = $ML_y3
generate double `prob1r' = $ML_y4
generate double `prob2r' = $ML_y5

generate double `m1' = $ML_y6
generate double `m2' = $ML_y7
```

```
generate double `m3' = $ML_y8
generate double `m4' = $ML_y9

*Left lottery first
*Gains

generate double `dw_prob1l_ga'=.
generate double `dw_prob2l_ga'=.

replace    `dw_prob2l_ga'= exp(-(-ln($ML_y3))^`gamma_plus')        if `m2'>=0
replace    `dw_prob2l_ga'= 0                                        if $ML_y3==0 & `m2'>=0
replace    `dw_prob1l_ga'= 1- `dw_prob2l_ga'                        if `m2'>=0
*Losses
generate double `dw_prob1l_lo'=.
generate double `dw_prob2l_lo'=.

replace    `dw_prob1l_lo'= exp(-(-ln($ML_y2))^`gamma_minus')        if `m1'<0
replace    `dw_prob1l_lo'= 0                                        if $ML_y2==0 & `m1'<0
replace    `dw_prob2l_lo'= 1- `dw_prob1l_lo'                        if `m1'<0

*Right lottery now
*Gains
generate double `dw_prob1r_ga'=.
generate double `dw_prob2r_ga'=.

replace    `dw_prob2r_ga'= exp(-(-ln($ML_y5))^`gamma_plus')        if `m4'>=0
replace    `dw_prob2r_ga'= 0                                        if $ML_y5==0 & `m4'>=0
replace    `dw_prob1r_ga'= 1- `dw_prob2r_ga'                        if `m4'>=0

*Losses
generate double `dw_prob1r_lo'=.
generate double `dw_prob2r_lo'=.

replace    `dw_prob1r_lo'= exp(-(-ln($ML_y4))^`gamma_minus')        if `m3'<0
replace    `dw_prob1r_lo'= 0                                        if $ML_y4==0 & `m3'<0
replace    `dw_prob2r_lo'= 1- `dw_prob1r_lo'                        if `m3'<0

*Utility evaluation

generate double `y1left' = .
replace `y1left' = ( `m1')^(`alpha') if `m1'>=0
replace `y1left' = -(-`m1')^(`beta') if `m1'<0

generate double `y2left' = .
replace `y2left' = ( `m2')^(`alpha') if `m2'>=0
replace `y2left' = -(-`m2')^(`beta') if `m2'<0

generate double `y1right' = .
replace `y1right' = ( `m3')^(`alpha') if `m3'>=0
replace `y1right' = -(-`m3')^(`beta') if `m3'<0

generate double `y2right' = .
replace `y2right' = ( `m4')^(`alpha') if `m4'>=0
```

```
replace `y2right' = -(-`m4')^(`beta') if `m4'<0

*Generate the final decision weights

generate double `dw_prob1l' =.
generate double `dw_prob2l' =.
generate double `dw_prob1r' =.
generate double `dw_prob2r' =.

replace  `dw_prob1l'=`dw_prob1l_ga'   if sign2==1
replace  `dw_prob1l'=`dw_prob1l_lo'   if sign2==2

replace  `dw_prob2l'=`dw_prob1l_ga'   if sign2==1
replace  `dw_prob2l'=`dw_prob1l_lo'   if sign2==2

replace  `dw_prob1r'=`dw_prob1r_ga'   if sign2==1
replace  `dw_prob1r'=`dw_prob1r_lo'   if sign2==2

replace  `dw_prob2r'=`dw_prob2r_ga'   if sign2==1
replace  `dw_prob2r'=`dw_prob2r_lo'   if sign2==2

*The utility of each lottery

generate double `euL' = (`dw_prob1l'*`y1left')+(`dw_prob2l'*`y2left')
generate double `euR' = (`dw_prob1r'*`y1right')+(`dw_prob2r'*`y2right')

generate double `euDiff' = (`euR' - `euL')/`noise'

replace `lnf' = ln(normal( `euDiff')) if $ML_y1==1
replace `lnf' = ln(normal(-`euDiff')) if $ML_y1==0
}
end

ml model lf CPT_sep_prelec1_noi (alpha: option p1left p2left p1right p2right prize1 prize2 prize3 prize4= )
(beta: ) (gamma_plus: ) (gamma_minus: ) (noise: ), cluster(id) technique(bfgs) maximize

ml display
```

Chapter 4

The impact of higher stakes on loss aversion: An experimental investigation

Abstract

In the controlled environment of the laboratory, we investigate experimentally the effect of stakes size on Cumulative Prospect Theory with a particular focus on loss aversion. We find that loss aversion increases substantially and could be doubled although the starting point for loss aversion implies loss neutral risk behavior. This spike of loss aversion is apparently unaffected by the stakes impact on probability weighting and utility curvature. Moreover, if we control explicitly for this spike in loss aversion, the parameters in the gain domain are affected more than the corresponding parameters in the loss domain. These results reveal the importance of loss aversion and its volatile nature and the Cumulative Prospect Theory mechanisms behind itwhen the stakes size increases.

4.1 Introduction

Risky decision making is an integral part of everyday life. The examples are abundant and include decisions about investment, consumption and saving future plans, buying retirement annuities and household insurance. Such decisions could be options between gains or losses, or mixed combinations of them where both gains and losses are at stake. Prospect Theory (PT) by Kahneman and Tversky (1979) (hereafter K&T (1979)), as well as its successor Cumulative Prospect Theory (CPT) also introduced by Tversky and Kahneman (1992) (hereafter T&K (1992)) utilized such mixed outcomes to establish the concept of loss aversion, that losses loom larger than gains of equal magnitude. Loss aversion has been used to interpret phenomena like the endowment effect, the status quo bias, the sunk cost fallacy and has become one of the main tenets of behavioral economics and modern decision theory. But loss aversion could be affected by a number of factors and given the potentially large variability of outcomes, the effect of higher stakes is apparently one such major factor. The literature has generally shown that when the monetary outcomes at stake are higher, preferences may not necessarily remain the same. However, the literature has not really been expanded to include mixed outcomes, so the effect of higher stakes on loss aversion has not been fully scrutinised. This is the central question of this chapter and will be investigated through a lab experiment.

CPT constituted an important departure from the dominant rational choice model of Expected Utility Theory (EUT). A crucial point was the introduction of a reference dependence feature, in the sense that outcomes can be treated separately as gains or losses depending on being above or below a reference point. This feature implies that derived utility depends on changes of wealth and not on final levels of wealth and it is this feature upon which PT and CPT were built. Furthermore, according to CPT changes in preferences are felt more intensely near the reference point i.e. the difference between £5 and £10 seems larger that the difference between £105 and £110 on either domain. This reflects the principle of diminishing sensitivity, which in turn is closely related to the psychophysics of quantity and leads to the usual S-shape of the value function, the function that evaluates risky outcomes in the CPT jargon. Reference dependence paves the way for loss aversion, the most important feature of CPT (Kahneman, 2003), the notion that the disutility of losses is larger than the utility of equally-sized gains, represented by a kink of the value function at the reference point denoting larger steepness for losses than for gains.

Loss aversion quickly found numerous applications and has been utilized for the explanation of many research questions in many different areas of economics[34]. The well-known value of loss aversion equal to 2.25 as reported by T&K (1992) should not be considered a constant number panacea though. Beauchamp et al. (2012) have shown that the loss aversion value can be dependent on the experimental design and it could assume lower values which signal loss neutral behavior and likewise Plott and Zeiler (2005) stress the importance of framing effects for riskless

[34] Some examples include the optimal pricing strategy decided by a firm (Spiegler, 2012; Heidhues and Kőszegi 2014), consumer and saving behavior (Bowman et al., 1999; Thaler and Benartzi, 2004), a downward-sloping labour supply indicating a negative relation between effort elasticity and loss aversion (Camerer et al., 1997; Goette et al., 2004), the equity premium puzzle interpretation (Benartzi and Thaler, 1995; Haigh and List, 2005), market failure (Baharad and Kliger, 2013) and riskless choices for consumption goods due to the endowment effect (Thaler, 1980; Kahneman et al., 1990).

choices. The economic literature has not really focused on this issue, but the relevant literature, especially the psychology literature, has examined more broadly the nature of loss aversion. Birnbaum and Bahra (2007), Ert and Erev (2013) and Walasek and Stewart (2015) all show through the use of experimental data that loss aversion is volatile and context-dependent. Of course, that variability of loss aversion could be due to differences in loss aversion definitions[35], different elicitation techniques or differences in the subject pools of the participants. However, it could also be related to the difficulty in identifying the "proper" reference point for CPT. It is likely that different reference point specifications would lead to different coding of the outcomes as gains or losses and hence to different loss aversion estimates[36].

The importance of higher stakes and its possible influence on risk preferences have a long history in decision theory. Markowitz (1952) accounted explicitly for stake-dependent preferences for both gains and losses, by observing that for small outcomes people were risk seeking for gains and risk averse for losses whereas for larger outcomes there was a reversal in preferences with people being risk averse in gains and risk seeking in losses. His approach however included only utility parameters with changing convexity types within each domain and that was a feature difficult to track down empirically. Since then, higher stakes have been used in economic experiments in the field and in the lab in order to check the stability of risk preferences (e.g. Binswanger and Silliers 1983; Kachelmeier and Shehata, 1992; Harrison et al., 2007; Drichoutis and Lusk, 2016), focusing mostly on the gain domain, with the usual finding that risk aversion tends to increase when higher outcomes are on offer. But there are only a few studies that have examined the impact of higher stakes on losses (Hogarth and Einhorn, 1990; Etchard-Vincent, 2004; Laury and Holt, 2008; Fehr-Duda et al., 2010) and they also report the risk attitudes can also be affected albeit the overall picture for such effects is not as clear as for gains. K&T (1979) state that a positive relationship between loss aversion and stakes size should be expected for mixed gambles (K&T, 1979, p. 279) but they offer no further elaboration on this claim and they mention nothing about the stakes impact on the other parameters. The literature has not really addressed the impact of higher stakes on loss aversion through mixed gambles. Andersen et al. (2010) report that loss aversion can increase substantially when the endowment on offer increases, too. Vieider (2012), who uses rather moderate stake variations, Andrikogiannopoulou and Papakonstantinou (2017) who use betting industry data also report varying values of loss aversion but they do not estimate explicit treatment effects and they offer no statistical confirmation. On the other hand Booij and van de Kuilen (2009) find practically no loss aversion variation in a population sample but they use hypothetical payoffs and have a rather limited variation in outcome and probability range.

Higher stakes could also allow us to investigate experimentally the impact on probability weighting. It is expected that changes in outcomes would be reflected in an equivalent way only

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[35] Two kinds of definitions of loss aversion exist in the literature, local and global definitions. The former, derived from values of gains and losses close to the reference point, has prevailed in the literature. Unfortunately, the local definition can be conceptually restrictive but it still permits the clear estimation of experimental treatments on model parameters as the higher stakes treatment of this chapter. Global definitions make impossible the separation of loss aversion from utility curvature, therefore are beyond the scope of this chapter.

[36]Reference point has proven to be a difficult issue which was not fully addressed by K&T (1979) and T&K (1992) and the theoretical treatments of it (Kőszegi and Rabin, 2006; 2007) is unclear how to be implemented in an empirical context.

on the utility and not in the probability parameters, which means a separability condition between probability weighting and outcome values, a fact T&K (1992) support empirically (see also Prelec (1998) for a similar argument). We also refer the reader back to the definition of separability given in p. 3. Although recent papers have shown that this assumption could be violated (Fehr-Duda et al., 2010; Bouchouicha and Vieider, 2017),to our knowledge it hasn't been investigated explicitly in the light of loss aversion. Then, the existence of separability could imply a relationship between probability weighting and loss aversion albeit there are no empirical applications to establish this, only papers from a theoretical perspective (Schmidt and Zank, 2008; Zank, 2010). In any case, the employment of higher stakes has proven to be a major challenge to decision theories under risk like EUT and CPT as seminal papers like Rabin (2000) and Fehr-Duda et al. (2010) have shown respectively. This fact along with the apparent instability of loss aversion, is a major motive to investigate the behavior of loss aversion.

To contribute on the literature on CPT and the nature of loss aversion, we conduct a lab experiment where we employ a treatment with much higher stakes by a factor of six. This allows us to examine how risk attitude is affected when stake dependence becomes in essence an additional factor of CPT. This is one of the very first attempts to investigate the impact of higher stakes on a CPT model with mixed gambles in the context of risky choices. We also employ the statistical technique of maximum likelihood for the estimation of the treatment effects on all model parameters. Although there are a few papers that have utilized this technique before, they are constrained to gains and losses. We are unaware of any paper that uses this technique with options in the mixed domain to estimate the impact of higher stakes on loss aversion. Moreover, to our knowledge, this is the only attempt along with Harrison and Swarthout (2016) that uses lotteries with more than two outcomes in all domains (gains, losses, mixed) for a CPT model. The estimation of probability treatment effects allows us to investigate the existence of separability after controlling explicitly for loss aversion, something that has not been attempted before in the literature. Finally, we employ the Dual Theory (DT) model to investigate the same issues as previously mentioned under CPT. This is a model rarely used in the literature (Vieider et al. (2015) and Harrison and Swarthout (2016) are two exceptions) and its main usefulness is that it allows for no confounding between utility and loss aversion since the former is assumed to be linear.

The analysis of our experimental data shows clear treatment effects on loss aversion under various treatment scenarios for both the CPT and the DT models. The results indicate that under higher stakes the loss aversion parameter increases substantially to numbers beyond the usual 2.25 indicating persistently high levels of loss averse behavior. Note though that the starting point for loss aversion when the low stakes are used reveals no evidence of loss averse behavior in our data. Furthermore, if we control for no treatment effects on loss aversion specifically, then the utility estimates for gains change considerably but for losses only slightly, signalling qualitatively different utility effects per domain. The fourfold pattern for the probability weighting functions as predicted by T&K (1992) is confirmed only for gains but not for losses. As for separability, generally it does not arise in our data except for models where we avoid controlling for treatment effects on the loss aversion parameter. Finally, the DT model offers similar results to the CPT model regarding the loss aversion and the probability parameter which is happening because the utility curvature parameters of CPT are very close to being linear.

The chapter is organized as follows: Section 4.2discusses the details of the experimental design, Section 4.3 discusses the decision theory models and the methodological approach. Section 4.4 presents the results and Section 4.5draws some conclusions.

4.2 The Experiment

This section describes the experimental design, the novelties it incorporates, the treatment implementation and the procedures behind the experiment.

4.2.1 The experiment set-up

One hundred and nineteen students (119) from the University of Kent at Canterbury, participated in the experiment. The recruited students (both undergraduate and postgraduate) were primarily members of the School of Economics or the Business School and the rest (about 1/3 of the participants) belonged to various academic departments. All data were collected in October 2017 during a series of experimental sessions lasted less than 1 hour and each student participated in just one session. Before the experimental sessions, all participants had been notified that each of them would receive a £5 participation fee irrespective of their answers and furthermore, they would have the chance to get additional money, up to £60. This would be determined by their answers in the questions during the experiment. Detailed instructions along with examples of the questions and explanations of the payment process were distributed to the participants at first. Afterwards, the paper sheets with the questions were distributed. Full anonymity was ensured throughout the experiment.

When the experimental session was over, the payment took place in private by selecting a binding question in random and based on the participant's answer to that question. The participants themselves determined the payment process by throwing a 12-sided and a 10-sided dices.

4.2.2 The experimental design

The experimental design consisted of a series of binary choices between two options, A and B. Option A consisted of three different outcomes being offered at different probability levels whereas Option B was always a sure thing[37]. The two options were presented as pie charts and the participants could choose one option, A or B. For gains, the outcomes of the options were generated from a range of values between £0 and £10 incremented by 0.5 i.e. (0, 0.5, 1, 1.5,…, 10); similarly for losses, the values' range was (-10, -9.5, -9,…, 0) and for the mixed domain options their range was (-10, -9.5, -9,…, 0, 0.5, 1, 1.5,…, 10). The probabilities of winning these outcomes assumed a range of values from 0 to 1 incremented by 0.05 i.e. (0, 0.05, 0.1, 0.15, 0.2,…, 1). For the generation of the options we imposed interval constraints for the model parameters: the utility parameters based on a power function were between 0.1 and 1.5 for gains and between 0.1 and 2 for losses as well as for the probability weighting function

[37] We decided not to alternate the sure thing between the options, A or B. This was done in order to reduce the cognitive difficulty for the participants and the time required answering the questions. Therefore Option A was always the left option whereas Option B was always the right option (see Table 4.1).

parameters based on a Prelec weighting function; the loss aversion parameter could range between 0.5 and 5. Note that the relative wide range of these interval constraints aimed at uncovering the treatment effects due to higher stakes. The aforementioned process results in a richer and more flexible dataset that allows more precise estimates of participants' preferences compared to other popular experimental designs e.g. Holt and Laury (2002) and Harrison and Rutström (2009).

This experimental design incorporates two major characteristics: first, we exclude pairs of options for which participants offer the same answers which implies certainty about their preferences and thus, we receive no additional information because the determinant of the information matrix is maximized for those options. This is a principle that has been exploited before in the development of optimal experimental designs (Moffatt, 2015). Second, we exclude the pairs of options which if considered in pairs, do not offer additional information than if considered alone. This ensures that no pair of options is redundant and subsequently that different pairs of options can accommodate different perspectives. Again, this is directly related with a basic principle in information theory according to which the entropy (information) of a variable declines when a second variable is observed, so if a pair of options offer no additional information it can be excluded (see Balcombe and Fraser (2017) for more details).

We chose 99 questions from the simulation process to be used in the experiment. To accommodate this large number of questions, we divided them into three different blocks. More precisely, participants faced 12 questions in the gain domain as well as in the loss domain and 9 questions in the mixed domain, altogether 33 observations from each participant. In the mixed domain especially, we were careful to have an approximately equal number of positive and negative outcomes in the right option to avoid any bias to be diffused in the loss aversion estimation. We decided the numbers for gains and losses to be the same in order not to jeopardize the reflection effect hypothesis as well as the utility curvature equality which is necessary for the loss aversion identification (see below). The questions in the mixed domain were slightly fewer due to time constraints and because we expected mixed options to have an impact primarily on loss aversion identification given the definition of which we adopt later. Table 4.1 contains the options used for gains in the first block. All the options for all domains are in Appendix A while the experimental instructions and an example of the questions can be found in Appendix B.

We also employed a treatment, called magnitude treatment where all outcomes for each question and in every domain are scaled up by a factor of six. Therefore, apart from the first set of questions described earlier with outcomes up to £10 (the baseline treatment), we have another set of choices where the only change is the up-scaling of the outcomes up to £60. Thus, the total number of questions per participant was 66, the total number of questions to be used was 198 and this was translated to 7851 observations overall[38]. As a result, we have a within-subject design with choices from participants across both treatments. The combination of these

[38]Note that each of the 119 subjects answered 66 questions. We had to drop three missing values, so instead of 119*66=7854, we had 7851 observations.

two different sets of choices allows us to estimate the impact of higher stakes i.e. the treatment effects on the model parameters[39].

Table 4.1 Gain domain options-First block

x11	x12	x13	p11	p12	p13	x21	x22	x23	p21	p22	p23
1.5	5	10	0.3	0.1	0.6	0	6.5	0	0	1	0
2.5	3	9	0.1	0.55	0.35	0	4.5	0	0	1	0
2.5	5	9.5	0.55	0.2	0.25	0	4	0	0	1	0
0	7.5	10	0.45	0.05	0.5	0	4	0	0	1	0
2	9.5	10	0.45	0.05	0.5	0	6	0	0	1	0
1	0	9.5	0.55	0	0.45	0	3.5	0	0	1	0
1.5	6	10	0.25	0.15	0.6	0	7	0	0	1	0
0	4	9.5	0	0.6	0.4	0	6	0	0	1	0
3	3.5	9	0.4	0.2	0.4	0	5.5	0	0	1	0
0	1.5	8.5	0.05	0.35	0.6	0	5	0	0	1	0
0	0.5	8.5	0.05	0.6	0.35	0	2	0	0	1	0
0	9	9.5	0.65	0.15	0.2	0	3	0	0	1	0

Given the within-subject experimental design we use, there may be some disquiet over the presence of possible order effects since it is not unlikely to believe that the participants' choices would be affected from what they have already learned from the previous questions. To control for this concern, we randomize the order of appearance of all questions in every domain and for both treatments (Charness et al., 2012).

We have chosen to use real monetary incentives so that the salience principle of experimental economics holds (Smith, 1982). Given budget constraints, we decided to pay 20% of the participants in each experimental session. This approach is supported by the comprehensive survey of Charness et al. (2016) who report that paying a subsample of the participants, usually 10% (Harrison et al., 2007; von Gaudecker et al., 2011; Beaud and Willinger, 2015) does not negatively affect the participants' motivation and the validity of the random lottery incentive scheme. For the questions that included negative outcomes, a fixed endowment was used for each question which was given if such a question was chosen for payment at the end of the experiment. This fixed endowment equalled the largest possible loss that could be realised during the experiment and its value could vary between £0 and £60, so the participants would never lose money. This was a necessary step to be taken in order to avoid paying negative outcomes to any of the participants. Note that an endowment that covers losses is the standard procedure of dealing with negative outcomes in economic experiments e.g. Fehr-Duda et al. (2010) and Vieider et al. (2015)[40]. An issue that may arise because of this endowment is that it

[39] The hourly wage rate in UK for 2017 was £5.60 for ages 18 to 20 and £7.05 for ages 21 to 24. Three quarters of the participants in the experiment are up to 24, so they could earn money 10.71 or 8.51 times higher than working elsewhere.

[40]Actually, Etchart-Vincent and l'Haridon (2011) offer an experimental confirmation for this approach since they report no significant difference between payments for losses from an endowment or hypothetical losses.

may be integrated (asset integration) with the negative outcomes and participants may not necessarily understand the losses. Subsequently, this could affect the reference point formulation since participants' choices may not reflect perceptions of changes of wealth and this in turn could lead to a biased estimation of loss aversion, potentially an underestimation of it. We believe this is not happening given the results we report later where loss aversion is emphatically present and there is a clear discrepancy between gains and losses in terms of probability weighting and utility curvature when the equality restriction is omitted.

4.3 Methodology

This section describes the formulation of the CPT and DT models and their subsequent employment in the econometric analysis. Both CPT and DT are treated as sign-dependent models and around the same reference point, considered to be zero.

4.3.1 Model formulations

To proceed with the CPT formulation, we need a specific functional form for the value function which would allow the estimation of the utility curvature parameters. This function, called value function in the jargon of CPT, shows clearly two desirable features of CPT, sign-dependence and reference-dependence. We make use of the most popular functional form in the literature, the piece-wise power function with different specifications for gains and losses:

$$u(x) = \begin{cases} x^{\alpha} & if\ x \geq 0 \\ -\lambda(-x)^{\beta} & if\ x < 0 \end{cases} \qquad (4.1)$$

The exponents $\alpha, \beta (\alpha > 0, \beta > 0)$represent the utility curvature parameters for the gain and loss domain respectively and λ $(\lambda > 0)$ is the loss aversion parameter where $\lambda > 1$ indicates loss aversion. Graphically, the most commonly found pattern is that of the S-shape where the utility shapes for gains and losses are convex and concave segments respectively whereas the loss aversion impact is depicted as a kink at the origin to show that losses matter more than equivalent gains.

We also remain consistent with the literature and we impose the constraint $\alpha = \beta$ in the estimation process of the model parameters. This constraint is almost unavoidable otherwise it is possible to end up with situations where for some x in the domain of the value function to have $\mathrm{u}(x) > -u(-x)$ which obviously contradicts the notion that "losses loom larger than gains" (K&T, 1979, p.279)[41]. Furthermore, if the constraint $\alpha = \beta$ was absent, the utility curvature in the loss domain would be confounded between β and λ and would make it difficult to identify separately and reliably the treatment effects on each parameter[42]. That difficulty

[41] Recall that that in order to have loss aversion, that is, steeper curvature for losses than for gains, for $x, y \in \mathbb{R}^{+}, x > y$ it should $u(-y) - u(-x) > u(x) - u(y)$ and if $y = 0$ then the previous inequality becomes $u(x) < u(-x)$ (see K&T, 1979; p. 279).

[42] Actually, if $\alpha \neq \beta$, then it is always $\alpha < \beta$ and $\lambda \ll 1$and close to zero, an indication of loss seeking behavior which in general contradicts the literature. Obviously this is happening due to the confounding between loss aversion and utility curvature in the loss domain (see also Nilsson et al. (2011) who report similar findings using a Bayesian

stems from the implicit assumption that loss aversion has a local definition based on preferences close to the reference point. Essentially, we adopt the loss aversion definition of T&K (1992) where $\lambda = -u(-1)/u(1)$ and after assuming that the value function $u(\cdot)$ is approximately linear around the reference point (at the closed interval $[-1, 1]$) and differentiable at it, then loss aversion could result in the familiar kink at the reference point[43]. The nature of this definition is an inherent disadvantage regarding the empirical tractability of CPT but it doesn't hinder us in investigating the impact of higher stakes through the combination of different sets of choices of the two treatments. Note that this definition coupled with the constraint $\alpha = \beta$ implies that the identification of loss aversion is based on the mixed outcomes (Wakker, 2010, p.259).

As for the probability weighting function, we employ the probability weighting function introduced by Prelec (1998)

$$w(p) = e^{-(-lnp)^{\gamma}}, 0 < p < 1, \gamma > 0 \qquad (4.2)$$

where p is the probability argument and the parameter γrepresents the curvature, the slope of the probability weighting function. When $\gamma < 1$, the probability graph is the characteristic inverse S-shaped graph (T&K, 1992) whereas when $\gamma > 1$it's an S-shaped graph. Obviously when $\gamma = 1$, it is $w(p) = p$, so the probability graph is a straight line. In our analysis, we estimate the probability weighting function conditional on the sign of the outcomes, so we can write it as follows:

$$w(p) = \begin{cases} w^{+}(p) = e^{-(-lnp)^{\gamma^{+}}} & if\ x \geq 0 \\ w^{-}(p) = e^{-(-lnp)^{\gamma^{-}}} & if\ x < 0 \end{cases} \qquad (4.3)$$

According to CPT, the outcomes of each option are ranked in all three domains, gains, losses and mixed. For gains and losses, it is always $|x_1| < |x_2| < |x_3|$ and thus[44], the utility derived from choosing each option is equal to

$$V = rw(p_1)u(x_1) + rw(p_2)u(x_2) + rw(p_3)u(x_3) \qquad (4.4)$$

where the ranked probability weights are defined as follows

$$rw(p_3) = w(p_3),$$

$$rw(p_2) = w(p_2 + p_3) - w(p_3)$$

$$rw(p_1) = 1 - rw(p_2) - rw(p_3)$$

modelling approach). Note that the necessity of the constraint $\alpha = \beta$ also holds for other CRRA utility functional forms which nest the power function like the expo-power function (Harrison and Swarthout, 2016, p.19).

[43]Note that in their seminal paper on loss aversion, Köbberling and Wakker (2005) formalized an alternative definition for loss aversion as the ratio of the two sided derivatives at the reference point i.e. $\lambda = U'_{-}(0)/U'_{+}(0)$, but the differentiability of such CRRA functions may not be straightforward; nonetheless, if $\alpha = \beta$, this definition can still be meaningful.

[44] For expository purposes, we treat the right option as having three outcomes, x_1, x_2, x_3. Recall that the right option is a sure thing and it is always $x_1 = x_3 = 0$. Of course, the validity of the model formulation still holds.

and $u(x_1), u(x_2), u(x_3)$are the corresponding values respectively that a participant assigns to each of the three outcomes $x_1, x_2, x_3$of each option. As for the mixed domain, the ranking takes place only for the two positive outcomes x_2, x_3, $(x_1 < 0 \leq x_2 < x_3)$ and it is

$$rw^+(p_3) = w^+(p_3), rw^+(p_2) = 1 - w^+(p_3).$$

Then, the cumulative prospective utilities of the negative outcome $x_1$and of the two positive outcomes x_2, x_3 are respectively:

$$V^- = w^-(p_1)u(x_1)$$

$$V^+ = rw^+(p_2)u(x_2) + rw^+(p_3)u(x_3)$$

Adding them up and we have $V = V^- + V^+$, so that equation (4.4) is satisfied.

The other model we employ is the Dual Theory (DT) model, introduced by Yaari (1987). More recently, Schmidt and Zank (2007, 2009) extended this model to incorporate reference-dependence. This DT model retains all the basic features of CPT listed above, reference-dependence, sign-dependence and rank-dependence and the probabilities are still weighted through the Prelec function. The difference with the CPT model is that the value function is piece-wise linear:

$$u(x) = \begin{cases} x & if\ x \geq 0 \\ -\lambda(-x) & if\ x < 0 \end{cases} \qquad (4.5)$$

As previously mentioned, the utility for choosing either option comprised of three outcomes x_1, x_2, x_3, is again given by (4.4)but this time $u(x_1), u(x_2), u(x_3)$are described by the linear value function of equation (4.5), not equation (4.1) as in CPT. A potential advantage of the DT over the CPT model is that the former constrains the treatment effects only on the probability weighting and the loss aversion parameters. In that way we avoid any possible confounding between utility curvature and loss aversion as in CPT and we isolate the treatment effects that could possibly affect utility only on the loss aversion parameter. Furthermore, since DT has fewer parameters than CPT, it allows us to reduce any potential issues of multicollinearity, an almost unavoidable problem especially in computationally intensive models like ours.

As in Chapter 3, we assume a homogeneity of risk attitudes for all participants, i.e. their preferences are described either by CPT or DT in Chapter 4, too. We recognize that this is obviously a restriction which could prohibit us from capturing the full picture of risk attitudes in our sample. There are two possible ways through which we could account for heterogeneity. First, we could adopt a finite mixture model with CPT and DT as components of this mixture model. This is an approach which to our knowledge has not been utilized with models which explicitly incorporate loss aversion. Second, we could have accounted for multiple levels of heterogeneity in the values of all model parameters by using simulation techniques (maximum simulated likelihood) in a way similar to Conte et al. (2011) and von Gaudecker et al. (2011) (see also Moffatt (2015)). This is an interesting approach but it is computationally demanding and does not address the concerns about interaction among utility, probability and loss aversion. This brief discussion about heterogeneity involves some legitimate concerns regarding econometric methodology. However, the above complicate our analysis and therefore are beyond the scope of this chapter.

4.3.2 Econometric modelling

The estimation procedure we follow to estimate the aforementioned model parameters is based on the maximum likelihood technique. Employing a random utility approach (Andersen et al., 2008), we assume that a participant $j \in \{1, ... J\}$, faces a series of questions $i \in \{1, ... I\}$where a binary choice is made between k options where $k \in \{A, B\}$. Then, the utility $U_{ij,k}$ of each participant is

$$U_{ij,k} = V_{ij,k} + \epsilon_{ij,k} \qquad (4.6)$$

where $\epsilon_{ij,k}$ are independent of each other across i, j, k and represent a stochastic specification that is typically assume to follow the standard logistic distribution.

Given the notation we introduced and equation (4.4), the utility of an individual from choosing either option can be written as

$$V_{ij,k} = rw(p_{1ij,k})u(x_{1ij,k}) + rw(p_{2ij,k})u(x_{2ij,k}) + rw(p_{3ij,k})u(x_{3ij,k}) \quad (4.7)$$

Thus, the choice of option A over option B implies that

$$U_{ij,A} > U_{ij,B} \Longrightarrow V_{ij,A} - V_{ij,B} > \epsilon_{ij,B} - \epsilon_{ij,A}$$

and this probability equals

$$\Pr(\mathrm{A}) = \Lambda\left(\frac{V_{ij,A} - V_{ij,B}}{\sigma}\right) (4.8)$$

where $\Lambda(\cdot)$ is the cumulative logistic distribution function i.e. $\Lambda(x) = 1/(1 + e^{-x})$ and σ is its standard deviation[45]. Note that Stott (2006) has shown that the utility power function coupled with Prelec probability weighting function of a single parameter and the logit specification is the combination providing the best explanatory performance for CPT. This is the model specification we use in this chapter.

To estimate the treatment effect of the higher stakes on the model parameters, we use a dummy variable that corresponds to the higher stakes and we condition the utility curvature, the probability weighting and the loss aversion parameters on this dummy variable e.g. $\zeta = \zeta_0 + \zeta_1 * stake$; in this simple regression, the intercept ζ_0 indicates the baseline treatment, ζ_1 indicates the treatment effect and ζ the estimated parameter after the treatment implementation (see Fehr-Duda et al., 2010). For the error term the interpretation has to be conceptually different since the impact of higher stakes in essence represents an upscaling of the initial standard deviation σ which is now equal to $s = \tau * \sigma$ where τ is the scale parameter. In that way, τ represents the increased likelihood in decision making errors for the participants when the magnitude treatment is applied. (see von Gaudecker et al. (2011)).

[45] This standard deviation is considered to be equal to $\pi/\sqrt{3} \cong 1.814$ and practically it represents the decision making errors of the participants.

Therefore, we estimate the vector of parameters $\theta' = (\alpha_l, \beta_l, \lambda_l, \gamma_l^+, \gamma_l^-, \tau)$ where the subscript $l \in \{0, st\}$ denotes the baseline and the magnitude treatment respectively. Note that we will also later report the standard deviation of the baseline treatment (σ) in order to better show the error term volatility. Then, the maximum likelihood function via which the estimation of vector θ of each model (CPT and DT) takes place through a logit specification is:

$$\arg\max_{\theta} \log\mathrm{L} = \sum_{i=1}^{I}\sum_{j=1}^{J}[y_{ij}(\ln(\Pr(A))\,|\theta) + (1 - y_{ij})(\ln(1 - \Pr(A))\,|\theta)] \quad (4.9)$$

where $y_{ij} = 1$ if option A is preferred and $y_{ij} = 0$ if option B is preferred[46].

Note that the standard errors are clustered for each participant. This is happening since it is plausible to assume that a within-correlation for the answers of each participant may exist, and thus, the standard errors are not independent and this correlation has to be corrected through clustering. Finally, when the identification of model parameters is over, we utilize the Likelihood Ratio test to examine which model, CPT or DT, fits the data best. Note that we are going to compare the corresponding DT and CPT models, that is, models where the treatment effects are applied to the same parameters so that the comparison is meaningful. The program for the maximum likelihood estimation has been written in Stata 15. In Appendix C of this chapter a sample code for the CPT model has been included.

4.4 Results

In this section we present the results of the econometric analysis. At first, we examine the behavior of the CPT model in our data and then we switch to the DT model. But before we discuss the results, first we present a brief description of the participants' patterns of choices made. Table 4.2 below shows how the choices made (right and left) are disentangled per domain and per treatment. For the gain and loss domain, there is a switch from the left to the right option (the sure thing), equal to around 6%. For the mixed domain, this switch is larger and it is equal to almost 10%. It is this last switch which is reflected econometrically in a statistically significant increase of loss aversion as we explain in a while.

[46] Of course, the construction of the maximum likelihood is generic and is not affected by the type of models and is the same for both CPT and DT.

Table 4.2 Choices per domain and treatment

	Baseline		Magnitude	
Domain	Right	Left	Right	Left
Gains	46.99%	53.01%	53.08%	46.92%
Losses	60.50%	39.50%	66.88%	33.12%
Mixed	45.47%	54.43%	55.37%	44.63%

4.4.1 CPT models

By employing the CPT model, we investigate the impact of different treatment scenarios on the model parameters, by concentrating on loss aversion and utility curvature initially and subsequently on probability weighting. We summarise the models and the different application of treatments on utility, probability and loss aversion in Table 4.3:

Table 4.3 Treatment effects application

	Models						
Treatments application	[1]	[2]	[3]	[4]	[5]	[6]	[7]
Utility (α_{st}, β_{st})				✓	✓	✓	✓
Probability ($\gamma_{st}^{+}, \gamma_{st}^{-}$)	✓		✓	✓	✓		
Loss aversion (λ_{st})		✓	✓	✓		✓	

4.4.1.1 Loss aversion and utility in CPT

All the results of the CPT models we discuss are presented in Table 4.4. We start with model [1] to determine the impact of higher stakes on the probability parameters only. We first notice that the utility of the model is very close to one and statistically equal to one i.e. $\alpha = \beta = 1$ ($p =$ 0.111) and so it can be comfortably considered to be a straight line. The loss aversion parameter is $\lambda = 1.576$ and can assume values close to 2 since it is $\lambda = 1.9$ ($p = 0.104$). Of course, an issue that arises here is that this value does not necessarily reflect the impact of higher stakes and therefore it could well be biased. Yet, the presence of a loss averse behavior is established comfortably here. This model with this specific treatment implementation is useful in examining probability weighting and separability issues which we discuss later.

Table 4.4 CPT models (Standard errors in parentheses)[47]

	[1]	[2]	[3]	[4]	[5]	[6]	[7]
α_0	1.099***	1.146***	1.15***	1.031***	1.031***	1.025***	1.01***
	(0.062)	(0.066)	(0.067)	(0.049)	(0.049)	(0.05)	(0.046)
α_{st}				0.343**	-0.416***	0.338**	-0.352***
				(0.153)	(0.061)	(0.137)	(0.061)
β_0	1.099***	1.146***	1.15***	1.031***	1.031***	1.025***	1.01***
	(0.062)	(0.066)	(0.067)	(0.049)	(0.049)	(0.05)	(0.046)
β_{st}				0.343**	0.428***	0.338**	0.445***
				(0.153)	(0.089)	(0.137)	(0.091)
γ_0^+	0.896***	0.895***	0.839***	0.899***	0.899***	0.926***	1.048***
	(0.127)	(0.131)	(0.11)	(0.102)	(0.102)	(0.121)	(0.126)
γ_{st}^+	0.087		0.265	0.297	0.375***		
	(0.125)		(0.213)	(0.412)	(0.132)		
γ_0^-	1.643***	1.813***	1.814***	1.794***	1.794***	1.813***	1.729***
	(0.125)	(0.151)	(0.166)	(0.162)	(0.162)	(0.153)	(0.148)
γ_{st}^-	0.558*		0.017	0.06	-0.152		
	(0.319)		(0.184)	(0.19)	(0.167)		
λ_0	1.576***	1.116***	1.103***	1.14***	1.14***	1.137***	1.215***
	(0.199)	(0.122)	(0.118)	(0.119)	(0.119)	(0.118)	(0.132)
λ_{st}		1.487***	1.668***	2.177**	0.039*	1.909**	0.042*
		(0.433)	(0.523)	(1.059)	(0.0192)	(0.769)	(0.021)
τ	7.76***	12.88***	14.58***	82.31	0.368	70.19	0.612
	(1.191)	(3.13)	(3.708)	(84.09)	(0.357)	(62.38)	(0.497)
σ	3.253***	3.257***	3.219***	2.173***	2.173***	2.161***	2.153***
	(0.945)	(0.749)	(0.77)	(0.378)	(0.378)	(0.376)	(0.382)
N	119	119	119	119	119	119	119
T	66	66	66	66	66	66	66
$logL$	-5068.24	-5052.4	-5051.14	-5044.94	-5007.85	-5045.63	-5013.26

Statistical significance: ***p<0.01, **p<0.05, *p<0.1

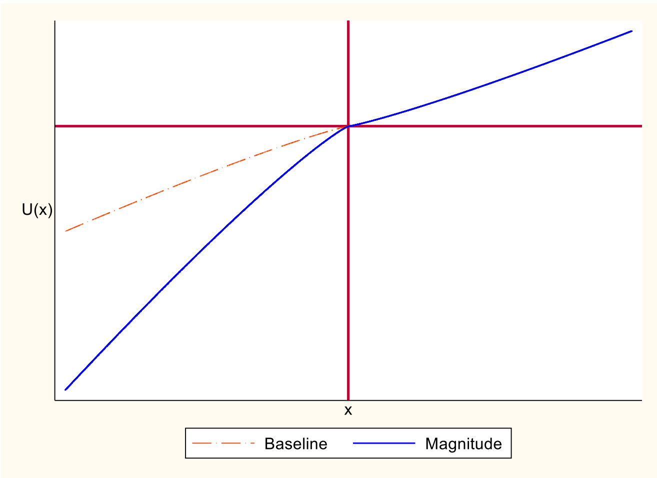
Model [2], where treatment is confined to loss aversion only, offers an isolation of the higher stakes impact on loss aversion and thus, a first tangible estimation of it. The loss aversion for the baseline treatment is $\lambda_0 = 1.115$ and we can safely assume a loss neutral behavior ($\lambda_0 = 1$, $p =$ 0.345). Under higher stakes the treatment effect is $\lambda_{st} = 1.487$, which leads to a substantial increase in loss aversion since $(\lambda_{st}/\lambda_0) = 1.33$; for the total loss aversion under higher stakes, after adding up the baseline coefficient and the treatment effect, we end up with a value equal to $\lambda_0 + \lambda_{st} = 2.6$. However, from a statistical point of view, loss aversion can assume even larger values, above 3 ($\lambda_0 + \lambda_{st}$ =3.35, $p = 0.11$). Thus, after decomposing loss aversion into two values corresponding to the two treatments we have shown that loss neutral behavior can be transformed into a strongly loss averse behavior when higher stakes are in use. Another observation in model [2] is that utility curvature is a bit larger than one, $\alpha = \beta = 1.14$, and this also holds statistically ($\alpha = \beta = 1$, $p = 0.026$). Inevitably the utility findings expose a possible

[47] We had $N = 119$ participants who completed $T = 66$ questions. As mentioned previously, three questions were unanswered and as a result we had 7851 observations, not 7854.

collapse of the S-shape value function. It is unclear the source of the problem here but this issue is re-examined under different treatment combinations later.

In model [3] treatment effects on the probability parameters are added on top of those of loss aversion. The advantage this model is that it may hint at a connection between loss aversion and probability weighting under higher stakes, if it exists, through the comparison with the previous model [2]. Loss aversion at the baseline treatment is minimal with a value at $\lambda_0 = 1.103$ ($\lambda_0 = 1$, $p = 0.384$) which jumps by $\lambda_{st} = 1.668$ ($\lambda_{st}/\lambda_0 = 1.511$) under higher stakes. Ultimately, in the presence of higher stakes loss aversion is elevated at $\lambda_0 + \lambda_{st} = 2.77$, and which statistically can be above 3.5 ($\lambda_0 + \lambda_{st} = 3.65$, $p = 0.11$). The bottom line is that loss aversion again increases substantially with values slightly larger than those of model [2]. The similarity in values between the two models implies a narrow probability impact for loss aversion. The utility curvature parameters at 1.15 are statistically larger than one ($\alpha = \beta = 1, p = 0.025$) and the S-shape value function collapses, albeit marginally, once more. This can be seen in Fig. 4.1a below[48].

Fig. 4.1a Value function graph for CPT (model [3])



We now turn our attention to the pair of models, [4] and [5] where treatment effects are applied to all parameters. First in model [4], where we impose a double linear constraint on the utility parameters for each treatment i.e. $\alpha_0 = \beta_0$, $\alpha_{st} = \beta_{st}$. This double constraint is necessary in order for loss aversion to be properly identified both in the baseline (λ_0) and in the magnitude treatment as well (λ_{st}). The loss aversion for the baseline treatment is the same as that of models [2] and [3] and statistically it is $\lambda_0 = 1$ ($p = 0.239$). Nonetheless, the impact of higher stakes on loss aversion is almost double that of the baseline treatment since according to the delta method it is $(\lambda_{st}/\lambda_0) = 1.91$. This means that the loss aversion in the magnitude treatment is quite large since algebraically it is $\lambda_0 + \lambda_{st} = 3.318$, assuming potentially really large values close to five, i.e. $\lambda_0 + \lambda_{st} = 5$ ($p = 0.126$). This is a striking result that shows that loss aversion

[48] Because the parameters of the CPT models are quite close to each other, for brevity of space we only present the graph for the value function of model [3]. Likewise, for probability weighting, we later present the graphs only for model [3], too.

can be very volatile. There are two caveats here: the first is the variability of the treatment effects since λ_{st}has a large standard error (see Table 4.4). The second is that this apparent spike in loss aversion is partly offset by a rise in the utility for gains since α_{st} = 0.343, on top of a practically linear utility specification for the baseline treatment i.e. $\alpha_0 = \beta_0$ =1 ($p =$ 0.531). This is a puzzling result because conditional on the linearity of probability weighting for gains ($\gamma_0^+ + \gamma_{st}^+$ =1, $p =$ 0.671) it implies risk seeking behavior under higher stakes for gains. On the other hand, the equal treatment effect for losses, β_{st} = 0.343, leads to a concave value function for losses and thus, offsetting the behavior in the gain domain. The large values for the treatment effects on utility seem non-intuitive and probably emerge because of the double linear constraint. Perhaps re-arranging or loosening these constraints could offer another modelling perspective. Note that previously we were able to talk about risk averse behavior in the gain domain simply because there are no treatment effects on probability and thus, utility suffices to describe risk preferences; if probability weighting was not linear, this claim would not have been valid (Chateauneuf and Cohen, 1994).

An obvious question that arises is what would happen if we had explicitly controlled for no treatment effects on loss aversion. This would have isolated the impact of higher stakes on utility and probability alone. In fact, we have tried to disentangle utility curvature from loss aversion, but contrary to model [3], this happens with treatments effects to have been applied on utility; model [5] presents this complementary approach. A single linear constraint only for the baseline treatment is applied i.e. $\alpha_0 = \beta_0$ along with the standard assumption that loss aversion is positive ($\lambda > 0$)[49]. The results for the baseline treatment for all the parameters of model [5] do not change compared to model [4]. Furthermore, there are few changes in the loss domain where the utility treatment effects for losses, (β_{st} =0.428) are statistically significant indicating again a concave value function for losses and they are also quite close in value with those of model [4] where β_{st} =0.343; neither of the probability treatment effects are affected and remain statistically insignificant. Subsequently, only a small increase in utility curvature reflects the changes in risk preferences in the loss domain. On the other hand, in the gain domain there is a clear effect on utility that is negative (α_{st} = -0.416) along with a probability treatment effect (γ_{st}^+ =0.375). However, probability is always perceived linear here since it is $\gamma_0^+ = 1$ ($p =$ 0.326) and $\gamma_0^+ + \gamma_{st}^+ = 1$ ($p =$ 0.124). Thus, risk behavior again is driven primarily by utility and not probability, signalling risk averse behavior.

The general conclusion we derive from all the above, coupled with the results of model [4], is an apparent trade-off between treatment effects of loss aversion (λ_{st}) and the utility for gains (α_{st}). Notably, it illustrates the prominence of loss aversion over utility curvature in the loss domain and the importance of disjointing these two factors in order to properly interpret the empirical findings of CPT. Of course, this conclusion reflects the mechanism behind the estimation of loss aversion as we have explained earlier where it tends to be $\alpha \ll \beta$ and λ to be close to zero. Yet,

[49] We reported previously that if the constraint $\alpha = \beta$ is absent in the power utility function then $\lambda \to 0$. This is also happening here for the loss aversion under the magnitude treatment$(\lambda_0 + \lambda_{st}) \to 0$. So, had we not assumed that $\lambda > 0$ we would end up with very low loss aversion for higher stakes, which given the aforementioned is a nonsensical result and it is not prevalent in the literature. Note that if loss aversion could assume negative values then the utility for losses could be non-negative ($U(-x) > 0$). Obviously, irrespective of the imposition $\lambda > 0$, the estimates of the other model parameters remain unaffected.

it reveals an insensitivity in the utility for losses under higher stakes irrespective of the presence of loss aversion, which in turn implies that loss aversion is the factor that carries the effect of higher stakes in the loss domain. Note that an insensitivity in the value function for losses has been reported before in the literature (Etchart-Vincent, 2004; Fehr-Duda et al., 2010) even though it was about the lack of treatment effects and additionally, loss aversion was not present in the modelling process.

We draw similar conclusions from the other pair of models [6] & [7] even though in this case the probability treatment effects have not been applied. Again for model [6] a double linear constraint is imposed ($\alpha_0 = \beta_0$ and $\alpha_{st} = \beta_{st}$); the utility treatment effects are sufficient enough ($\alpha_{st} = \beta_{st}$ =0.338) to lead a linearly assessed utility for the baseline treatment ($\alpha_0 = \beta_0 = 1$, $p = 0.616$) to a concave value function for losses and convex for gains. As for loss aversion, an initially loss neutral behavior where ($\lambda_0 = 1$, $p = 0.246$) becomes a more definite loss averse behavior where($\lambda_{st}/\lambda_0) = 1.68$, $\lambda_0 + \lambda_{st} =$ 3.05and which ultimately could give rise to large loss aversion values $\lambda_0 + \lambda_{st}$ =4.3 ($p = 0.12$) the variability of which can also be quite large. All in all, these results are in line with model [4].

For model [7] where we only apply the constraint $\alpha_0 = \beta_0$, the effects in utility for losses are significant, quite large in value ($\beta_{st} = 0.445$) but close to that of model [6] (i.e. $\beta_{st} = 0.338$) resulting to a concave value function. For the gain domain, we end up the effect with a negative effect on utility ($\alpha_{st} =$ -0.352) whereas probability weighting has practically no impact since it is $\gamma^+ = 1$ ($p = 0.702$). The bottom line is that a similar kind of inverse relationship between loss aversion and utility for gains arises. So, loss aversion again emerges as the crucial behavior-driven factor in CPT capturing the higher stakes effect; as for the probability factor, it does not appear to be particularly crucial after all.

We have not commented yet on the error parameters of the CPT models. We report the scale parameter τ that shows the rise in error variance under the magnitude treatment. In addition, we also report the error term, σ, for the baseline treatment in order to show the complete picture of the error term variation. The values that σ assumes (up to 3.25) are relatively close to the standard deviation of the logistic distribution. For models [1]-[3] τ can assume relatively large values, signalling that higher stakes might lead to a substantial increase in the error variance. On the other hand, for models [4]-[7], we find via the delta method that τ is always statistically insignificant and equal to one[50]. This implies that conditioning all the CPT parameters on higher stakes (apart perhaps from probability, see models [6], [7]) leads to practically no change in the error variance and thus, no change in the error judgement in the decision making process. This is an important point to consider that demonstrates vividly how stochastic errors could vary when treatments or potentially other explanatory variables are applied. Relatively high error rates as those of models [1] to [3] have long been reported in the literature (Camerer, 1989) and beyond lab experiments (von Gaudecker et al., 2011). Other error term specifications are theoretically possible e.g. the employment of a tremble error or errors that are specific to each individual, but are not examined in this chapter.

[50]These p-values of the hypothesis $\tau = 1$ for models [4] to [7] are 0.333, 0.077, 0.267, 0.436 respectively.

4.4.1.2 Discussion of results

A fundamental conclusion we draw from the empirical analysis of the CPT models is the sharp rise in loss aversion, which can more than double, when treatment effects are applied. This rise is independent of the presence of treatment effects on utility and probability. Such a spike in loss aversion may well mirror a change in preferences which is probably related to the tight budget constraint of most students who participated in the experiment (see Novemsky and Kahneman (2005) for an amplification of this argument). However, it might also convey a more emotionally-related fear for losses which our experimental design cannot capture. Note that in this experiment, we only vary the scale of the magnitude of the rewards while participants are not subject to framing effects. The existence of such effects could force loss aversion not only to its increase but also to its elimination as Beauchamp et al. (2012) have shown. Moreover, this conclusion can be related to the volatility of loss aversion that arises due to changes in the framing context in riskless choices which has been documented in different areas of economics (e.g. Horowitz and McConnell (2002); Sayman and Öncüler (2005); Plott and Zeiler (2005)). In any case, it is important to stress that loss aversion can increase with more than two outcomes in the mixed domain and with probabilities of winning that are not necessarily fifty-fifty. This is a small vindication for K&T (1979) and shows the robustness of their initial insight about the stake-dependence of loss aversion even when more elaborate experimental designs are in place.

Another major finding about loss aversion, which is reproduced in the DT models as well, is the absence of loss aversion in the baseline treatment. This is in agreement with recent papers on structural CPT modelling which report similar numbers well below the almost sacrosanct loss aversion value of around two (Harrison and Rutström, 2009; Nilsson et al., 2011; Zeisberger et al., 2012; Harrison and Swarthout, 2016; Murphy and ten Bricke, 2018). Unfortunately, we don't have a definite answer why this is happening, we can only speculate. One reason could bethat the relatively low money of the baseline treatment, up to £10, simply does not induce loss aversion. Another reason could be the experimental design itself, in the sense that the large number of questions and the existence of options with more than two outcomes fail to capture properly the fundamental insight of loss aversion, the preference differential between gains and losses for mixed options (Rieskamp, 2008). An alternative and perhaps a bit heretical interpretation is that there is nothing wrong with this finding: the parameter estimates of T&K (1992) were median estimates derived from non-linear least squares which may not be comparable to estimates based on maximum likelihood; this is a very difficult problem to solve since it reflects the contrast of different methodological approaches both in terms of design and parameter estimation[51].

We have also found that the usual S-shape of the value function for CPT could be violated when higher stakes are employed. This violation of the S-shape means that diminishing sensitivity (risk aversion in the gain domain and risk seeking in the loss domain) which is one basic tenet of CPT encounters difficulties in replication. In the literature there have been reports of a concave or a linear utility for losses (Fennema and van Assen, 1999; Abdellaoui, 2000; Etchart-Vincent, 2004;

[51] We want to remain agnostic about the true value of loss aversion and we hold no prior beliefs about its existence or not. Therefore throughout this chapter we avoid reporting one-tail t-tests for the hypothesis $\lambda = 1$ and we stick with the conventional two-tailed t-tests.

Wakker et al., 2007); the empirical evidence tends to be more supportive for the concavity of gains literature albeit this has also been challenged (Malul et al., 2013). One explanation for this violation is the imposition of linear constraints for the full identification of loss aversion which leads to computational complexity and makes it easier for a non S-shape value function to follow[52]. This observation highlights the genuine difficulties in fully separating utility and loss aversion and controlling for their interactions even when a local definition of the latter is utilized. There may be one additional reason for the concavity for losses and the convexity for gains: perhaps the participants perceive the outcomes as too large, so that a miscalculation could turn out to be near ruinous for them (this could well be the case since the participants are students). In this case, the usual S-shaped value function is deemed inadequate to describe risk preferences (Kahneman, 2003). Put simply, the elicitation of stake dependent preferences poses a big hurdle for the value function shape of CPT.

4.4.1.3 Probability weighting in CPT

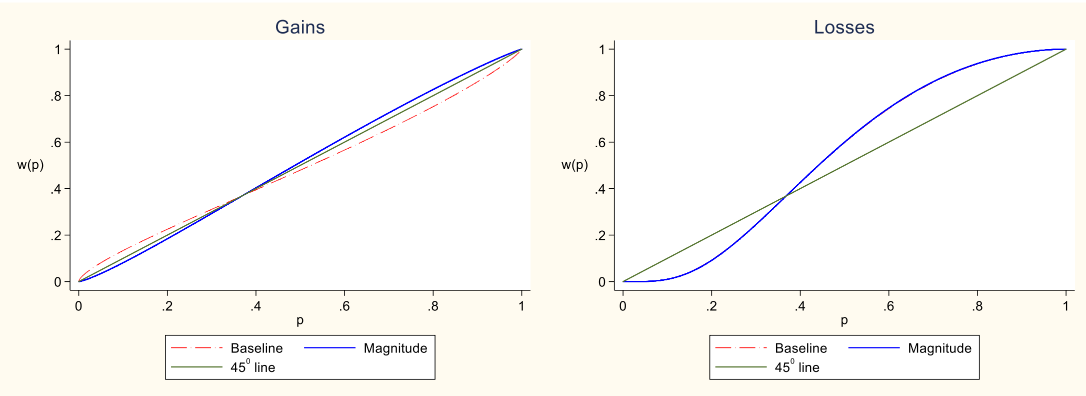
We now turn our attention to probability weighting. For gains and in the baseline treatment, models [1] to [6] have values very close to 0.9. So, the fact that it is $\gamma_0^+ < 1$ confirms the fourfold pattern of T&K (1992), although for model [7] with no treatment effects on probability and loss aversion, the probability curvature is slightly above 1; yet, for all models, statistically it is $\gamma_0^+ = 1$ meaning an approximately linear probability perception in the gain domain that holds even when higher are present (models [1], [3], [4] and [5]) given that statistically it is $\gamma_0^+ + \gamma_{st}^+ = 1$, thus, the usual inverse S-shape dictated by the fourfold is only partly replicated. On the other hand, in the loss domain probability curvature is always larger than one i.e. $\gamma_0^- > 1$ resulting in an S-shape probability pattern, exactly the opposite of what the fourfold pattern assumes. This pattern remains unchanged under higher stakes. An S-shape implies a probabilistic risk seeking for low probability losses and probabilistic risk aversion for high probability losses respectively. In Fig. 4.1b below, we present the probability weighting graphs for model [3].

Although less common, S-shaped patterns for the probability weighting function have been reported before in the literature (Fennema and Wakker, 1997; Harbaugh et al., 2002; Harbaugh et al., 2010). In an extensive modeling exercise, Balcombe and Fraser (2015) even report that non-inverse S-shape weighting functions are more prevalent in their data than inverse S-shape patterns. It's not unthinkable that a considerable degree of heterogeneity exists in our data that could distort conventional probability weighting and ultimately gives rise to other patterns than the usual inverse S-shape (see also Fehr-Duda and Epper (2012)). Furthermore, most experimental designs rely predominantly on large and small probabilities and less on intermediate ones to elicit observations; yet, this practice could inadvertently lead to a better fit of the data through the inverse S-shape pattern, something that may help explain the dominance of this pattern (Stewart et al., 2015). In addition, probability parameters tend to be estimated in the gain and loss domains without considering mixed options where the outcomes are separately evaluated in each domain and then they are added up. Thus, in the context of CPT with more than two outcomes, probability weighting in either domain could possibly interact with loss aversion. Harrison and Swarthout (2016) who have attempted to estimate probability parameters conditional on loss aversion and by using options with three outcomes, also report

[52] Had we omitted the linear constraints, the utility curvature for gains would always be less than one and concave.

non-inverse S-shaped weighting functions for losses. Note that in the original version of PT, K&T (1979) report discontinuity at both ends of the probability scale graph which closely resembles a convex weighing function with a potentially high curvature parameter as in our case. So, the fourfold pattern should not be taken as a panacea for the probability weighting function graphs.

Fig. 4.1b Probability weighting graphs for CPT per domain (model [3])



Regarding the probability treatment effects, they exist only for model [1] in the loss domain where $\gamma_{st}^{-} = 0.558$ as well as for model [5] in the gain domain where γ_{st}^{+} =0.375. This means that separability is present only when loss aversion treatment effects are non-existent (see models [1] and [5]). The definition of separability is given in p. 3. An explanation could be that the presence of treatment effects on loss aversion and utility invalidates separability because apparently the full force of higher stakes is not absorbed by probability weighting alone as in model [1]. This may also be due to our experimental design which is more dense and it does not focus mostly at the two ends of the probability range as happens with the designs of Fehr-Duda et al. (2010) and Bouchouicha and Vieider (2017) who report separability violations. For model [5] in particular, the arisen separability in the gain domain is part of the aforementioned impact on the gain domain parameters when the loss aversion treatment effect has been controlled. Despite its existence, separability is not substantial is not substantial in revealing any important role for probability weighting since the shape of the weighting function remains practically linear for model [5] i.e. $\gamma_0^{+} + \gamma_{st}^{+} = 1$ ($p = 0.124$) while for model [1], the weighing function retains the clear S-shape. Finally, the rather limited presence of separability makes us doubt about any sizeable contribution of the probability factor towards loss aversion, at least under higher stakes and in the manner of Zank (2010), although we cannot offer statistical confirmation because our analysis is not based just on fifty-fifty options in the mixed domain. All these results leave as an open-ended question the existence of an underlying relationship between loss aversion and probability weighting. This question is reconsidered under the DT model.

4.4.2 DT models

Now we turn our attention to the DT model. As with CPT, we first examine loss aversion and then shift to probability weighting. Since there are no utility parameters under DT, we have only three models to estimate. The parameter estimates for the DT models are shown in Table 4.5 below.

Note that comparison is made with the corresponding models of CPT where the treatment applications are similar: these are the pairs of models [1]-[8], [2]-[9] and [3]-[10]. In model [8], where treatment effects are applied only to probability, loss aversion has a value 1.507, pretty close to that of 1.576 of model [1]. This implies that the role of the utility curvature may be rather limited in affecting loss aversion. The absence of treatment effects on loss aversion does not allow us to estimate the exact impact of higher stakes making the 1.507 loss aversion value uninformative since it's a confound between the two treatments.

In model [9] now, treatment effects are applied only on loss aversion. Initially loss aversion is equal to 1.128 ($\lambda_0 = 1$, $p = 0.495$) but after considering the higher stakes it jumps by an almost equal value, that is, $\lambda_{st} = 1.199$ and $(\lambda_{st}/\lambda_0) = 1.062$. In turn, higher stakes give rise to a loss aversion parameter equal to $\lambda_0 + \lambda_{st} = 2.328$ which statistically can be larger and close to 3 ($\lambda_0 + \lambda_{st} = 2.84$, $p = 0.101$). These results are again very close to these of model [2] (see Table 4.4). The crucial difference with the CPT model is that utility is deemed linear here and the value function is just a dichotomous straight line. Hence, the fact that loss aversion remains qualitatively unaffected by the employment of the DT model means that the violation of the S-shape value function in model [2] is not a major source of concern.

Table 4.5 DT models (Standard errors in parentheses)[53]

	[8]	[9]	[10]
γ_0^+	0.938***	0.974***	0.918***
	(0.106)	(0.107)	(0.089)
γ_{st}^+	0.119		0.228
	(0.116)		(0.172)
γ_0^-	1.66***	1.862***	1.802***
	(0.118)	(0.151)	(0.158)
γ_{st}^-	0.693**		0.138
	(0.32)		(0.189)
λ_0	1.507***	1.128***	1.144***
	(0.152)	(0.121)	(0.121)
λ_{st}		1.199***	1.267***
		(0.292)	(0.341)
τ	7.078***	8.99***	10.344***
	(1.058)	(1.253)	(1.783)
σ	2.22***	2.037***	1.97***
	(0.29)	(0.22)	(0.199)
N	119	119	119
T	66	66	66
$logL$	-5072.69	-5061.55	-5060.25

Statistical significance: ***p<0.01, **p<0.05*p<0.10

In model [10] the picture is very similar to that of model [9] in spite of the application of treatment effects on the probability parameters as well: the loss aversion for the baseline

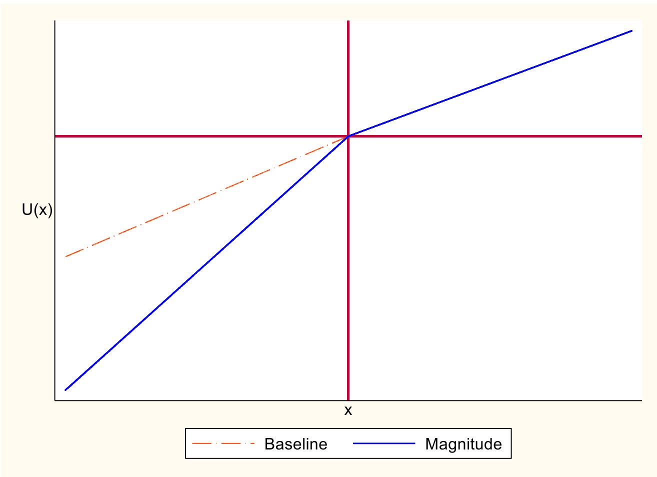
[53] The number of participants $N = 119$ and the number of tasks (T =66) remain the same for the DT model.

treatment is 1.144 ($\lambda_0 = 1$, $p = 0.234$) discloses loss neutrality converted to a loss averse behavior after higher stakes kick in, since $\lambda_{st} = 1.267$ and $(\lambda_{st}/\lambda_0) = 1.107$. This is translated to a total loss aversion value of $\lambda_0 + \lambda_{st} = 2.411$ and a statistical upper limit equal to 3 ($\lambda_0 + \lambda_{st} = 3$, $p = 0.101$). The closeness with model [9] reveals once again that the impact of probability treatments is minimal. Furthermore, the loss aversion results appear to be a bit smaller than in the corresponding CPT model, [3]. It's likely that this is a computational issue attributed to the existence of a constraint for CPT coupled with the larger number of parameters present.

All in all, the results of DT models so far show that loss aversion does not really change compared to the corresponding CPT models. This is a considerable advantage of DT given its simpler value function form. This chapter confirms previous findings that it is not inconceivable to expect a linearity or near linearity of utility to emerge for relatively small stakes (Wakker, 2010; Åstebro et al., 2015), validating thus, the employment of a DT model. Besides, the employment of the DT model removes any concerns about violations of the S-shape of the value function which appears as a side-effect in attempting to estimate treatment effects on loss aversion. Fig. 4.2a below shows the value function for model [10] which has the same treatment effects implementations as model [3] in CPT whose graphs were reported earlier.

As with the CPT models, higher stakes cause a considerable increase in the variance of the stochastic error in all three models. Note that the values of τ are close with the τ values for the corresponding CPT models, [1], [2], [3]. Furthermore, the error term for the baseline treatment, σ, is very close to the standard deviation of the logistic distribution. However, the fewer parameters in DT mean that the levels of noise cannot be alleviated and the error is always high under higher stakes. So, in terms of data fitting this could prove to be a small advantage for CPT, as reflected in models [4]-[7], despite the similar values that DT returns for loss aversion and probability weighting. We attempt later to offer a formal model comparison perspective through the Likelihood Ratio test.

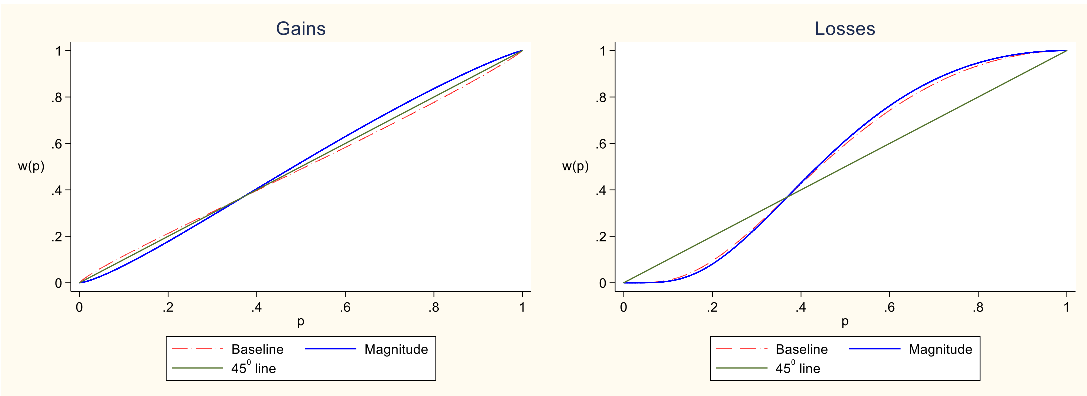
Fig. 4.2a Value function graph for DT (model [10])



From Table 4.5, we can see that in the gain domain, the probability parameters of all the DT models for the baseline treatment are less than one in value, so the fourfold pattern is satisfied. The numbers are only slightly larger compared to those for the CPT model. This picture is not altered when we consider the treatment effects where for both models [8] and [10], it is $\gamma_0^+ + \gamma_{st}^+ = 1$, so the linearity of the probability is not affected, but the fourfold pattern, at least in principle, is not satisfied. In the loss domain, the probability parameters are also very close to those for the CPT models and since it is always $\gamma_0^- > 1$, the probability weighting function graph is an S-shape exactly as under CPT, so again the fourfold pattern is violated. The above point to an unaffected role for probability as in CPT despite the omission of utility curvature. Fig. 4.2b below shows the probability weighting graphs for models [10].

As for separability under DT, it arises only for model [8] in the loss domain where γ_{st}^- =0.693 ($p = 0.03$). Recall that the definition of separability is given in p. 3. This means that the results for DT are close and in accordance with the results for the corresponding CPT model, that is, separability exists only when the effect of higher stakes on loss aversion is controlled. Again, the S-shape of the weighting function in the loss domain remains unaffected under higher stakes. So, the general conclusion we can draw from both CPT and DT is that separability only arises under very specific circumstances, particularly when loss aversion treatment effects are absent. Thus, one should be cautious in emphasizing the existence of separability and the importance of probability weighting under higher stakes[54].

Fig. 4.2b Probability weighting graphs for DT per domain (model [10])



4.4.3 Models comparison

Finally, we can also use the Likelihood Ratio test (1989) to see which of the two models, the CPT or the DT best describes our data. We do not compare models where treatment effects are applied differently because such models obviously examine the impact of higher stakes under different perspectives. So, we test for three different models pairs of CPT and DT: [1]-[8], [2]-[9] and [3]-[10]. For the models pair [1]-[8], the Likelihood Ratio test is 8.9, much larger than the

[54]Note that the divergence of the probability parameters for gains and losses in the baseline treatment for both CPT and DT could imply a connection between loss aversion and probability. Yet, this is a question beyond the scope of this chapter.

critical value $X^2_{(4)0.95} = 0.711$ (or even $X^2_{(8)0.95} = 2.733$ if we take into account the presence of treatment effects in increasing the degrees of freedom), and reveals a preference for CPT over EUT. Likewise, for the models pair [2]-[9], the Likelihood Ratio test returns 18.3 and for the models pair [3]-[10] it returns 18.22. Thus, for all pairs of models the CPT model is comfortably preferred over the DT model in offering a better data fit despite the latter returning similar results for loss aversion and probability weighting.

4.5 Conclusions

In this chapter we have studied the effect of substantially higher payoffs on CPT, the most comprehensive decision theory for modelling human behavior. We have adopted an experimental approach where we have not taken any of the basic stipulations of CPT for granted, on the contrary all of them were tested. Our empirical analysis has concentrated on loss aversion. The main result of this study is the sizeable rise of loss aversion under higher stakes, a result independent of the treatment applications on other parameters. Although the exact magnitude of this rise can vary, potentially greater than three, and can be conditional on the treatments imposed, this is nonetheless evidence that loss aversion is a complex concept such that a single number around two is simply inadequate to represent it. The establishment of this result, unreported before for risky choices, strengthens the hypothesis of K&T (1979) about the loss aversion and the connection with stakes since it has taken place in the context of CPT and with options that are not simply fifty-fifty. We believe that our finding is not unrelated to the experimental evidence on loss aversion instability in riskless choices where valuations are context dependent (Kahneman et al., 1999). As such, loss aversion, and the whole of CPT in general, should be subject to more intense experimental investigation to further quantify loss aversion.

A second conclusion about loss aversion is the non-existence of it in the baseline treatment with low stakes, up to £10. Obviously this is not in accord with the famous phrase "losses loom larger than gains", but it is not an uncommon finding when more advanced computational models of CPT have been deployed more extensively (see Harrison and Swarthout (2016) for a review). We can only surmise why this result occurs. In principle it could be that the money offered in that treatment were considered low or that the questions in the mixed domain were not the simple fifty-fifty options or even that the participants were integrating losses with the endowment so that losses are not felt severely by the participants. This is a difficult point that ought to be picked by researchers in the future.

We also report an apparently inverse relationship between the treatment effects for loss aversion and the utility for gains by manipulating the constraints we impose. This result, identifies the role of loss aversion as a crucial factor in the mechanics of CPT, when experimental treatments are implemented. It further highlights the hidden dangers in utilizing global definitions of loss aversion where the confounding between utility and loss aversion is unavoidable (Abdellaoui et al., 2007). A potentially peripheral finding is the non S-shape value function, although it is very marginal, when treatment effects are applied on loss aversion. The most troubling aspect of this is the resulting convexity of gains and less the concavity for losses.

This reflects largely computational issues regarding the interactions between loss aversion and utility and the presence of linear constraints. But it also hints at a local loss aversion definition may be insufficient in order to estimate accurate treatment effects. In this case, DT is a useful alternative modelling option that overcomes some of these problems.

The evidence for the existence of separability is rather limited and in particularly they reveal that separability is present conditional on the absence of treatment effects on loss aversion. We are unsure if this is a side-effect of the computations behind the maximum likelihood estimation or if indeed it reveals any closer than hitherto thought connection between loss aversion and probability weighting. We do not allow ourselves to rush into conclusions and we strongly believe that this is a question that merits further research. Another interesting finding that has emerged is the S-shape of the probability weighting function for the loss domain. We suspect that this is happening due to the presence of loss aversion, hidden heterogeneity in the data or even due to the employment of up to three outcomes and not the usual two outcomes for an option. Acknowledging the lack of empirical studies on structural CPT models, we believe that the probability weighting patterns ought to be further examined conditional on the presence of loss aversion. Perhaps this shape of the weighting function is an additional empirical finding that challenges specific regularities of CPT (Harrison and Ross, 2017).

Note finally that the DT model offers a high degree of parsimony since it’s a simpler model than CPT. This can proven to be a very useful feature especially outside the lab: when a plethora of individual characteristics are elicited, then a potentially very large number of parameters would need to be identified. DT as a simpler model could possibly increase the computational easiness without sacrificing the estimation accuracy. This could stand as an opportunity in the decision theory literature to reconsider this often overlooked model.

It remains an open question how one ought to handle the reference dependence feature of CPT. The previously mentioned theoretical developments on the reference point formulation are not easy to be translated into an empirical model specification and as a result, the questions about the existence of a degree of asset integration are not easily answerable. Thus, this remains a moot point in the literature. Nonetheless, the implementation of appropriate implemented treatments in an experimental design which could test for a possible shift in reference point when higher stakes are utilized seems to be feasible in the same spirit as the techniques of this chapter. But still, even if such a shift is observable, the mechanism behind the development of reference points seems to be a black box.

Another undecided matter is the complicated nature of loss aversion. Camerer (2005) claimed that loss aversion may not only be a preference manifestation but also an emotional reaction or even a judgment mistake. The role of emotions and feelings in particular is a factor that merits further investigation implying a hedonic-related experience which could better reveal loss aversion and its variability mechanisms. The literature offers answers which are largely context-dependent and show that loss aversion is present as long as gains and losses are expressed in the same context (McGraw et al., 2010), it may be present only under higher stakes after employing experienced utility based techniques (Carter and McBride, 2013) as well as when feelings are extrapolated on decision choices (Charpentier et al., 2016) or it may not exist at all if gains and losses are measured under attention-based models (Yechiam and Hochman, 2013).

In any case, matching the loss aversion parameter from detailed-descriptive choice questions to the derived feelings from these choices, or the reverse process of it, and all these in the light of treatment effects, it's a challenging experimental attempt and furthermore, it's a difficult question to be tackled econometrically since we are unaware of an approach that accounts for emotional reactions and has been put in the context of a structural model requiring simultaneous parameter estimation.

It would also be interesting to investigate how higher stakes may interact with other explanatory variables (e.g. age, gender, educational level, income, cultural characteristics etc.) and impact loss aversion and the other CPT parameters in the context of a field experiment. In that way we could account for observed heterogeneity which has been absent in our analysis since the sample of the students is quite homogeneous. Besides, it may be also interesting to try to model loss aversion at the individual level, too, since aggregation could mask different individual-based trends for the model parameters. This is a promising approach but it also raises issues of computational complexity and is likely to require the employment of powerful algorithms (hierarchical bayesian modelling) in order to be fruitful. These are definitely challenging computational tasks. All the aforementioned constitute some challenges researchers could embark on in the future.

Appendix A: The questions

Table 4.6 Gain domain options-Second block

x11	x12	x13	p11	p12	p13	x21	x22	x23	p21	p22	p23
0	2.5	10	0	0.8	0.2	0	3.5	0	0	1	0
0	1.5	9.5	0.15	0.2	0.65	0	6	0	0	1	0
0	8	9	0.75	0.05	0.2	0	1.5	0	0	1	0
0	1.5	10	0	0.5	0.5	0	5	0	0	1	0
0	8.5	9.5	0.1	0.15	0.75	0	8	0	0	1	0
5	0	10	0.7	0	0.3	0	6.5	0	0	1	0
0	5.5	10	0.1	0.55	0.35	0	6	0	0	1	0
0	5.5	10	0.05	0.5	0.45	0	7	0	0	1	0
0	1.5	10	0.1	0.3	0.6	0	6.5	0	0	1	0
0	3	9	0.3	0.1	0.6	0	5	0	0	1	0
0	1	10	0.25	0.6	0.15	0	1.5	0	0	1	0
0	3	9.5	0.15	0.3	0.55	0	4.5	0	0	1	0

Table 4.7 Gain domain options-Third block

x11	x12	x13	p11	p12	p13	x21	x22	x23	p21	p22	p23
0	0	10	0.6	0	0.4	0	2.5	0	0	1	0
0	1	10	0.2	0.35	0.45	0	3.5	0	0	1	0
0	0	9.5	0.35	0	0.65	0	6	0	0	1	0
0.5	8.5	10	0.1	0.55	0.35	0	8	0	0	1	0
0.5	6.5	9.5	0.6	0.15	0.25	0	2.5	0	0	1	0
0	0.5	10	0.1	0.05	0.85	0	7.5	0	0	1	0
0	0.5	10	0	0.75	0.25	0	2	0	0	1	0
1.5	5	9.5	0.3	0.3	0.4	0	5	0	0	1	0
0.5	0	9.5	0.3	0	0.7	0	5.5	0	0	1	0
0	2.5	9.5	0	0.15	0.85	0	8.5	0	0	1	0
0	5.5	10	0.05	0.5	0.45	0	6.5	0	0	1	0
0	2	9	0.05	0.5	0.45	0	3.5	0	0	1	0

Table 4.8 Loss domain options-First block

x11	x12	x13	p11	p12	p13	x21	x22	x23	p21	p22	p23
-9.5	0	0	0.55	0	0.45	0	-5	0	0	1	0
-10	-1	0	0.5	0.45	0.05	0	-5.5	0	0	1	0
-10	-5.5	0	0.6	0.35	0.05	0	-7.5	0	0	1	0
-9.5	0	0	0.25	0	0.75	0	-2	0	0	1	0
-8.5	-0.5	0	0.2	0.8	0	0	-1.5	0	0	1	0
-9	-3	0	0.35	0.65	0	0	-4.5	0	0	1	0
-8.5	0	0	0.75	0	0.25	0	-6.5	0	0	1	0
-9.5	-5	-1.5	0.3	0.3	0.4	0	-5	0	0	1	0
-10	-4	0	0.35	0.65	0	0	-5.5	0	0	1	0
-9	0	0	0.45	0	0.55	0	-4	0	0	1	0
-8.5	0	-2.5	0.25	0	0.75	0	-3.5	0	0	1	0
-9.5	-1.5	0	0.6	0.05	0.35	0	-6.5	0	0	1	0

Table 4.9 Loss domain options-Second block

x11	x12	x13	p11	p12	p13	x21	x22	x23	p21	p22	p23
-10	-4	0	0.6	0.4	0	0	-7.5	0	0	1	0
-9.5	-6.5	-0.5	0.6	0.15	0.25	0	-7	0	0	1	0
-10	-3.5	0	0.65	0.35	0	0	-8	0	0	1	0
0	-9	-2	0	0.45	0.55	0	-5	0	0	1	0
-10	-7.5	0	0.45	0.05	0.5	0	-4	0	0	1	0
-9.5	-5.5	-2	0.1	0.05	0.85	0	-3	0	0	1	0
-8	-7.5	-0.5	0.65	0.1	0.25	0	-6	0	0	1	0
-9	-7	0	0.45	0.4	0.15	0	-6.5	0	0	1	0
-10	-3.5	0	0.25	0.75	0	0	-4.5	0	0	1	0
-9.5	-5	-1.5	0.3	0.3	0.4	0	-4.5	0	0	1	0
-10	-9	-2.5	0.25	0.3	0.45	0	-6.5	0	0	1	0
-9	-1.5	0	0.4	0.6	0	0	-3.5	0	0	1	0

Table 4.10 Loss domain options-Third block

x11	x12	x13	p11	p12	p13	x21	x22	x23	p21	p22	p23
-9.5	-1.5	0	0.75	0.25	0	0	-7.5	0	0	1	0
-9.5	-2.5	0	0.55	0.45	0	0	-6	0	0	1	0
-9.5	0	-0.5	0.1	0	0.9	0	-1.5	0	0	1	0
-10	-3	0	0.35	0.05	0.6	0	-3	0	0	1	0
-8.5	-3.5	0	0.65	0.05	0.3	0	-6	0	0	1	0
-9.5	-1	0	0.65	0.35	0	0	-7	0	0	1	0
0	-9	-1.5	0	0.35	0.65	0	-4	0	0	1	0
-9	-3.5	0	0.65	0.05	0.3	0	-5.5	0	0	1	0
-9.5	0	0	0.6	0	0.4	0	-4.5	0	0	1	0
-10	-3.5	0	0.65	0.35	0	0	-7.5	0	0	1	0
-9.5	-3.5	0	0.25	0.6	0.15	0	-4.5	0	0	1	0
-10	-1.5	0	0.65	0.35	0	0	-6	0	0	1	0

Table 4.11 Mixed domain options-First block

x11	x12	x13	p11	p12	p13	x21	x22	x23	p21	p22	p23
-10	0	8.5	0.75	0.1	0.15	0	-7	0	0	1	0
-8	2	5.5	0.05	0.5	0.45	0	2.5	0	0	1	0
-0.5	0	5.5	0.25	0.2	0.55	0	2.5	0	0	1	0
-10	0	0	0.65	0.35	0	0	-6.5	0	0	1	0
-7.5	0.5	0	0.35	0.65	0	0	-1.5	0	0	1	0
-9	0	6.5	0.25	0.65	0.1	0	-2.5	0	0	1	0
-4.5	0	10	0.3	0	0.7	0	2	0	0	1	0
-0.5	0	9	0.05	0.4	0.55	0	3	0	0	1	0
-10	0	6.5	0.35	0.6	0.05	0	-1	0	0	1	0

Table 4.12 Mixed domain options-Second block

x11	x12	x13	p11	p12	p13	x21	x22	x23	p21	p22	p23
-8.5	0	8	0.15	0.05	0.8	0	2	0	0	1	0
-9.5	0	9	0.25	0.6	0.15	0	-1	0	0	1	0
-8.5	0	4.5	0.8	0.05	0.15	0	-5.5	0	0	1	0
-10	0	3	0.1	0	0.9	0	1	0	0	1	0
-0.5	0	7.5	0.45	0	0.55	0	1.5	0	0	1	0
-7	0	9	0.05	0.55	0.4	0	2.5	0	0	1	0
-9	0	8.5	0.05	0.8	0.15	0	0	0	0	1	0
-10	0	0	0.15	0	0.85	0	-1.5	0	0	1	0
-9.5	0	4	0.8	0.1	0.1	0	-4.5	0	0	1	0

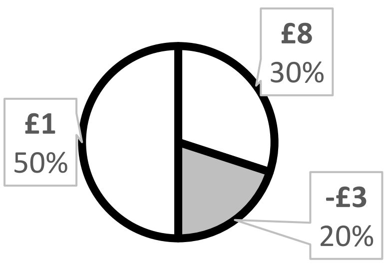
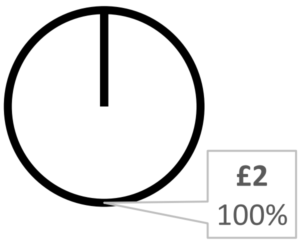
Table 4.13 Mixed domain options-Third block

x11	x12	x13	p11	p12	p13	x21	x22	x23	p21	p22	p23
-9	3	0	0.45	0.55	0	0	-3	0	0	1	0
-7	0	8.5	0.5	0.05	0.45	0	-1.5	0	0	1	0
-7.5	0	9	0.05	0.35	0.6	0	4.5	0	0	1	0
-8	0	8	0.65	0.3	0.05	0	-5	0	0	1	0
-9	0	1	0.6	0	0.4	0	-5.5	0	0	1	0
-1.5	0	9	0.7	0.1	0.2	0	0	0	0	1	0
-9.5	0	7.5	0.5	0.45	0.05	0	-4	0	0	1	0
-8.5	0	8.5	0.05	0.25	0.7	0	2	0	0	1	0
-5	0	9	0.25	0.55	0.2	0	0.5	0	0	1	0

Appendix B: Experimental instructions

Welcome! You are going to participate in an economic experiment on decision making under uncertainty. Please put in silent mode your mobile phones. All your decisions will be anonymous and ***the data generated will be treated strictly confidentially.***

The experiment is consisted of 6 parts and in each part you will be asked to answer a series of questions, where you will have to choose between different two different options. The pair of options consist of a Left and a Right Option. You are asked to indicate which of the two options, Left or Right, you prefer to buy. Below you can see an example of how the questions you will face in a while will look like:

<table>
<tr><td></td><td>Left Option</td><td>Right Option</td><td></td></tr>
<tr><td>0</td><td>
</td><td>
</td><td>Left Right

<u>The endowment is £3</u></td></tr>
</table>

Both options are presented in the form of pie charts. The rewards are presented as separate regions and the size of each region is proportional to the chance of winning of the reward. Next to each region you can see labels which specify the exact reward and its corresponding chance of winning. So, the Left Option consists of the rewards £8 and £1 with 30% and50% chance of winning them respectively and the negative reward (loss) -£3 (grey area) with 20% chance of winning. On the other hand, the Right Option consists of a single and certain reward of £2.

To indicate your choice, you circle either Left or Right in the last column next to the options. *You circle only one option,* either Left or Right.

For most questions you will have a cash endowment (written next to the options). In this example it is £3, so the potential losses would be deducted from the endowment. *This means that you don't pay anything out of your pocket.* The endowment could change from question to question, but it will always be equal to the larger possible loss you may face. Note that the endowment is applicable only to losses, not gains.

The Right Option will always be a single and certain reward but that reward could change from question to question. Note also that losses will always be depicted as grey areas.

Apart from the above mixed Left Option, you will also face questions where the rewards are only gains or only losses, too. When the rewards are only losses, again all potential losses will be deducted from the question-specific endowment. The rewards and the corresponding chance of winning could change from question to question and you will also face questions where the rewards will be much larger, up to £60. Furthermore, you may also face questions where the Left Option has two rewards but not options with more than three rewards.

Payment process:

Assume that the above decision question has been randomly selected for payment at the end of the experiment and you have chosen the Left Option. A random number between 1 and 100 will be drawn by using a 10-sided dice. If the number drawn is between, and including, 1 and 20 (20% chance of winning) you lose £3 out of your endowment, that is your earnings would be £3-£3=£0; if the number is between 21 and 70 (50% chance of winning), you receive £1. Finally, if the number is between 71 and 100 (30% chance of winning), you will receive £8. Of course, if you choose the Right Option, you will receive £2.

The payment process for options with only gains or only losses will be of similar nature.

At the end of the session each one of you will receive £5 as a participation fee. In addition, 1 in 5 of you will be randomly chosen by picking a number out of a hat and will be given the opportunity to receive rewards up to £60, based on their answers in a randomly selected decision question. All rewards are in cash and are in addition to the £5 show-up fee.

For statistical needs, *please answer all the questions*. There are no correct or wrong answers. Just give the answer you consider that most closely describes your preferences.

Any question?

Appendix C: Sample code for the CPT model

```
capture program drop CPT_prelec1_log_rev

program define CPT_prelec1_log_rev

args lnf alpha beta gamma_plus gamma_minus lambda noise

tempvar prob1l prob2l prob3l prob1r prob2r prob3r m1 m2 m3 m4 m5 m6 dw_prob1l_ga  dw_prob2l_ga

tempvar dw_prob3l_ga  dw_prob1r_ga  dw_prob2r_ga  dw_prob3r_ga

tempvar dw_prob1l_lo  dw_prob2l_lo  dw_prob3l_lo  dw_prob1r_lo  dw_prob2r_lo  dw_prob3r_lo

tempvar dw_prob2l_mix dw_prob3l_mix dw_prob2r_mix dw_prob3r_mix we_min_le_mx we_min_ri_mx

tempvar y1left y2left y3left y1right y2right y3right euL euR euDiff

 quietly {

generate double `prob1l'=$ML_y2

generate double `prob2l'=$ML_y3
```

```
generate double `prob3l'=$ML_y4
generate double `prob1r'=$ML_y5
generate double `prob2r'=$ML_y6
generate double `prob3r'=$ML_y7
generate double `m1' = $ML_y8
generate double `m2' = $ML_y9
generate double `m3' = $ML_y10
generate double `m4' = $ML_y11
generate double `m5' = $ML_y12
generate double `m6' = $ML_y13
*Left lottery first
*Gains
generate double `dw_prob1l_ga'=.
generate double `dw_prob2l_ga'=.
generate double `dw_prob3l_ga'=.

replace   `dw_prob3l_ga'=exp(-(-ln(`prob3l'))^ `gamma_plus')                  if  sign2==1
replace   `dw_prob3l_ga'=0                                                    if  `prob3l'==0 & sign2==1
replace   `dw_prob2l_ga'=exp(-(-ln(`prob2l' + `prob3l'))^ `gamma_plus') - `dw_prob3l_ga'     if  sign2==1
replace   `dw_prob2l_ga'=0                                                    if  `prob2l'==0 & `prob3l'==0 & sign2==1
replace   `dw_prob1l_ga'=1 - `dw_prob3l_ga' - `dw_prob2l_ga'                  if  sign2==1
replace   `dw_prob1l_ga'=0                                                    if  `prob1l'==0 & sign2==1
*Left lottery
*Losses
generate double `dw_prob1l_lo'=.
generate double `dw_prob2l_lo'=.
generate double `dw_prob3l_lo'=.

replace   `dw_prob1l_lo'=exp(-(-ln(`prob1l'))^ `gamma_minus')                 if  sign2==2
replace   `dw_prob1l_lo'=0                                                    if `prob1l'==0 & sign2==2
replace   `dw_prob2l_lo'=exp(-(-ln(`prob2l' + `prob1l'))^ `gamma_minus') - `dw_prob1l_lo'    if  sign2==2
replace   `dw_prob2l_lo'=0                                                    if  `prob2l'==0 & `prob1l'==0 & sign2==2
replace   `dw_prob3l_lo'=1 - `dw_prob1l_lo' - `dw_prob2l_lo'                  if  sign2==2
```

```
replace    `dw_prob3l_lo'=0    if `prob3l'==0 & sign2==2
*Right lottery now
*Gains
generate double `dw_prob1r_ga'=.
generate double `dw_prob2r_ga'=.
generate double `dw_prob3r_ga'=.

replace    `dw_prob3r_ga'=exp(-(-ln(`prob3r'))^ `gamma_plus')    if  sign2==1
replace    `dw_prob3r_ga'=0    if `prob3r'==0 & sign2==1
replace    `dw_prob2r_ga'=exp(-(-ln(`prob2r' + `prob3r'))^ `gamma_plus') - `dw_prob3r_ga'    if  sign2==1
replace    `dw_prob2r_ga'=0    if  `prob2r'==0 & `prob3r'==0 & sign2==1
replace    `dw_prob1r_ga'=1 - `dw_prob3r_ga' - `dw_prob2r_ga'    if  sign2==1
replace    `dw_prob1r_ga'=0    if `prob1r'==0 & sign2==1
*Right lottery
*Losses
generate double `dw_prob1r_lo'=.
generate double `dw_prob2r_lo'=.
generate double `dw_prob3r_lo'=.

replace    `dw_prob1r_lo'=exp(-(-ln(`prob1r'))^ `gamma_minus')    if  sign2==2
replace    `dw_prob1r_lo'=0    if  `prob1r'==0 & sign2==2
replace    `dw_prob2r_lo'=exp(-(-ln(`prob2r' + `prob1r'))^ `gamma_minus') - `dw_prob1r_lo'    if  sign2==2
replace    `dw_prob2r_lo'=0    if   `prob2r'==0 & `prob1r'==0 & sign2==2
replace    `dw_prob3r_lo'=1 - `dw_prob1r_lo' - `dw_prob2r_lo'    if  sign2==2
replace    `dw_prob3r_lo'=0    if  `prob3r'==0 & sign2==2
*Mixed gambles now
*Left lottery
generate double  `we_min_le_mx'=.
replace    `we_min_le_mx'= exp(-(-ln(`prob1l'))^ `gamma_minus')    if  sign2==3
replace    `we_min_le_mx'=0    if  `prob1l'==0 & sign2==3

generate double `dw_prob2l_mix'=.
generate double `dw_prob3l_mix'=.
```

```
replace     `dw_prob3l_mix'= exp(-(-ln(`prob3l'))^`gamma_plus')        if  sign2==3
replace     `dw_prob3l_mix'= 0                                         if  `prob3l'==0 & sign2==3
replace     `dw_prob2l_mix'= 1 - `dw_prob3l_mix' - `we_min_le_mx'      if  sign2==3
replace     `dw_prob2l_mix'= 0                                         if  `prob2l'==0 & sign2==3
*Right lottery
generate double  `we_min_ri_mx'=.
replace      `we_min_ri_mx'= exp(-(-ln(`prob1r'))^ `gamma_minus')      if sign2==3
replace      `we_min_ri_mx'= 0                                         if `prob1r'==0 & sign2==3

generate double `dw_prob2r_mix'=.
generate double `dw_prob3r_mix'=.

replace     `dw_prob3r_mix'= exp(-(-ln(`prob3r'))^`gamma_plus')        if  sign2==3
replace     `dw_prob3r_mix'= 0                                         if  `prob3r'==0 & sign2==3
replace     `dw_prob2r_mix'= 1 - `dw_prob3r_mix' - `we_min_ri_mx'      if  sign2==3
replace     `dw_prob2r_mix'= 0                                         if  `prob2r'==0 & sign2==3
*Evaluating the utility function
*Left lottery first
generate double `y1left' = .
replace `y1left' = ( `m1')^(`alpha')          if sign2==1 | (sign2==3 & `m1'>=0)
replace `y1left' = -`lambda'*(-`m1')^(`beta')   if sign2==2 | (sign2==3 & `m1'<0)

generate double `y2left' = .
replace `y2left' = ( `m2')^(`alpha')          if sign2==1 | (sign2==3 & `m2'>=0)
replace `y2left' = -`lambda'*(-`m2')^(`beta')   if sign2==2 | (sign2==3 & `m2'<0)

generate double `y3left' = .
replace `y3left' = ( `m3')^(`alpha')          if sign2==1 | (sign2==3 & `m3'>=0)
replace `y3left' = -`lambda'*(-`m3')^(`beta')   if sign2==2 | (sign2==3 & `m3'<0)

*Right lottery now
generate double `y1right' = .
```

```
replace `y1right' = ( `m4')^(`alpha')          if sign2==1 | (sign2==3 & `m4'>=0)
replace `y1right' = -`lambda'*(-`m4')^(`beta')  if sign2==2 | (sign2==3 & `m4'<0)

generate double `y2right' = .
replace `y2right' = ( `m5')^(`alpha')          if sign2==1 | (sign2==3 & `m5'>=0)
replace `y2right' = -`lambda'*(-`m5')^(`beta')  if sign2==2 | (sign2==3 & `m5'<0)

generate double `y3right' = .
replace `y3right' = ( `m6')^(`alpha')          if sign2==1 | (sign2==3 & `m6'>=0)
replace `y3right' = -`lambda'*(-`m6')^(`beta')  if sign2==2 | (sign2==3 & `m6'<0)
*The utility of each lottery
generate double `euL'=.
replace    `euL'= (`dw_prob1l_ga'*`y1left')+(`dw_prob2l_ga'*`y2left')+(`dw_prob3l_ga'*`y3left')       if sign2==1
replace    `euL'= (`dw_prob1l_lo'*`y1left')+(`dw_prob2l_lo'*`y2left')+(`dw_prob3l_lo'*`y3left')       if sign2==2
replace   `euL'= (`we_min_le_mx'*`y1left')+(`dw_prob2l_mix'*`y2left')+(`dw_prob3l_mix'*`y3left')    if sign2==3

generate double `euR'=.
replace   `euR'= (`dw_prob1r_ga'*`y1right')+(`dw_prob2r_ga'*`y2right')+(`dw_prob3r_ga'*`y3right')   if sign2==1
replace   `euR'= (`dw_prob1r_lo'*`y1right')+(`dw_prob2r_lo'*`y2right')+(`dw_prob3r_lo'*`y3right')   if sign2==2
replace  `euR'= (`we_min_ri_mx'*`y1right')+(`dw_prob2r_mix'*`y2right')+(`dw_prob3r_mix'*`y3right')  if sign2==3
generate double `euDiff' = (`euR' - `euL')/`noise'
replace `lnf' = ln(invlogit( `euDiff')) if $ML_y1==1
replace `lnf' = ln(invlogit(-`euDiff')) if $ML_y1==0
}
end
ml model lf CPT_prelec1_log_rev (alpha: option p1left p2left p3left p1right p2right p3right prize1 prize2 prize3 prize4 prize5 prize6= ) (beta: ) (gamma_plus: ) (gamma_minus: ) (lambda: ) (noise: ), cluster(id) technique(bfgs) maximize
ml display
```

Chapter 5

Conclusions

In this dissertation, we have investigated experimentally in three different lab experiments, the decision making process under risk conditional on the presence of higher stakes and time delay. To obtain a picture of risk preferences which is as complete as possible and to examine their variation when payoffs are higher or delayed, our econometric analysis utilizes the two most well-known decision theory models, EUT and CPT, as well as the lesser known DT model. Our analysis is extended in three chapters and even though it is initially confined in the gain domain only (Chapter 2), then it is expanded to include losses (Chapter 3) and finally mixed options (Chapter 4), the latter necessary for the estimation of loss aversion.

In Chapter 2 we conducted an experiment where we tried to establish if any link between the risk and time parameters exists and in addition to determine how their relationship is affected when payments are delayed. The results show a shift towards rising risk tolerance as time passes. Yet, we have not succeeded in showing a clear relationship between patience and risk preferences because attitudes with respect to time change only marginally. So, our overall conclusions are limited to risk preferences only. Apparently, it seems that our experimental design was not dense enough in terms of the range of time delays, and thus, it failed to capture changes in time attitudes. There is also evidence about a stabilization of preferences for both risk and time dimensions. Construal Level Theory (CLT) offers theoretical foundation that could possibly explain such an outcome (Sagristano et al., 2002), but this is a finding that should also be tested under different experimental designs as well. We have also made use of the Eckel-Grossman (2008) (EG) method, which is a method based on the choice participants make among different options rather than the initial matching process. This method confirms much more emphatically the switch towards a risk tolerant behavior since almost half of the participants report change in risk attitudes after four months. It is likely that these more emphatic results are attributable to the nature of the EG method which returns interval estimates of risk parameters, making thus more discernable the changes in risk preferences.

All in all, in Chapter 2 we have shown that risk attitudes are susceptible to change when time delay is an explicit factor in decision making process. Our failure to show any relationship between patience and risk preferences demonstrates the necessity of using other types of experimental designs, too. The use of iterative bidding processes or Multiple Price Lists like the one advocated by Holt and Laury (2002) for risk elicitation and Coller and Williams (1999) for time elicitation could be useful for such a task. Moreover, multiple time delays are necessary in order to manifest clearly the tendency towards stabilization for risk and time preferences. In any case, the question about the relationship between risk and time has not been fully addressed by the economics literature (Coble and Lusk (2010) is an exception) and we believe that it is an interesting question that merits future research.

Chapter 3 also studied risk behavior under time delay, but in contrast to Chapter 2 we also examined risk behavior for the loss domain as well as the potential impact of higher stakes in both domains. The popular Holt and Laury (2002) (HL) method was employed for the elicitation of risk preferences, which were modelled after Expected Utility Theory (EUT) and Cumulative Prospect Theory (CPT). Under higher stakes and employing the sign-dependent EUT model, we can confirm the validity of Markowitz's (1952) utility-based fourfold pattern, which causes changes in utility curvature. These changes are also present in the CPT model where we found that higher stakes weaken reflection effect leading to the rejection of this hypothesis, implying different behavioural responses per domain in terms of utility curvature. In addition, a second layer of differential responses is found in probability weighting where treatment effects exist only in the loss domain; the outcome is risk averse behaviour for both gains and losses, an outcome that is due to the elevation parameter of the probability weighting functions. When the lotteries were delayed, the validity of the reflection effect was unaffected since the time delay impact on utility is minimal. Treatment effects are detectable only on probability weighting in the gain domain and they show a rise in risk tolerance, in line with the results of Chapter 2 which were obtained under different statistical methodology. In addition, the non-existence of treatment effects in the loss domain reveals an asymmetry between risk preferences for temporal gains and losses. This is in agreement with the sign effect in delay discounting (Loewenstein and Prelec, 1992), but it is centred on temporal risk preferences, not time preferences.

The above results show the inherent difficulties that EUT and CPT face in handling higher stakes and furthermore, they show the importance of probability weighting in the modelling process, both for atemporal and temporal risk preferences as well. Another factor that ought to be taken into account here is the influence of emotions on decision making (Lo et al., 2005; Chapurat et al., 2013). This constitutes an important parameter not considered in this dissertation that is likely to be responsible for the existence of probability treatment effects. More elaborate econometric techniques, like a finite mixture model approach that would allow the combination of both EUT and CPT so that to account for unobserved heterogeneity in risk preferences is a potentially appealing path to follow, even though the HL design may not be appropriate for such a modelling exercise since it has been shown to bias probability weighting and subsequently CPT over EUT (Drichoutis and Lusk, 2016). A potential drawback in the outlined analysis of Chapter 3 is the non-elicitation of time discount rates. Although this is a straightforward process for the gain domain based on the approach by Coller and Williams (1999), we are unaware of any implementation of their approach in the loss domain and under an analytic economic approach as that of Chapter 3. This is an issue that researchers could consider for the future.

In Chapter 4 we adopted an experimental design that accounted for the two main deficiencies of the HL design: first, the few outcomes that might not be enough to capture accurately utility curvature and second, the absence of mixed options containing both gains and losses in order the loss aversion parameter to be properly identifiable. We used options with up to three outcomes and we tested how the CPT model parameters react when higher stakes are employed and especially how loss aversion is affected. The main conclusion that follows from Chapter 4 is the volatility of loss aversion since this parameter assumes larger values, potentially more than double, when higher stakes are utilized. This spike in the value of loss aversion is unrelated to various treatment effects implementations or to the modelling process of loss aversion after CPT or DT. However, for lower stakes we failed to confirm experimentally the presence of loss aversion since this parameter is always considered to equal one and loss neutral behavior follows naturally. After having controlled for no treatment effects on loss aversion, we found slight change on the utility curvature for losses, but much larger for utility in the gain domain. This demonstrates the importance of loss aversion over utility, and on the other hand, it shows that loss aversion along with the utility for gains are the main drivers of the change in preferences under higher stakes. We found weak evidence for the existence of probability treatment effects under higher stakes; nonetheless, they do appear when treatment effects on loss aversion are not implemented. The relationship between probability weighting and loss aversion is a difficult issue that has not been considered empirically and deserves future research (Fehr-Duda and Epper, 2012).Finally, we have found that the DT model is almost equally suitable in describing our data as the CPT model without compromising the accuracy of probability weighting parameters and loss aversion. This could be a useful finding for applied researchers who want to measure risk preferences in the field, where controlling for demographic variables leads to a rise in the dimensionality of the estimated parameters vector and thus, numerical estimation becomes more difficult. Such a situation necessitates the employment of a simpler model like DT.

The above results show that loss aversion is a concept the value of which cannot easily be quantified. The abrupt increase in its value may conceal elements of an emotional shift in the light of higher losses (Camerer, 2005); then, risk preferences alone may be insufficient to justify this increase. This could well imply that tracking the emotional reactions of the participants is necessary in order firm conclusions to be drawn. We are also unsure about how to explain the loss neutral behavior for lower stakes; perhaps, the magnitude of the outcomes has played a role here, but this is a point that could be further examined using multiple ranges of outcomes as experimental treatments. It is also possible that these findings hide heterogeneity at the individual level; this is a difficult issue to handle that in order to be modelled requires advanced econometric techniques and powerful algorithms. Furthermore, loss aversion could be potentially affected by non-experimental factors like culture, religion (Wang et al., 2017). All these are factors not examined in this dissertation but a fresh look on them as loss aversion explanatories could be worthwhile.

This dissertation has studied preferences for decisions under risk and has shown that risk attitudes formed according to popular decision theory models like EUT and CPT, are context dependent when higher stakes are on offer or when the payments are available in future dates. The role of probability weighting and the volatility of loss aversion has been highlighted in Chapters 3 and 4. These are factors that future researchers could have a fresh look upon. Nonetheless, we recognize that our econometric approach in Chapters 3 and 4 has a potential limitation in the fact that it fails to account for the existence of heterogeneity. We have already hinted at Chapters 3 and 4 at two different types of heterogeneity which could be appropriate for our lab experiments: the unobserved heterogeneity which could be tackled by using finite mixture models where more than one decision theory models can account for risk attitudes, and the continuous heterogeneity with respect to the model parameters where the latter are better described by a distribution indicating the between-subject variation in risk attitudes (Moffatt, 2015). These are interesting econometric avenues for future analysis since they have not been employed regarding intertemporal choice or the nature of loss aversion.

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