Essays on the measurement sensitivity of risk aversion and causal effects in education
Booij, A. S.

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The economists' traditional view of the expected utility model as describing decision under risk has long been challenged. The measurement of risk attitudes and the associations thereof with individual characteristics, however, have only recently been adapted to accommodate for the contemporary views on behavior. This thesis shows that the measurement of risk attitudes may be confounded with time preferences if individuals are credit constrained. What is actually impatience will be wrongfully attributed to risk aversion in that case. Likewise, if we view behavior through the lens of prospect theory, this thesis shows that individuals' small stake risk aversion is mainly caused by loss aversion and that differences in risk-taking behavior by gender and schooling are wrongfully ascribed to marginal utility of wealth in the traditional model. The non-linear transformation of utilities also adds to this bias. In the final chapter a general risk attitude measure is constructed. It is found that higher education students in the Netherlands who are more risk averse borrow less from the government to finance their studies. The study shows that informing students about loans is not an effective instrument to increase borrowing.

Adam Booij (1979) studied economics at the University of Amsterdam (UvA). In 2004 he completed the Tinbergen Master of Philosophy in Economics after which he started a PhD in behavioral economics at the UvA. Having entered close to applied micro economists he also got interested in the field of education economics, and in 2007 he obtained a Marie Curie scholarship to work on this topic at the Centre de Recherche en Économie et Statistique in Paris, where he stayed for 15 months. To finalize the dissertation he returned to the UvA where he still continues research on education issues at the TIER Institute. His current research interests include both behavioral economics and applied micro economics.

Adam Booij

Research Series
Universiteit van Amsterdam

Invitation to the public defence of the doctoral thesis

Essays on the Measurement Sensitivity of Risk Aversion and Causal Effects in Education

by Adam Sanoé Booij

on Thursday, April 9th 2009 at 14:00

in the Agnietenkapel of the Universiteit van Amsterdam
(Oudezijds Voorburgwal 231)

After the defence you are kindly invited to the reception that will be held in the same building

Should you have any questions please contact 'de paranimen'

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ESSAYS ON THE MEASUREMENT SENSITIVITY OF RISK AVERSION AND CAUSAL EFFECTS IN EDUCATION

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Well known economic measures such as inflation, unemployment and growth are all estimated on the basis of assumptions that are not innocuous. Should inflation measures be based on past or current bundles of goods? The former may give an overstatement and the latter an understatement of the welfare effect of price changes. Should unemployment rates be based on registry records of individuals that have applied for benefits, or should it be based on peoples’ statements in labor surveys? The first method generally gives much lower rates than the second because not all people that think of themselves as being unemployed register themselves as such. In France this difference led to considerable debate when the national bureau of statistics changed the unemployment definition (EUBusiness 2007). Likewise, growth measures are sensitive to which goods are defined as intermediary goods and which as final goods, because expenditure on intermediary goods should be deducted from total expenditure to arrive at the total value added. Differences in growth rate measures are not inconsequential because the performance of governments is often judged on them, and governments use growth measures and forecasts to determine planned expenditure.

Economic quantities that do not appear on the foreground as much as these measures but that are of great interest to (micro) economists, are measures of risk attitudes. Risk attitudes can be thought of as the preferences that govern people’s choices between risky or uncertain alternatives. Risky alternatives are probability distributions over outcomes, also called prospects, with all probabilities and outcomes known to the individual. Uncertainty designates the more general situation where not all probabilities or outcomes are known.

Risk attitudes play a central role in nearly every model of individual decision making used in economics where risk or uncertainty are involved, be it in a model of lifecycle consumption-smoothing decisions, of the choice of portfolio composition, insurance, education choice, or bidding strategies in auction theory. Hence, a good understanding of
risk attitudes is important, at least in theory, for predicting behavior in these different settings.

The first and major part of this thesis consists of three papers that concern the measurement of risk attitudes, and in particular the sensitivity to some of the assumptions made to measure them. In the second part we consider an empirical application where risk attitudes appear as one of the determinants of behavior. For simplicity, we will only consider decision making under risk, with money taken as outcomes.

Since its axiomatization by Von Neumann and Morgenstern in 1947, economists have used the expected utility model to describe behavior under risk. In this classical model the value of a prospect is given by the probability weighted sum of utilities of the outcomes. Risk attitudes are then fully determined by the curvature of the utility function of wealth. More precisely, in the expected utility model risk aversion (preferring the expected value of a prospect to the prospect itself) follows from diminishing marginal utility of wealth, and the “degree” of risk aversion increases if utility becomes more concave, that is if marginal utility diminishes more rapidly. This may be individual specific. For an individual agent utility curvature can be measured from observed risky choices. The obtained measure can then, in principle, be used to predict or explain behavior in other risky choice situations. This approach is not valid, however, if individuals do not behave according to the expected utility model, i.e. if one (or more) of the models’ assumptions fails descriptively. The first part of this thesis investigates what happens to the obtained measures of utility curvature when we depart from the classical assumptions.

In chapter 2, we consider what happens to the obtained measure of utility curvature if it is assumed that individuals cannot borrow from future income, which is implicitly assumed in the expected utility model. It turns out that this assumption is relevant when individuals are impatient and their income profile is flat. Then additional income is not fully integrated with wealth because its effect is spread over only a short period. This reduces the measured degree of risk aversion. This point is illustrated by an empirical application where risk aversion is measured using the hypothetical valuation of a series of lotteries by a representative sample individuals.

In chapters 3 and 4 we depart from expected utility in a different way. There we assume that behavior under risk is described by the more general prospect theory (Kahneman and
Introduction

Tversky 1979; Tversky and Kahneman 1992). According to this theory, risk attitudes are not only driven by utility curvature, but also by the subjective weighting of (cumulative) probabilities and loss aversion, which is the psychological overweighting of losses compared to gains with respect to a flexible reference point. Using a non-parametric measurement method that is invariant to this departure from classical assumptions, lab experiments with students reveal that utility curvature is far more linear than traditional measurements suggest. In chapter 3 we use the same tool to extend this finding to a representative sample of the population, which gives indirect evidence of the presence of the non-linear weighting of probabilities.

Chapter 4 provides complementary evidence for this result. There we estimate a fully parametric version of the prospect theory model, jointly estimating utility and probability weighting at the aggregate level. This approach confirms the approximate linearity of utility for small stakes and presents in-sample evidence of probability weighting for a representative subject pool. Because chapters 3 and 4 are written as independent papers, both provide a review of the empirical literature and a description of the data. Hence, the reader is forewarned that there is some repetition in the exposition put forward in these chapters.

The second part of this thesis diverges from the first. There a particular application is presented where risk attitudes are associated with student-borrowing behavior in the Netherlands. An even stronger association, however, is observed with degree of knowledge the students have with the loan-conditions, which are the rules set out by the government for student borrowing. This association vanishes if students’ knowledge is manipulated by a randomly assigned information treatment, which gives an example of how the relaxation of the classical exogeneity assumption made in regression analysis may lead to a very different picture of causal effects. Moreover, the direct policy implication of the study is that students’ lack of knowledge about the borrowing conditions is not constraining their borrowing behavior, questioning the need for an information campaign.

In summary, this thesis consists of two parts. In part I we consider three papers that fall under the heading of the measurement sensitivity of risk aversion. Chapter 2 starts with an analysis of how different assumptions about consumption smoothing over time can influence the estimate of risk aversion. Chapter 3 departs from the classical theory in a
different way, by assuming loss aversion and allowing for the non-linear weighting of probabilities. Chapter 4 extends these results by providing measures of the probability weights. The last chapter is categorized in part II that deals with the measurement sensitivity of causal effects in education. There we investigate the interpretation of students’ ignorance with - and an associated low take-up of - student loans in the Netherlands.
I Sensitivity of Risk Aversion Measurements
A simultaneous approach to the estimation of Risk Aversion and the Subjective Time Discount Rate*

2.1 Introduction

In standard economic analysis, decisions that involve a risk or a time dimension are traditionally analyzed separately within the framework of expected- or discounted-utility respectively. Many choice situations, however, concern both dimensions. For example, if we observe an investor who is reluctant to invest in a project promising large but risky long run profits, should we infer from this that he is risk averse, or should we ascribe his reluctance to impatience, preferring consumption now to later? Similarly, are students who quit school early impatient, or are they more inclined to take the current, more certain wage offer because they are more risk averse?

The general problem that both risk and time preferences can affect choices simultaneously has been acknowledged for some time in the macro-economic literature, where both the discount rate and relative risk aversion play a role in the estimation of the Euler equation of aggregate consumption. The separation of risk and time preferences has received considerable attention in this field, both theoretically and empirically (Kreps and Porteus 1978; Hall 1988; Epstein and Zin 1989; Weil 1990). In the micro-econometric literature that is concerned with the elicitation of these preferences at the individual level, however, risk and time dimensions are almost always treated separately (see for instance Barsky et al. 1997; or Harrison et al. 2005b). In order to see how this can affect the results, consider the willingness to pay for a simple lottery. In this context risk aversion is often

* This chapter is based on Booij and van Praag (2008).
estimated without acknowledging that the potential gains from such a lottery, in case they are big, will not be spent immediately but will be spread over time. Hence, the value of the lottery-prize, and consequently the lottery, will differ between patient- and impatient-individuals, making time preferences a confounding factor. Similarly, when estimating time preferences the uncertainty associated with delay, and also utility curvature, is often neglected resulting in an estimation bias (Frederick et al. 2002; Andersen et al. 2008).

The aim of this chapter is to show how, under plausible assumptions on consumption, time preferences affect risky decision making. To illustrate this, we model the willingness to pay for a lottery in the discounted expected utility framework, acknowledging that a large prize will not be consumed immediately but spread optimally over time. Assuming that individuals are borrowing constrained, consumption will be spread over a finite period that is endogenously determined. This model forms an intermediate case between two extremes: (i) no smoothing, current consumption equals current income, and (ii) no capital constraints. In the first case only current consumption is affected, while in the second the prize is integrated into total wealth. In that case time preferences determine the shape of the optimal profile, but not the curvature of the utility of wealth, making time preferences irrelevant. We will see that these assumptions have a great influence on the estimated degree of risk aversion because of their differing levels of asset integration. The novelty of our model is that the level of asset integration is endogenously determined and that risk and time preferences are estimated jointly.

To estimate the model, we use a large survey in which we ask for the willingness to pay for different lotteries that differ with respect to chance, prize, and timing of the draw. Using our model these data allow for the joint estimation of the coefficients of relative risk aversion and the time preference rate. The variation in these parameters can be explained by individual characteristics such as income, age, education, gender, intensity of religious participation, entrepreneurship, and other variables. In all estimated equations most effects are significant, plausible and consistent with the findings in most studies that relate risk and time preferences to demographics.

According to our knowledge there are only a few studies that simultaneously report estimates on risk and time preferences at the micro level. Even if these studies have data on choices with a risk and/or a time dimension, the risk and time effects are analyzed
Measuring Risk and Time Preferences

separately (Barsky et al. 1997; Anderhub et al. 2001; Eckel et al. 2005; Harrison et al. 2005b). The only exception is the study by Andersen et al. (2008), who simultaneously estimate risk and time preferences for a representative sample of the Danish population. Contrary to our model however, these authors do not model how the prize is consumed, which is what is done in this chapter.

The structure of the present chapter is as follows. Section 2.2 gives more background on the estimation of risk and time preferences in the literature. The model is outlined in section 2.3, followed by a description of the data in section 2.4. Section 2.5 presents an analysis of the survey results assuming homogeneity in preferences, an assumption that is dropped in section 2.6. Section 2.7 concludes, followed by section 2.8 that provides appendices that give derivations of the key mathematical equations in this chapter.

2.2 Background

Decisions under uncertainty are, traditionally, described by the Von Neumann - Morgenstern expected utility (EU) model, which defines the utility to be maximized as the expectation of the utilities of the random alternatives. The classical expected utility model is not beyond discussion. We refer to Allais (1953), Kahneman and Tversky (1979), Tversky and Kahneman (1992) and Rabin and Thaler (2001) for critique and alternatives. An important ingredient in this framework is the specification of the utility function. The most popular one-parameter specification is the constant relative risk aversion (CRRA) function defined by \( u(y) = y^{1-\gamma} / (1 - \gamma) \), where the coefficient of relative risk aversion is constant and given by \( \gamma \). Empirical estimates of this parameter vary greatly at the micro level, and they seem to be particularly sensitive to the magnitude of the stakes and whether outcomes are modeled in terms of final wealth or in terms of gains and losses (Rabin 2000a; Rabin and Thaler 2002; Meyer and Meyer 2005; Wakker 2005). Most studies of risk aversion look either at gambles, at decisions on the choice of risky assets in portfolios, or at the choice of insurance policies.\(^1\) Another important source of individual risk aversion estimates are

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\(^1\) Examples of studies that look at gambles: Jullien and Salanié (2000) and Beetsma and Schotman (2001); portfolio composition: Pällson (1996); insurance: Halek and Eisenhauer (2001).
experiments.\textsuperscript{2} Finally, measures of risk aversion obtained through hypothetical questions have also been used to explain choice under uncertainty.\textsuperscript{3}

A very similar model, the discounted utility model (DU), describes the problem of decisions over time where utilities at different moments in time are exponentially weighted by a subjective time discount rate $\rho$. Also this model is not beyond discussion, as is clear from the extensive list of anomalies that have been reported in the literature (e.g. Loewenstein and Prelec 1991; Frederick et al. 2002). The empirical estimates of the parameter $\rho$ vary a great deal. They are mostly derived from consumption-smoothing models, experimental choice situations, or hypothetical questions.\textsuperscript{4} In the first type of model, identification of time preferences relies on the assumption that agents have access to perfect capital markets and that they smooth their consumption according to their rate of time preferences. Data on an individual’s consumption flow serve to assess this rate. Most studies of time preference, however, exploit the last two types of data. Here, time preferences are identified by looking at individual choices between income streams. Then restrictions have to be put on either the possibilities of intertemporal arbitrage, or the subjects’ optimizing behavior. The implicit assumption in most studies seems to be that individuals ignore the possibility of intertemporal arbitrage either because they are unaware of it or because they are unable to exploit it (Pender 1996).\textsuperscript{5} The fact that imputed interest rates do not converge to market interest rates justifies this assumption (Frederick et al., 2002, p. 381). Estimated discount rates vary from 10\% to well over 100\% (Frederick et al., 2002, p. 377-381) per year.

As said before, the only study integrating both risk and time preferences at the individual level is Andersen et al. (2008).\textsuperscript{6} Using responses to a list of (binary) choices between either

\textsuperscript{2} Examples are Anderhub et al. (2001), Holt and Laury (2002) and Harrison et al. (2005).
\textsuperscript{3} Examples of this approach can be found in Barsky et al. (1997), Donkers et al. (2001), Hartog et al. (2002), Guiso and Paiella (2006) and Dohmen et al. (2006).
\textsuperscript{4} Examples of estimated time preferences using a consumption smoothing model: Trostel and Taylor (2001); experiments: Benzion et al. (1989), Coller and Williams (1999), Read (2001), Anderhub et al. (2001) and Harrison et al. (2002); hypothetical questions: Barsky et al. (1997), Donkers et al. (1999), Lazaro et al. (2001) and Kapteyn and Teppa (2003).
\textsuperscript{5} Coller and Williams (1999) and Harrison et al. (2002) form notable exceptions. In these studies of time preference the authors explicitly take censoring due to market interest rates into account.
\textsuperscript{6} Technically, studies that estimate the reference wealth level (Heinemann 2007; Harrison et al. 2007) can be thought to estimate a reduced form of a model that includes a time dimension. Since these studies do not explicitly model the time dimension, we do not consider them to belong to the class of models that simultaneously integrate risk and time preferences.
lotteries or payoff time-profiles, these authors simultaneously identify risk and time preferences. Under the assumption of expected utility (over money gains) their risk aversion task pins down utility curvature, which is then used to obtain an estimate of the subjective time discount rate, corrected for concavity of the utility function. The correction decreases the estimates, confirming the existence of an upward bias when utility curvature is neglected.

In their setup, risk aversion affects the estimated rate of time preference (through utility curvature), but not the other way round. Hence, the estimated level of risk aversion does not control for the fact that the consumption of the lottery gains will be spread over time. Since the stakes are relatively low in their study, this is unlikely to pose a big problem because consumption can be assumed to be approximately immediate in that case. When the stakes are large however, time preferences will also affect how outcomes are evaluated. In that setting also the consumption profile has to be modeled. This will be illustrated by the simple model in the next section.

2.3 The Model

In this section we consider the value of a lottery that is, the maximum amount an individual is willing to pay for a ticket for a specific lottery. First we will describe this problem using the classical expected utility model without a time dimension. Then we consider the problem in an intertemporal framework. The classical model turns out to be a special case where individuals face no liquidity constraints, while the model that does not include wealth corresponds to the case where consumption is immediate and borrowing and saving are not possible. Then we present an intermediate case where saving is possible but borrowing is not, and see that time preferences become an additional parameter in the problem.

Let us consider an individual with non-stochastic monthly income $y$, and let $W$ denote the net present value of this income stream. Suppose that he gets an offer to participate in a lottery that will give prize $Z$ with chance $\pi$. Moreover, let the price of a ticket be denoted by $a$ and the individual’s utility of wealth be denoted by $U(\cdot)$. Then, the expected utility of accepting the offer will be $(1-\pi)U(W-a)+\pi U(W-a+Z)$. The maximum amount an
individual is prepared to pay for taking part in the lottery is the amount $A$, which solves the indifference equation

$$(1-\pi)U(W-A) + \pi U(W-A+Z) = U(W).$$

(2.3.1)

We call $A$ the \textit{value of the lottery} or \textit{the reservation price}. This is the classical, timeless, (normative) framework that is used to model decisions under risk. In this model all money involved in the lottery is integrated into lifetime wealth, and the individuals’ risk aversion is determined by the degree of concavity of utility with respect to wealth.\textsuperscript{7}

Now we view the same problem within an intertemporal framework. We assume the discounted expected utility model in continuous time with a CRRA instantaneous utility function $u(\cdot)$ defined over present consumption $c(t)$, and (subjective) discount rate $\rho$. The utility of a consumption profile $c$ is then given by $\int_{t=0}^{\infty} e^{-\rho t} u(c(t)) dt$.

If there are no liquidity constraints, the individual has preferences only over present discounted sums of money. This is true because, through intertemporal arbitrage, all income streams with the same discounted value give rise to the same consumption possibilities. Hence, in this setting time preferences do not matter and additional money is simply integrated with wealth. The utility of an amount of wealth $W$ is given by the instantaneous utility function $u(W)$.\textsuperscript{8} Hence, the indifference equation under the assumption of full consumption smoothing is

$$(1-\pi)u(W-A) + \pi u(W-A+Z) = u(W).$$

(2.3.2)

Thus, the \textit{standard} expected utility model defined over wealth can be interpreted as describing decision under risk under full consumption smoothing.

If we now suppose the other extreme (i.e. that it is not possible to borrow or save), then current income equals current consumption. In that case only the present (month) is

\textsuperscript{7} There is a debate in the literature on whether the expected utility model presupposes that outcomes are defined in terms of final wealth or not. Both Cox and Sadiraj (2006) and Rubinstein (2006) argue that it is not and subsequently conclude that Rabin’s (2000a) critique of the model does not necessarily hold. Wakker (2005), however, argues in a working paper that even though the fundamental axioms of expected utility do not say anything about the nature of outcomes, the model only has normative content if defined over final wealth. Hence, in this thesis we assume the expected utility model to be defined over wealth.

\textsuperscript{8} We refer to Schechter (2007) for the technical details on the intertemporal optimization problem.
affected, with consumption equal to \( y - A + Z \) if the prize is won, and \( y - A \) otherwise. We will call this the *immediate* model. The indifference equation for this model is

\[
(1 - \pi)u(y - A) + \pi u(y - A + Z) = u(y).
\]  
(2.3.3)

In both cases the level of risk aversion is determined by the curvature of the instantaneous utility function. Let this function be defined over changes-in-wealth \( x \), plus some reference level \( R \), that is \( u(R + x) \). The standard model then corresponds to the case where the reference point is wealth (i.e. \( R = W \)), whereas in the immediate model it is present consumption (i.e. \( R = y \)). This difference has serious repercussions for the inferred level of relative risk aversion. Various authors have noted that the estimate of relative risk aversion is very sensitive to the level of the outcome dimension. Wakker (2008), for example, states that the CRRA family is not invariant to the level of inputs, and Meyer and Meyer (2005) show more specifically that the inferred measure of relative risk aversion increases (almost) proportionally with the assumed origin of the input scale. A simple numerical example illustrates this.

Consider an individual earning \( y = 500 \) per month, with corresponding lifetime wealth \( W = 200.000 \). Say this individual is prepared to pay \( A = 100 \) for a lottery with \( (\pi, Z) = (0.5, 1000) \). Then, if we assume the immediate model holds (\( R = W \)), we would infer that \( \hat{\gamma} \approx 4 \), while we get an estimate of \( \hat{\gamma} \approx 1385 \) if the standard model (\( R = W \)) holds! More generally, if we gradually increase \( R = \{500, 1000, 5000, 10000, 100.000, 200.000\} \), we find \( \hat{\gamma} = \{4, 7.5, 35, 70, 693, 1385\} \) respectively. Hence, the assumptions made about the consumption profile are of crucial importance. A practical example is provided by Schechter (2007), who reports estimates of relative risk aversion close to 2 if the reference level is daily consumption and estimates of over 2000 if outcomes are added to lifetime wealth.

The intuition behind this is that if the consumption of a given amount of small money is spread over the entire lifetime, the effect on each period’s consumption will be negligible. To generate appreciable risk aversion, the per-period utility function must then be very concave, translating into a high estimate of relative risk aversion. Rabin (2000a) shows that this has bizarre implications for high stake risk aversion. If consumption is confined to the
present period, however, the relative impact of the same amount of money is much larger. In that case mild curvature can generate the same small stake risk aversion, circumventing Rabin’s extreme implication. Indeed, most studies that find appreciable small stake risk aversion do not integrate outcomes with wealth and, thereby, find moderate values of risk aversion, mostly below 10. Rabin and Thaler (2002) suggest that wealth is often neglected not only because it is hard to measure, but also because “it would make referees worry” if the extreme measures of relative risk aversion were reported that are implied by these studies had outcomes been added to wealth (see for example Holt and Laury 2002; Harrison et al. 2005b; Dohmen et al. 2006).

An intermediate case: asset integration endogenously determined

The assumptions underlying both previous models may be seen as extreme positions. If we take an intermediate position, as we do in this chapter, where saving is assumed possible while borrowing is not, the consumption of the prize will be spread over time, albeit over a finite period. In that case the outcomes affect future periods, but they are not fully integrated into lifetime wealth as in the standard model. To see this, we consider the same model with a borrowing constraint. If it is not possible to borrow and individuals are assumed to be impatient (i.e. \( \rho > 0 \)), then baseline consumption is equal to monthly income (i.e. \( c(t) = y(t) = y \)). Now we will make some specific assumptions about the timing of the income flows associated with the lottery. These assumptions are made for simplicity. A different specification will yield different quantitative results, but they do not affect the main qualitative message of this chapter that if one introduces capital restrictions, both risk and time preferences operate simultaneously and the level of asset integration becomes endogenous.

Let the lottery ticket be bought at price \( A \), the cost of which is assumed to be spread evenly during the period \([0, \alpha]\) before the draw of the lottery, which occurs later, at time \( \alpha \). Hence, in the period before the draw of the lottery, consumption is reduced to \( (y - \frac{A}{\alpha}) \). If the prize, an amount \( Z \), has been won, it becomes available at time \( \alpha \) and may be gradually

\[ \hat{y} = 1 + \frac{\ln(z - y)}{\alpha} \]

which is nearly proportional in \( W \).

\[ \hat{y} = 1 + \frac{\ln(z - y)}{\alpha} W \]
spent over the period in the future $[\alpha, \infty)$. Let $P(t)$ denote the fraction of $Z$ that is spent up to time $t \in (\alpha, \infty)$ and let $p(t)$ denote its derivative. Trivially, we may define $p(t) \equiv 0$ for $0 \leq t < \alpha$. We have the constraints

$$\int_0^\alpha p(t)\,dt = 1 \text{ and } p(t) \geq 0 \text{ for all } t > 0.$$  \hspace{1cm} (2.3.4)

Finally, the lottery buyer may or may not take into account that his prize may bear interest at a rate $r$ when deposited in a savings account. Given these assumptions, the value $A$ of the lottery is found by equating the utility value without buying a ticket to the discounted expected utility when buying a ticket. We have

$$\int_0^\alpha e^{-\rho t}u(y - \gamma)\,dt + \pi\int_0^\alpha e^{-\rho t}u\left(y + e^{\rho(t-\alpha)}p(t)Z\right)\,dt$$

$$+(1 - \pi)\int_0^\alpha e^{-\rho t}u(y)\,dt = \int_0^\alpha e^{-\rho t}u(y)\,dt.$$  \hspace{1cm} (2.3.5)

It follows that the value of $A$ also depends on the spending pattern $p(t)$ according to which the prize is spent over time. If we assume that the consumption pattern for the windfall gain can be chosen at will, there will be an optimal spending pattern $\hat{p}(t)$. Then, the value $A$ of the lottery is found from the equation

$$\frac{1}{\rho}(1 - e^{-\rho \tau})\left(u(y) - u(y - \gamma)\right)$$

$$= \pi e^{-\rho \tau}\max_{\hat{p}(\tau)}\int_0^\tau e^{-\rho \tau} \left[u(y + e^r(\tau + \alpha)Z) - u(y)\right]d\tau$$  \hspace{1cm} (2.3.6)

$$= \pi e^{-\rho \tau}\int_0^\tau e^{-\rho \tau} \left[u(y + e^r(\hat{\tau} + \alpha)Z) - u(y)\right]d\tau,$$

where $\tau = t - \alpha$ denotes time, with the draw of the lottery taken as the starting point. This equation basically says that the utility loss associated with the payment of the lottery ticket should equal the expected future gains from it. We can derive the optimum pattern $\hat{p}(t)$ of how the prize $Z$ should be spent over future periods from the Euler condition for this problem. This is given by

$$e^{-\rho \tau}u(y + e^r(\hat{\tau} + \alpha)Z)e^\tau Z = C, \forall \tau \geq 0,$$  \hspace{1cm} (2.3.7)

where $C$ stands for a constant. This equation and the constraints in (2.3.4) imply the optimal spending pattern
\[ \hat{p}(\tau + \alpha) = \begin{cases} ce^{-B\tau} - \psi e^{-\tau} & \text{if } 0 \leq \tau \leq T_{\text{max}} \\ 0 & \text{if } \tau > T_{\text{max}} \end{cases}, \quad (2.3.8) \]

with \( B \equiv \frac{\psi - r}{\tau} + r \), \( \psi \equiv \frac{\tau}{Z} > 0 \), and an unknown constant, \( c \). The spending path is decreasing and intersects the horizontal axis in finite time \( T_{\text{max}} \). This point is endogenously determined and depends on \( B \), which measures the psychological trade-off between diminishing instantaneous utility and delay, the ‘relative prize’ \( \psi^{-1} = \frac{\tau}{Z} > 0 \), and the (monthly) interest rate \( r \). Hence, the winnings only affect a finite period \([0, T_{\text{max}}]\). This is a key difference with both previous models that can be viewed as having \( T_{\text{max}} = \infty \) and \( T_{\text{max}} = 1 \), respectively. In section 2.8.1 we present more details about the determination of the unknown constants \( c \) and \( T_{\text{max}} \) that pin down the optimal path.

In order to get some idea of how \( T_{\text{max}} \) varies with the three parameters we present Table 2.1. We see that \( T_{\text{max}} \) increases with the relative prize. For instance, let us consider an individual with a monthly income of €2000 with \( \gamma \) equal to 2, a time discount \( \rho \) of 2\% (per month), and an interest rate \( r = 4\% \) per year, that is 0.32\% per month. Consequently, his \( B \) is calculated to be 0.012. The spending period of a prize of one hundred times his monthly income, that is €200,000, will be 134 months, that is, approximately 11 years. Notice that for most configurations the spending period will be fairly short. The prize is then considered a windfall profit, to be consumed almost immediately.

| Table 2.1: \( T_{\text{max}} \) for different preferences and different relative prizes |
|---------------------------------|---------|---------|---------|---------|---------|---------|---------|---------|---------|
| \( r = 0\% \) & \( \psi \) & \( r = 0.32\% \) & \( \psi \) |
| \( 0.01 \) & \( 0.1 \) & \( 1 \) & \( 10 \) | \( 100 \) | \( 0.09 \) | \( 0.07 \) | \( 0.05 \) | \( 0.03 \) | \( 0.01 \) |
| \( 10 \) | 0.69 | 0.47 | 0.26 | 0.11 | 0.04 |
| \( B \) & \( 1 \) & \( 4.66 \) & \( 2.61 \) & \( 1.15 \) & \( 0.42 \) & \( 0.14 \) |
| \( 0.1 \) | 26.11 | 11.46 | 4.16 | 1.38 | 0.44 |
| \( 0.01 \) | 114.6 | 41.62 | 11.82 | 4.44 | 1.41 |
| \( B \) & \( 1 \) & 4.68 | 2.62 | 1.15 | 0.42 | 0.14 |
| \( 0.1 \) | 26.90 | 11.75 | 4.25 | 1.41 | 0.45 |
| \( 0.01 \) | 153.7 | 52.74 | 17.07 | 5.44 | 1.72 |

From calculations with a variety of realistic interest rates, we found that the effect of \( r \) on \( T_{\text{max}} \) is negligible for small prizes and reasonable ratios \( \rho / \gamma \). Intuitively, a higher interest rate affects consumption smoothing behavior only when the (relative) prize is very large or
when an individual is very patient or risk averse (which makes consumption smoothing more attractive).

Now that we know the optimal spending path, it is possible to evaluate the first part of the integral in (2.3.6) and subsequently determine the value of the lottery $A$. More precisely, we have

$$A = A(\gamma, \rho; y, \pi, Z, \alpha, r).$$  \hspace{1cm} (2.3.9)

An explicit analytical expression cannot be given (see section 2.8.2 for more details). Nevertheless, the question arises whether it would be possible to derive information on $\gamma$ and $\rho$ from equation (2.3.9). More precisely, let us assume an individual $n$ characterized by a specific $(\gamma_n, \rho_n; y_n, r_n)$ combination, where $r_n$ is known. If we offer this individual two different lotteries with different payoff dates, say $(\pi_i, Z_i, \alpha_i)$ $(i=1,2)$, and ask for the reservation prices $(A_{1n}, A_{2n})$ of both lotteries, it will be possible to derive the values $(\gamma_n, \rho_n)$ from his answers $A_{in}$ by solving the system

$$A_{in} = A(\gamma_n, \rho_n; y_n, \pi_i, Z_i, \alpha_i, r_n), \ i=1,2.$$  \hspace{1cm} (2.3.10)

Indeed (2.3.10) is a system of two equations in $(\gamma_n, \rho_n)$. It stands to reason that the system is highly non-linear. Nevertheless, the two unknown parameters are identifiable.

2.4 The data

The data source used for the empirical analysis is the NIPO Post Initial Schooling Survey that was administered by TNS NIPO, a Dutch (commercial) market research company, in December 2005. It is the third in a series of surveys jointly commissioned by the project group SCHOLAR of the Faculty of Economics and the Max Goote Centre, both of the University of Amsterdam, focusing on issues of educational attainment of employed individuals. Unlike the previous surveys, where individuals where contacted by phone, the 2005 sample was obtained using an internet-questionnaire. Apart from a cost reduction, internet-based surveys make randomization of questions relatively easy, a feature that was used to obtain more variation in the data. TNS NIPO has a large database of about 200,000 people who have indicated that they are willing to take part in TNS questionnaires. Because a large amount of background characteristics of these respondents is readily available, it is possible to focus on specific groups in the population (i.e. to draw a random sample
conditional on these characteristics). As the NIPO Post Initial Schooling Survey focuses mainly on education of working individuals, a random sample of just over three thousand \((N = 3026)\) employed individuals between the ages of 16 and 65 was drawn.

Although the sample is a good reflection of the Dutch working population, it is, by construction, not representative for the population as a whole. This is not a major problem since there is sufficient heterogeneity in the sample to make it suitable for econometric analysis of the relationship between most variables. Whether the sample is selective with respect to our variables of interest, risk and time preferences, is hard to say since we have no out-of-sample statistics on these variables to compare with. The response to NIPO questionnaires is generally very high, however, because respondents have already indicated a willingness to cooperate. Hence, we assume that our results will not be dramatically affected by self-selection of participation in the survey. Whether the results also hold for unemployed is an open question that can only be resolved by using additional data. Using weights we can make the sample more representative for the total population with respect to the dimensions of age, income, and education. Finally, regarding the accuracy of the data, we should keep in mind that most respondents will not have spent too much time on answering the questions, given the overall size of the questionnaire. Consequently, for some questions there may be a considerable random error in the answers.

The questionnaire consisted of 70 questions focusing mainly on education and educational attainment while being employed. The question module on which we are concentrating in this chapter is that of the lottery-questions, posed at the end of the survey.\(^\text{10}\) This module runs as follows:

**Question 70 – i**

Suppose that a lottery ticket is offered to you for a lottery in which \(N_i\) people participate (so you have a chance of 1 in \(N_i\) that you will win). The prize is a money amount equal to \(\€ Z_i\). The draw of the lottery will be in \(\alpha_i\) months, but you will have to buy the ticket now in order to participate. What is the maximum amount you are willing to pay for the ticket? \(\€.....\)

---

\(^\text{10}\) \(\€ 1\) was equivalent to about \$1.26 at the moment (2006) of surveying.
Each respondent was confronted with six ($i=1,\ldots,6$) of these questions, where the parameter-triplets $(N_i, Z_i, \alpha_i)$ were randomly and independently drawn from discrete distributions with $N_i \in \{100, 10, 5, 4, 3, 2\}$, $Z_i \in \{1000, 3000, 5000, 10000, 50000, 1000000\}$ and $\alpha_i \in \{1, 3, 12\}$. No individual was given the same question twice. That is, per individual the parameter-triplet $(N_i, Z_i, \alpha_i)$ was drawn without replacement. The six lotteries differ with respect to the chances of winning, $p_i$, which are an element of $\left\{\frac{1}{100}, \frac{1}{10}, \frac{1}{5}, \frac{1}{4}, \frac{1}{3}, \frac{1}{2}\right\}$, with respect to the size of the prize $Z_i$, and also with respect to the time delay between the payment of the lottery ticket and the draw of the prize, $\alpha_i$. This randomization gives a lot of variation, both between and within subjects, and allows for the estimation of our parameters of interest, risk aversion and time preference. All 3026 subjects in the sample answered the six lottery questions that were posed to them, but 626 of them did not show any variation in their answers, which is likely due to a lack of interest or to misunderstanding of the lottery question.\footnote{This amount of non-response is quite common in large scale-hypothetical questions on risky choices, where subjects have to perform a matching task that is cognitively demanding. For instance, Guiso and Paiella (2003) and Dohmen et al. (2006) dropped 57% and 61% of their observations respectively, for risk aversion questions of lesser complexity posed to a cross-section of the Italian and German public respectively, because of inconsistency or irrationality in subjects’ responses.} We dropped these individuals from the sample, together with those who did not state their income. A total of $N=1832$ individuals and 10992 usable answers remain, spread randomly over the $6 \cdot 6 \cdot 3 = 108$ different questions. This gives rise to an average of about 102 answers for each lottery. Summary statistics of the answers are given in Table 2.2.
## Table 2.2: Summary statistics of the lottery questions

<table>
<thead>
<tr>
<th>$p$</th>
<th>1 month</th>
<th>3 months</th>
<th>12 months</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$Z$</td>
<td>$Z$</td>
<td>$Z$</td>
</tr>
<tr>
<td></td>
<td>$\langle 1000 \rangle$</td>
<td>$\langle 3000 \rangle$</td>
<td>$\langle 5000 \rangle$</td>
</tr>
<tr>
<td>-----</td>
<td>---------</td>
<td>----------</td>
<td>-----------</td>
</tr>
<tr>
<td>1/100</td>
<td>mean</td>
<td>9.9 12 11 19 47 38</td>
<td>6.2 8.6 15 24 28 181</td>
</tr>
<tr>
<td></td>
<td>sd</td>
<td>20.7 12 11 22 150 49</td>
<td>6.1 9.6 20 31 54 1002</td>
</tr>
<tr>
<td></td>
<td>median</td>
<td>5 10 10 10 10 15</td>
<td>5 5 10 10 10 20</td>
</tr>
<tr>
<td></td>
<td>n</td>
<td>102 118 98 106 91 93</td>
<td>110 95 102 98 113 104</td>
</tr>
<tr>
<td>1/10</td>
<td>mean</td>
<td>22 24 37 72 198 1083</td>
<td>16 35 40 73 78 140</td>
</tr>
<tr>
<td></td>
<td>sd</td>
<td>53 46 68 172 770 9611</td>
<td>17 70 82 163 174 497</td>
</tr>
<tr>
<td></td>
<td>median</td>
<td>10 10 21 25 20 37.5</td>
<td>10 10 10 20 25 50</td>
</tr>
<tr>
<td></td>
<td>n</td>
<td>98 107 94 91 67 108</td>
<td>90 104 90 87 108 111</td>
</tr>
<tr>
<td>1/5</td>
<td>mean</td>
<td>31 43 46 87 158 91</td>
<td>38 66 55 83 169 336</td>
</tr>
<tr>
<td></td>
<td>sd</td>
<td>43 68 132 160 328 5464</td>
<td>157 143 113 185 521 117</td>
</tr>
<tr>
<td></td>
<td>median</td>
<td>15 17.5 15 25 25 50</td>
<td>10 20 19 25 40 50</td>
</tr>
<tr>
<td></td>
<td>n</td>
<td>103 100 95 84 98 84</td>
<td>94 96 94 93 103 94</td>
</tr>
<tr>
<td>1/4</td>
<td>mean</td>
<td>29 43 92 83 335 292</td>
<td>27 41 83 105 345 485</td>
</tr>
<tr>
<td></td>
<td>sd</td>
<td>48 65 195 227 159 1113</td>
<td>38 80 272 325 1278 2115</td>
</tr>
<tr>
<td></td>
<td>median</td>
<td>10 20 25 25 30 50</td>
<td>10 15 20 25 25 100</td>
</tr>
<tr>
<td></td>
<td>n</td>
<td>109 97 99 103 99 84</td>
<td>102 88 111 103 93 95</td>
</tr>
<tr>
<td>1/3</td>
<td>mean</td>
<td>37 59 78 100 213 2149</td>
<td>29 55 78 67 325 524</td>
</tr>
<tr>
<td></td>
<td>sd</td>
<td>58 86 181 242 1069 19503</td>
<td>33 124 181 97 1358 1664</td>
</tr>
<tr>
<td></td>
<td>median</td>
<td>10 25 25 25 30 100</td>
<td>15 15 20 25 50 100</td>
</tr>
<tr>
<td></td>
<td>n</td>
<td>95 110 91 103 105</td>
<td>99 97 93 92 106 103</td>
</tr>
<tr>
<td>1/2</td>
<td>mean</td>
<td>67 119 201 330 457 1125</td>
<td>61 117 143 270 534 2316</td>
</tr>
<tr>
<td></td>
<td>sd</td>
<td>107 232 375 765 2092 5410</td>
<td>118 263 311 797 1534 12746</td>
</tr>
<tr>
<td></td>
<td>median</td>
<td>25 30 50 50 60 100</td>
<td>25 25 50 50 62.5 100</td>
</tr>
<tr>
<td></td>
<td>n</td>
<td>99 100 94 120 97 91</td>
<td>100 101 81 108 100 123</td>
</tr>
</tbody>
</table>
The table shows the great diversity in the proposed lotteries, with expected values ranging from just € 10 to € 500,000. Some of these fall within the range of Dutch popular lotteries (LOTTO, State Lottery) that are likely to be the frame of reference for most of our respondents. These lotteries typically have a very large prize and a very low probability of winning, with an expected value well below € 100.\textsuperscript{12} Most of the lotteries proposed in the table however, have a higher probability of success and consequently also a higher mathematical expectation.

The statistics of the answers given to the various questions reveal three things: (1) both the mean and the median answers demonstrate very high risk aversion, with the level of risk aversion (defined as the fraction of the lottery expectation that individuals are willing to pay for it) increasing with the size of the prize, (2) the mean and average answers show an increasing pattern in both chances and monetary outcomes, which means that the average person behaves rationally in the sense that he complies with first order stochastic dominance; the results for discounting appear more mixed, and (3) there is considerable variation in the answers, which is a first indication of heterogeneity in preferences.

The first finding, that of high risk aversion, is not uncommon with hypothetical questions on the willingness to pay for simple lotteries. For instance, using similar hypothetical questionnaires Guiso and Paiella (2006) and Hartog et al. (2002) find average willingness to pay of 36\% and 20\% respectively. In another study Dohmen et al. (2006) find that 60\% of subjects are not willing to invest anything in a hypothetical asset yielding a 200\% or 50\% return with equal probability, when given an initial endowment of € 100,000. This again points to high risk aversion, even when there are no potential losses. At first glance the high levels of risk aversion found in these studies may appear unrealistic, i.e. one might think that if the subjects were presented with the same choice in reality, they might display less risk aversion. Both Guiso and Paiella (2006) and Dohmen et al. (2006) show, however, that the obtained risk aversion measure has significant explanatory power in predicting risky behaviors, which suggests that simple lottery questions do provide reliable information about risk attitudes. Moreover, Dohmen et al. validate the answers of the simple lottery

\textsuperscript{12} The Dutch National State Lottery, for instance, with a monthly clientele of 3.5 million tickets, sold at a price of €13.50 in an adult population of about 13 million, offers a chance of success of about 1 in 10 million, with a prize
question by relating them to the choices made in a risk aversion experiment using real incentives and find that both responses correlate well. Also, there is evidence that real incentives do not affect mean results in simple choice tasks, but simply make responses more noisy (Camerer and Hogarth 1999). Finally, if individuals have an inclination not to reveal their true value, this so called hypothetical bias is generally found to be positive (List and Gallet 2001), that is, in the direction of overestimation. In our case, this would imply more risk aversion when real incentives are used, an effect that has also been found in choice experiments with risky prospects (e.g. Holt and Laury 2002, 2005). Given that subjects’ responses to the survey questions are already quite conservative we suspect that such an effect is unlikely in our case.

Although we are unaware of studies that show a hypothetical bias in the direction of more risk aversion, some observations suggest this could be the case here. In particular, the finding that the median person does not want to spend more than a hundred euros on a lottery yielding a million euros in a month with 50% probability suggests that people may simply think in terms of € 10 to € 100 to spend on a lottery. It is unlikely that this is driven by liquidity constraints, but it could be explained by the supposed familiarity of the respondents with popular lotteries. Without any learning opportunity, the choice heuristic adopted may be that of buying a “normal” lottery ticket. The discovered preference hypothesis says that, when given an opportunity to learn, individuals will discover their true preferences and act upon them (Plott 1996). This would probably yield less risk aversion in our case. Hence, we conjecture that what we measure is an estimate of single shot risk attitudes without any learning opportunities. Interestingly, however, also higher educated individuals, who can be expected to act upon their true preferences with fewer learning opportunities, show the same median values.

The second notable feature of Table 2.2 is that the median answers are mostly (weakly) increasing in both chance and money outcomes. This principle is violated only four times for outcomes and six times for probabilities, and it is an indication that people comply with dominance. The results with respect to discounting appear more mixed, with some later dated prizes valued less and others higher. Consistency can also be tested at the individual

between 1 and 10 million. An interesting comparison of the Dutch popular lotteries has been published in the
level by comparing the willingness to pay for pairs of lotteries, where one lottery dominates the other. If we have two lotteries \( L_1 = (p_1, Z_1, \alpha_1) \) and \( L_2 = (p_2, Z_2, \alpha_2) \) with \( p_1 \leq p_2, \ Z_1 \leq Z_2 \) and \( \alpha_1 \geq \alpha_2 \), then we call \( L_1 \) (weakly) dominated by \( L_2 \). Because the lotteries were drawn randomly, the number of within-individual lottery pairs where one lottery dominates the other differs between respondents. For the whole sample \( (N=3026) \), thus including individuals who did not report their income or showed no variation in their answers, there are, on average, 6.22 possible comparisons per individual. Of these, 94.5\% comply with the dominance prediction.\(^{13}\) This rate of consistency is high, and suggesting that the subjects took the questions seriously and thought them through, which strengthens the case that what we find are unbiased answers in a context without learning. It also suggests that the mixed pattern with respect to the time delay observed in the median data is due to individual heterogeneity.

The final observation that can be made from the table is that there is considerable variability in the answers. This can have two causes: (1) between-subject variation, caused by heterogeneity in preferences, and (2) within-subject random error (Hey, 2005). Both sources of variation have received considerable attention in the literature, but for different reasons. The first strand of literature is aimed at explaining and predicting risk attitudes (Barsky et al. 1997; Harrison et al. 2005b), while the second has focused on the implications of different error specifications on statistical inference and model comparison (Carbone and Hey 2000; Loomes 2005).\(^{14}\) The present study falls within the first class of articles. In section 2.5 we will analyze whether there is structural variation in the answers that can be explained by background characteristics.

### 2.5 The estimation procedure and first results

The answers \( A_\pi \) that are given by the respondent to the lottery questions \( \{(\pi_i, Z_i, \alpha_i)\}_{i=1}^6 \) may be seen as the respondent’s solutions to the above equation (2.3.6). With six lottery questions we have, in principle, six solutions \( A_{\pi \alpha} \) for each respondent \( \pi \). Given that we have more than

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\(^{13}\) The proposed consistency test gives a rough indication of individual rationality. See Choi et al. (2005) for a more elaborate test for consistency at the individual level.

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two observations per individual, we are not in the situation of equation system (2.3.10) where we have only two equations that exactly identify the parameters \((\gamma_n, \rho_n)\). It is obvious that there will not be an exact solution to the system in this case, so we add an i.i.d. normally distributed error term \(\varepsilon_{in} \sim N(0, \sigma_n)\) to the model. This gives the non-linear model

\[
\ln A_{in} = \ln A(\gamma_n, \rho_n; y_n, \pi_i, Z_{in}, \alpha_{in}, r_n) + \varepsilon_{in}, \, \forall i \in \{1, \ldots, 6\}, \, n = 1, \ldots, N.
\] (2.5.1)

We may consider (2.5.1) as consisting of \(N\) systems of six non-linear equations in the unknowns \((\gamma_n, \rho_n)\), where the \(A_{in}\) stand for the observed responses to the lottery questions and the unit of time is one month. The parameters \((\gamma_n, \rho_n)\) could be estimated for all \(n = 1, \ldots, N\) separately. These estimates will not be very precise, however, because the number of observations per individual is at most six. Also, estimators of non-linear models are, in general, not unbiased for small samples. Assuming homogeneity in preferences (i.e. \((\gamma_n, \rho_n) = (\gamma, \rho)\)) decreases the number of parameters dramatically, which makes the use of asymptotic theory more appropriate. We specify the log-likelihood of the model by

\[
\ell(\gamma, \rho) = \sum_{n=1}^N \sum_{i=1}^6 -\frac{1}{2} \ln 2\pi - \ln \sigma - \frac{1}{2} \left( \frac{\ln a_{in}}{\sigma} \right)^2,
\] (2.5.2)

with \(\ln a_{in} = \ln A_{in} - \ln A(\gamma, \rho; y_n, \pi_i, Z_{in}, \alpha_{in}, r_n)\). Because we can not observe the interest rate on savings, we estimate the model for different interest rates, ranging from 0 to 4\% per year. Estimation of the parameters \((\gamma, \rho)\) by means of maximum likelihood is straightforward.\(^{15}\)

The results are presented in Table 2.3, together with estimates of relative risk aversion for the immediate- and the standard-model.\(^{16}\)

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\(^{14}\) Only more recently have authors used within individual randomness to explain observed violations of expected utility (Schmidt and Hey 2004; Blavatskyy 2007).

\(^{15}\) Robust standard errors were calculated correcting for within-subject correlations in the answers due to possible unobserved heterogeneity by using Stata’s clustering option.

\(^{16}\) Lifetime wealth is calculated as the present value of the income stream, \(W = y / \alpha\). Likewise, the lottery prize is taken at present value (i.e. \(\exp(-\alpha)Z\)).
Table 2.3: Estimated preference parameters

<table>
<thead>
<tr>
<th></th>
<th>Immediate case (R=y)</th>
<th>Intermediate case</th>
<th>Standard model (R=W)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(r)</td>
<td>4%</td>
<td>0%</td>
<td>1%</td>
</tr>
<tr>
<td>(\gamma)</td>
<td>2.10***</td>
<td>81.71***</td>
<td>81.73***</td>
</tr>
<tr>
<td>(\rho)</td>
<td>(4.219)</td>
<td>(4.223)</td>
<td>(4.234)</td>
</tr>
<tr>
<td>(\omega)</td>
<td>0.0603***</td>
<td>0.0603***</td>
<td>0.0602***</td>
</tr>
<tr>
<td>(\sigma)</td>
<td>2.640***</td>
<td>1.767***</td>
<td>1.767***</td>
</tr>
<tr>
<td>(N)</td>
<td>1832</td>
<td>1832</td>
<td>1832</td>
</tr>
<tr>
<td>(t)</td>
<td>−19544.1</td>
<td>−16262.7</td>
<td>−16262.7</td>
</tr>
</tbody>
</table>

Note: Calculated standard errors robust to unobserved heterogeneity. Significance levels: *: 10%; **: 5%; ***: 1%.

The models are presented from left to right in increasing order of intertemporal flexibility. The first column reports the most constraining model, where present income equals present consumption, followed by the intermediate model where saving is allowed, given various assumed interest rates. The last column reports estimates of the standard model, where the lottery is integrated into lifetime wealth and consumption is spread over the entire lifetime. The table shows that the results for the intermediate case are insensitive to the choice of the interest rate. This is due to the fact that the estimated discount rate is higher by an order of magnitude. For convenience we take \(r = 4\%\), which is close to the rate of interest on government bonds in the Netherlands.

For the immediate model we find a moderate degree of risk aversion equal to 2, an estimate that seems to be most prevalent in the macroeconomic literature (Bliss and Panigirtzoglou 2004). Within this strand of literature, however, outcomes are taken in terms of wealth, as in the standard model. The risk aversion that we find in that case is higher by two orders of magnitude (i.e. 338). This result is similar to that of Schechter (2007) and it corresponds to Rabin and Thaler (2002) who note that the small-stake risk aversion that is found in the experimental literature (for example, Holt and Laury 2002; Harrison et al. 2005b) would translate into extreme values of relative risk aversion if outcomes would be integrated with wealth in the analysis. The estimated risk aversion for the intermediate model, where the level of asset integration is endogenously determined, falls between the two extremes. The estimate of \(\gamma = 82\) is high compared to the usual experimental estimates, but much lower than the estimates suggested by the ‘standard model’. With the small prizes
that are usually involved in the experimental literature, it may be argued that consumption is immediate, justifying the neglect of lifetime wealth. With larger stakes however, such as the ones applied here, consumption will not be immediate but spread over time. This increases the estimated level of relative risk aversion towards (but still short of) that of the standard model. This shows that we can obtain lower estimates of risk aversion than those implied by the standard model, while retaining the plausible assumption that consumption is not immediate. The estimates of the intermediate model are sensitive to the assumptions made with respect to the baseline income profile and the precise form of liquidity constraints. The qualitative conclusion, however, that a model with borrowing constraints yields estimates between the two extreme cases, holds in general.

The estimated rate of time preference of \( \hat{\rho} = 6\% \) per month is high, but falls within the range of values that have been found in the empirical literature. As our questions include a trade-off between the immediate present and the future, the estimated discount rate include preferences for immediate gratification. These preferences have been found to be strong compared to those of delayed rewards, yielding discount rates of a hundred or even a thousand percent (Frederick et al. 2002). This phenomenon has led researchers to formulate different models of time preferences that allow the discount rate to vary with time (Laibson 1997; Read 2001). We employ the simple exponential discounting model because we want to show how risk and time preferences interact in the standard model under different assumptions. Hence, we need to qualify our rate of time preference as including preferences for the present that have been found to be strong.

The large variation in the answers that is observed in Table 2.2 is captured by the estimated standard deviation of the error process, \( \hat{\sigma} = 1.76 \). Indeed there appears to be much variation which is not explained by the model. Fortunately, the estimated standard errors of the parameters, that are robust to individual heterogeneity, are quite small due to the large sample size and variation in \( (\pi, Z, \alpha) \). Some of the unexplained variation may be due to heterogeneity in preferences. Hence, in the next section we will parameterize risk and time preferences by a linear combination of individual characteristics.
2.6 Explanations by assuming heterogeneity

In this section we explain the individual parameters \((\gamma_n, \rho_n)\) by means of some independent variables (for other examples of studies that relate risk and/or time preferences to individual characteristics see Binswanger 1980; Pålsson 1996; Barsky et al. 1997; Coller and Williams 1999; Donkers and van Soest 1999; Halek and Eisenhauer 2001; Donkers et al. 2001; Harrison et al. 2002; Hartog et al. 2002; Kapteyn and Teppa 2002, 2003; Harrison et al. 2005b; Tu 2005; Dohmen et al. 2006).\(^{17}\) To allow for heterogeneity in preferences, we parameterize the preference parameters by \((\gamma_n, \rho_n) = (\beta_y x_{\gamma,y}, \beta_y x_{\rho,y})\). The log-likelihood of the model then becomes

\[
\ell(\beta_y, \beta_y') = \sum_{n=1}^{N} \sum_{i=1}^{6} -\frac{1}{2} \ln 2\pi - \ln \sigma - \frac{1}{2} \left( \frac{\ln a_{ni}}{\sigma} \right)^2,
\]

with \(\ln a_{ni} = \ln A_{ni} - \ln A(\beta_y x_{\gamma,y}, \beta_y x_{\rho,y}, y, \tau, Z, \alpha_{ni}, 4\%\).

Estimation of the parameters \((\beta_y', \beta_y')\) by maximum likelihood is, again, straightforward.

Demographic variables that can be thought to be exogenous in this model are the respondent’s gender (Male, a dummy equal to 1) and age (Age). Males are expected to be less risk-averse than females, which is one of the most consistent findings in the literature on heterogeneity in risk attitudes (see Charness and Gneezy 2007 for a recent investigation into this issue). The results with respect to time preferences vary, but studies that report a significant effect find women to be more patient than men when making decisions between sooner smaller and later larger rewards (Coller and Williams 1999; Donkers and van Soest 1999; Read and Read 2004; Tu 2005).

The effect of age on risk attitudes has not been the main point of focus of any study, but this variable has been included in most of the above-mentioned analyses. Risk aversion is generally found to be either increasing or U-shaped in age (Pålsson 1996; Donkers and van

---

\(^{17}\) There are also studies that reverse the relation and view risk and time preferences as explanatory variables for different kind of behaviors. For instance Wärneryd (1996) and Guiso and Paiella (2006) try to explain portfolio holdings by a measure of risk aversion, while Borghans and Golsteijn (2006) try to explain obesity by peoples level of impatience. Kapteyn and Teppa (2002), Barsky et al. (1997), Donkers and van Soest (1999) and Dohmen et al. (2006) apply both approaches to risk attitudes, disentangling risk aversion by background characteristics and using the risk aversion measure as an explanatory variable in portfolio holdings, home ownership or risky behaviors.
Soest 1999; Halek and Eisenhauer 2001; Hartog et al. 2002). It is unclear whether this is a cohort effect or a pure age effect since none of these studies exploit panel data, which would enable the separation of the two effects. With respect to the time discount rate, we observe that with aging the remaining lifetime shortens. This would suggest a shrinking time horizon and hence stronger time discounting.\textsuperscript{18} This effect is indeed found in most studies (Trostel and Taylor 2001; Kapteyn and Teppa 2003; Read and Read 2004; Harrison et al. 2002), although some studies also find young individuals to be more impatient, attributed to a lack of self-control.

Other socio-economic and behavioral variables are potentially endogenous such that their coefficients should be interpreted as a measure of association useful for detecting individual heterogeneity and for prediction, but not for causal inference. For instance education (Ed\textsubscript{u}), measured as the number of years spent on regular education, can reduce attitudes towards risks because individuals with more schooling are better able to judge the risks they are facing. On the other hand, schooling attainment can be seen as a risky investment, which will cause risk-neutral individuals to select themselves into higher education, assuming that wage dispersion is higher there (Hartog et al. 2004). Both effects imply a negative relation between risk-aversion and the level of schooling, but with a different direction of causality. For both reasons we expect that more educated people are less risk-averse, an effect that is found in most studies (Donkers et al. 2001; Hartog et al. 2002; Kapteyn and Teppa 2002; Dohmen et al. 2006), but certainly not in all (Halek and Eisenhauer 2001; Harrison et al. 2005b). Similarly, education is a long-term investment and such a long-term investment is triggered by a long time horizon. Hence, we expect that more education goes hand-in-hand with a lower discount rate (Harrison et al. 2002; Kapteyn and Teppa 2003).

It was already hypothesized by Arrow (1965) and van Praag (1971) that absolute risk premia are decreasing with \textit{wealth} (the hypothesis of decreasing absolute risk aversion (DARA)), because the same monetary risk becomes relatively less important when wealth increases. There is no \textit{a priori} reason why relative risk premiums, that are closely linked to relative risk aversion, should be increasing (IRRA) or decreasing (DRRA) with wealth, and the empirical evidence seems to support neither hypothesis (Gollier 2001; Halek and

\textsuperscript{18} A more theoretical reasoning is given by Becker and Mulligan (1997) and Trostel and Taylor (2001).
Eisenhauer 2001). Hence we are agnostic about the sign of the coefficient of monthly income $y$ (measured in euros), which we take as proxy for wealth. The results with respect to time preferences also vary, but most studies that report a significant effect find impatience to decrease with income (Pender 1996; Kapteyn and Teppa 2003; Read and Read 2004). Liquidity constraints may provide a reason for this, i.e. individuals with a larger income tend to be wealthier and can ‘afford’ to wait.

Since our sample consists of employed individuals only, we cannot test whether workers and non-workers have different risk and time preferences. The respondents in the sample do differ in the type of employment they have. Some interesting work-related variables are whether someone is a government employee or an entrepreneur. The former group is typically thought to have a higher risk aversion (Hartog et al. 2002), whereas the latter group is thought to be more inclined to take risks (Cramer et al. 2002). We hypothesize that entrepreneurs are more forward-looking, since these individuals typically undertake large investments that entail (expected) returns in the future.

Religion offers a way to understand unexplained phenomena and may give a feeling of safety and security. Hence, we may exact religion to be positively associated with risk aversion. Moreover, religious individuals are hypothesized to be more forward-looking (Becker and Mulligan 1997). We included a measure of religiousness, which varies over five categories, where 1 stands for non-religious and 5 for very religious.

Other demographic variables that are often related to risk and time preferences are whether the respondent is married, has children, lives in a small or large community, or belongs to an ethnic minority. No robust differences in preference parameters appear to have been found in this domain. Behavioral variables of an economic nature that are likely to be related to attitudes towards time delay and risk are whether someone buys insurance, plays the lotto, has savings, or possesses risky assets. Papers that investigate this mostly find the expected relations, albeit often not significant (Wärneryd 1996; Barsky et al. 1997; Guiso and Paiella 2006; Dohmen et al. 2006).

There has been some research on the relation between time preferences and unhealthy behaviors such as smoking, drinking, overeating and using drugs (see for instance Fuchs 1991; Bretteville-Jensen 1999; Komlos et al. 2003; Picone et al. 2004; Borghans and Golsteyn 2006). These studies view unhealthy behaviors, and consequently health, as a decision
outcome, dependent on either risk or time preferences. Fuchs for instance argues that impatient individuals have a shorter time horizon and, hence, do not think about the future consequences of unhealthy behaviors. We included several behavioral variables such as smoking, drinking and being overweight (measured by the Body Mass Index (BMI)). The estimates are presented in Table 2.4.

### Table 2.4: Maximum-likelihood estimates

<table>
<thead>
<tr>
<th></th>
<th>Summary statsa</th>
<th>coef.</th>
<th>s.e.</th>
<th>coef.</th>
<th>s.e.</th>
<th>coef.</th>
<th>s.e.</th>
</tr>
</thead>
<tbody>
<tr>
<td>ln(y)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>0.58</td>
<td>0.49</td>
<td>-0.677**</td>
<td>(0.270)</td>
<td>-0.715**</td>
<td>(0.284)</td>
<td>-0.705**</td>
</tr>
<tr>
<td>ln(Age)</td>
<td>39.14</td>
<td>10.54</td>
<td>-0.921</td>
<td>(0.571)</td>
<td>-0.844</td>
<td>(0.581)</td>
<td>-0.637</td>
</tr>
<tr>
<td>ln(Edu+1)</td>
<td>12.75</td>
<td>2.62</td>
<td>-0.822***</td>
<td>(0.316)</td>
<td>-0.816**</td>
<td>(0.324)</td>
<td>-0.885**</td>
</tr>
<tr>
<td>ln(y)</td>
<td>2127</td>
<td>1189</td>
<td>0.952***</td>
<td>(0.130)</td>
<td>0.988***</td>
<td>(0.132)</td>
<td>0.991***</td>
</tr>
<tr>
<td>Religionb</td>
<td>2.49</td>
<td>1.74</td>
<td>0.208</td>
<td>(0.205)</td>
<td>0.227</td>
<td>(0.221)</td>
<td>0.258</td>
</tr>
<tr>
<td>Entrepreneur</td>
<td>0.03</td>
<td>0.18</td>
<td>1.783***</td>
<td>(0.613)</td>
<td>1.790***</td>
<td>(0.619)</td>
<td>1.820***</td>
</tr>
<tr>
<td>Ln(BMI)</td>
<td>25.53</td>
<td>3.91</td>
<td>2.852**</td>
<td>(1.282)</td>
<td>2.792**</td>
<td>(1.305)</td>
<td>2.732**</td>
</tr>
<tr>
<td>Constant</td>
<td>-5.910</td>
<td></td>
<td></td>
<td>-6.180</td>
<td>(4.893)</td>
<td>-6.179</td>
<td>(4.836)</td>
</tr>
</tbody>
</table>

| demo. controls   | No             | Yes   | Yes   |
| beh. controls    | No             | No    | Yes   |

| ln(r)            |                |       |      |       |      |       |      |
| Male             | 0.58           | 0.49  | 0.599*  | (0.309) | 0.645*  | (0.331) | 0.661*  | (0.395) |
| ln(Age)          | 39.14          | 10.54 | 1.34**   | (0.641) | 1.245*  | (0.648) | 1.049   | (0.979) |
| ln(Edu+1)        | 12.75          | 2.62  | 0.592   | (0.463) | 0.595   | (0.481) | 0.722   | (0.606) |
| ln(y)            | 2127           | 1189  | -0.258* | (0.139) | -0.297** | (0.140) | -0.277** | (0.138) |
| Religionb        | 2.49           | 1.74  | -0.220  | (0.250) | -0.251  | (0.275) | -0.281  | (0.251) |
| Entrepreneur     | 0.03           | 0.18  | -3.445* | (1.790) | -3.434* | (1.814) | -3.529  | (2.175) |
| Ln(BMI)          | 25.53          | 3.91  | -2.420  | (1.669) | -2.337  | (1.708) | -2.436*  | (1.420) |
| Constant         | 0.014          |       | 0.195  | (6.089) | 0.566  | (6.058) |

| demo. variables  | No             | Yes   | Yes   |
| beh. variables   | No             | No    | Yes   |

| σ                | 1.692***       | (0.022) | 1.691*** | (0.022) | 1.687*** | (0.022) |
| i                | -15463         |        | -15450   |        | -15437  |        |
| N                | 1767           |        | 1767     |        | 1767    |        |

a: Summary statistics of untransformed variables.
b: This ordinal variable has been mapped on the real axis using a monotonic transformation described by van Praag et al. (2003).

**Note:** Calculated standard errors robust to unobserved heterogeneity. Significance levels: *: 10%; **: 5%; ***: 1%.

We see that most coefficients have the expected sign, but not all are statistically significant. Most of the demographic and behavioral variables are not significant and are, therefore, not reported in the table. The coefficients reported in the second and third column of point estimates, are subject to control for these covariates.
One of the most robust effects found in the empirical literature, the difference in risk aversion between males and females, is also found in our dataset; that is, males are much less risk-averse than females. The gender effect on time discounting is also strong in magnitude, women being more patient, but this effect is only marginally significant. Growing older is associated with a lower degree of risk aversion, contrary to what is usually found, but this effect is not significant. A higher age is also associated with a higher level of impatience, consistent with previous evidence. Using dummies for age classes did not reveal a non-monotonic relation, hence there does not appear to be a U-shaped pattern in our data.

A higher level of schooling of the respondent is associated with a lower risk aversion and a lower patience level. The latter effect is not as predicted, but insignificant. The estimated coefficient of relative risk aversion increases with income, which means that as wealth increases, gambles proportional to wealth become less attractive. Impatience is associated with a lower income level, consistent with what is mostly found, but this result is not significant.

The intensity of being religious has no significant effect on either parameter, but the signs are as expected. Entrepreneurs display more utility curvature than employees, which is surprising since they are generally thought to be more risk tolerant. Background risk may be an explanation for this result; it could be that because entrepreneurs generally face more uncertainty in their income than employees, they are more risk averse. Halek and Eisenhauer (2001) report the same effect. Entrepreneurs are found to be more patient, which is what we expected. We did not find an effect for other types of employment. Finally, obesity (being overweight) reduces the willingness to take risks, which is also what Dohmen et al. (2006) find, and increases the subject's time horizon. This last result is insignificant and contrasts with the hypotheses of Komlos et al. (2003), who argue that impatience could lead to over-eating and consequently being obese, but the empirical robustness of this effect has yet to be established (Borghans and Golsteyn 2006).

Clearly our findings correspond to most of the hypotheses, and fit in well with the existing literature, except for the negative effect of age and the positive effect of entrepreneurship on risk aversion. It must be noted, however, that apart from the gender effect on risk aversion, there do not appear to be many other robust empirical findings in the literature that explain risk and/or time preferences; that is, there is variation across studies in
the sign and significance of the estimated effect of most variables. Figure 1 plots the predicted preference parameters. Both distributions have an approximate log-normal shape. The peak at \( \hat{\rho} \) near zero is caused by the group of entrepreneurs that have a significantly higher time horizon.

**Figure 2.1**: Histogram of predicted parameters

(a) Histogram of \( \hat{\gamma} \).  
(b) Histogram of \( \hat{\rho} \).

### 2.7 Summary and conclusions

This chapter starts from the basic premise that many economic decision problems have both a risk and a time dimension. This was illustrated in the context of the valuation of simple lotteries. Traditionally, behavior in this context is modeled by looking at the risk dimension of decisions, neglecting the fact that the evaluation of the prize not only depends on the absolute amount of the prize, but also on the way in which the prize is spent over time. To illustrate how, in this context, the classical expected utility model can be extended to accommodate the additional time dimension, we formulated a simple discounted expected utility model. In this model we account for the opportunity to spread consumption optimally over time, while making the plausible assumption that individuals are borrowing constrained. In this case the consumption of the prize is spread over a finite period that is endogenously determined and depends on time preferences. This model forms an intermediate case between the expected utility model defined over wealth (the standard model) and defined over income (the immediate model). These models have dominated the literature on the measurement of risk aversion for large and small stakes respectively.

The empirical tractability of the model was shown by simultaneously estimating the coefficient of relative risk aversion and the subjective time discount rate, using a sample of
Measuring Risk and Time Preferences

1,832 subjects who were asked to state their willingness to pay for six different, randomly assigned lotteries. Most of the answers were consistent, with 94.5% of all possible within-subject comparisons complying with dominance and discounting. This suggests that, even though we did not provide monetary incentives, the subjects took the questions seriously.

The average coefficient of relative risk aversion $\gamma$ was estimated to be 82. While this estimate is high compared to what is usually reported, it falls between the estimates of the usual models. If consumption is assumed to be immediate, the inferred relative risk aversion is 2, while we find an estimate of 338 if full asset integration is assumed. This shows that we get lower estimates of risk aversion than those implied by the standard model if we assume that individuals are borrowing constrained, while retaining the plausible assumption that consumption is not immediate. The subjective time discount rate was estimated at 6% per month on average, which is high but falls within the range of values that have been found. The quantitative values of these estimates depend on the assumptions made about baseline consumption, the timing of the lottery, and the exact form of the liquidity constraints, but the quantitative conclusion hold in general.

Both $\gamma$ and $\rho$ vary strongly over individuals. This variation could be explained by income, age, gender and entrepreneurship, consistent with the majority of previous evidence. It suggests that the parameters of the model indeed capture preferences towards risk and time.

Our analysis shows that the estimates of relative risk aversion are sensitive to the assumptions made about consumption, and that it is possible to accommodate for the effects of both risk and time dimensions in subject’s decisions when considering simple lotteries. This finding generalizes to many other settings, where we may think of risky assets, portfolios, and so on. Obviously, this also holds inversely. If we try to estimate subjective time discount rates from the evaluation of risky assets over time, we cannot do this without simultaneously taking the attitude towards risk into account (see Andersen et al. 2008). We hope that this analysis will stimulate researchers of risk attitudes and time preferences to consider both the risk and time dimensions simultaneously when analyzing subject’s decisions.
2.8 Appendix to chapter 2

2.8.1 Determination of \((c, T_{\text{max}})\)

Dividing the Euler equation (eq. (2.3.7)) by that at \(\tau = 0\) and rearranging yields
\[
u'(y + e^{\tau} \hat{p}(\tau + \alpha) Z) = \hat{c} e^{(\rho - \gamma)\tau}, \quad \forall \tau > 0,
\]
with \(\hat{c} = C / Z\). Using the CRRA-specification and solving for the optimal profile we get
\[
\hat{p}(\tau + \alpha) = c e^{-B\tau} - \psi e^{-\gamma\tau}, \quad \forall \tau > 0,
\]
with \(B \equiv \frac{\rho - \gamma}{\gamma} + \tau\), \(\psi \equiv \frac{\rho}{Z} > 0\), and the constant \(c = \hat{c} e^{\frac{\rho}{Z}} / Z > 0\) to be determined. We notice that \(B > \tau\) if \(\rho > \tau\), irrespective of the value of \(\tau > 0\). Hence, eventually \(\hat{p}(\tau + \alpha)\) will become negative, which violates the non-negativity condition. The moment \(T_{\text{max}}\) at which this occurs is found by solving the equation
\[
\hat{p}(T_{\text{max}} + \alpha) = 0 \iff c = \psi e^{(B-\gamma)T_{\text{max}}} ,
\]
for \(T_{\text{max}}\). We see that \(T_{\text{max}}\) depends on the unknown \(c\). The additional constraint in (2.3.4), which states that the spending fractions should sum to one, can be used to solve the model. Substituting \(c\) from (2.8.3) into (2.3.8) we may rewrite this as
\[
\psi e^{(B-\gamma)T_{\text{max}}} \int_0^{T_{\text{max}}} e^{-B\tau} d\tau - \psi \int_0^{T_{\text{max}}} e^{-\gamma\tau} d\tau = 1,
\]
from which \(T_{\text{max}}\) and subsequently \(c\) can be solved numerically.\(^{19}\) An analytical solution cannot be given because this equation contains both exponential and linear terms. For completeness, we note that if \(\rho < \tau\), then \(\hat{p}(\tau + \alpha)\) would start being zero and become positive and increasing after \(T_{\text{max}}\). If that were the case, the integral in (2.8.4) would not converge. Therefore, we assume \(\rho > \tau\).

2.8.2 Determination of \(A\)

With the optimal profile \(\hat{p}(\tau + \alpha)\) fully specified, the maximum of the integral in (2.3.6) can be evaluated. To this end we can use equation (2.8.1), the fact that \(c = (c'Z)^{-\gamma}\), and the

\(^{19}\) Equation (2.8.4) has two solutions in \(T_{\text{max}}\), but only one root is positive as required.
relation \( u = \frac{1}{1-\gamma} (u')^{\frac{\gamma}{\gamma-1}} \), which holds for a CRRA utility-function \( u \) and its derivative \( u' \). This yields

\[
\int_0^{T_{\text{max}}} e^{-r\tau} u(y + e^{r\tau} \hat{p}(\tau + \alpha) Z) d\tau = \frac{(cZ)^{1-\gamma}}{1-\gamma} \int_0^{T_{\text{max}}} e^{-B\tau} d\tau = \frac{(cZ)^{1-\gamma}}{1-\gamma} \left( e^{-B_{\text{max}}} - 1 \right). \tag{2.8.5}
\]

The willingness to pay \( A \) can be solved from (2.3.6) by substitution of this expression.
3 A Parameter-Free Analysis of the Utility of Money for the General Population under Prospect Theory*

3.1 Introduction

Expected utility is the reigning economic theory of rational decision making under risk. In this classical framework, outcomes are transformed by a strictly increasing utility function and prospects are evaluated by the probability-weighted average utility. Therefore, risk attitudes are solely explained by utility curvature under expected utility. For example, risk aversion (preferring the expected value of a prospect to the prospect itself) holds if and only if the utility function is concave, implying diminishing marginal utility. However, several decades of extensive experimentation has convincingly shown that “risk aversion is more than the psychophysics of money” (Lopes 1987): numerous studies have systematically falsified expected utility as a descriptive theory of decision making (Allais 1953; Kahneman and Tversky 1979). This descriptive inadequacy has been the main inspiration for the development of many alternative theories of individual decision making under risk (Starmer 2000). The most prominent of these non-expected utility models is prospect theory (Kahneman and Tversky 1979; Tversky and Kahneman 1992).

Prospect theory entails that besides the transformation of outcomes, probabilities are transformed by a subjective probability weighting function, reflecting sensitivity towards probabilities. Additionally, prospect theory entails that outcomes are evaluated relative to a reference point, reflecting sensitivity towards whether outcomes are better or worse than the status quo. According to prospect theory, risk attitudes are thus determined by a

* This chapter is based on Booij and van de Kuilen (2007).
combination of utility curvature,\textsuperscript{20} subjective probability weighting, and the steepness of the utility function for negative outcomes (losses) relative to the steepness of the utility function for positive outcomes (gains), i.e. loss aversion. Consequently, in the prospect theory framework, the one-to-one relationship between utility curvature and risk attitudes no longer holds and the validity of classical measurements of risk attitudes can therefore be questioned, which explains why these measurements have often led to preference inconsistencies (Hershey and Schoemaker 1985) or theoretical implausibilities (Rabin 2000a).

A detailed separation of risk attitudes into a subjective probability weighting-, a utility curvature-, and a loss aversion component requires the collection of considerable data. The few studies that have used prospect theory to analyze risk attitudes for the general population were forced to adopt stringent parametric assumptions because not enough variation in the data was available for such a detailed separation of risk attitudes (e.g. Donkers et al. 2001; Tu 2005). Moreover, these studies assume homogeneity in preferences or model heterogeneity in an inflexible parametric way, such as through normally distributed random coefficients. The experimental approaches that use non-parametric methods to elicit utilities at the individual level (e.g. Abdellaoui 2000; Bleichrodt and Pinto 2000; Abdellaoui et al. 2007b) circumvent these problems, but the external validity of the results of these studies can be questioned if risk attitudes are related to socio-demographic characteristics that differ between the population and the student subject pools used in these experiments.

This chapter presents the results of an experiment that completely measures the utility part of risk attitudes for positive and negative monetary outcomes, using a large and representative sample of \( N = 1935 \) respondents from the Dutch population, in a completely parameter-free way. The utility measurement technique we use is the tradeoff method introduced by Wakker and Denef (1996). This method is robust against subjective probability distortion and is parameter-free in the sense that no prior assumptions about the true underlying functional form of the utility function have to be made. In addition, we obtain parameter-free measurements of “the core idea of prospect theory” (Kahneman, 2003,\textsuperscript{20} In this thesis we will refer to the outcome transformation as utility (Bleichrodt et al. 2001), though it is often designated by value function in the prospect theory literature to illustrate that the outcome transformation is a descriptive concept that may be distinct from intrinsic utility. Abdellaoui et al. (2007a) provide evidence that (for gains) the outcome transformation elicited under prospect theory coincides with strength of preference statements, and hence can be viewed as reflecting the intrinsic utility of money.)
p.1457), i.e. loss aversion. Empirical research has shown that loss aversion is a major component of risk attitudes (Kahneman et al. 1991), and it can explain a wide variety of anomalous behavior in the field (Camerer 2000). Unlike previous measurements of risk attitudes, this study thus provides the first measurement of risk attitudes of the general population that is valid under (cumulative) prospect theory, does not depend on a priori assumptions about the underlying functional form of the utility function, is externally valid, and does not rule out heterogeneity of individual preferences. The dataset also allows us to test whether utility curvature is more or less pronounced for losses than for gains, whether scaling up monetary outcomes leads to a higher or a lower degree of utility curvature or loss aversion, and to relate the obtained measurements of utility curvature and loss aversion to socio-demographic characteristics.

First, the results show that utility is concave for gains and convex for losses, reflecting diminishing sensitivity as predicted by prospect theory but contradicting the classical prediction of universal concavity. In addition, our result support Rabin’s (2000b, p.202) claim that diminishing marginal utility is an “implausible explanation for appreciable risk aversion, except when the stakes are very large”; we confirm that utility curvature is less pronounced than suggested by studies that, erroneously, assume the classical expected utility model. Second, our results confirm the common finding that females are more risk averse than males (e.g. Hartog et al. 2002; Cohen and Einav 2007; Fellner and Maciejovsky 2007). Unlike previous studies that were not able to unambiguously decompose the different components of risk attitudes and often ascribe this gender difference solely to differences in the degree of utility curvature, our results show that this phenomenon is to a large extent driven by the fact that females are more loss averse than males. Our results also show that highly educated respondents are less loss averse, suggesting that measurements of loss aversion based on highly educated student samples, as often used in the laboratory, lead to an underestimation of loss aversion. Finally, we did not find significant evidence for the hypothesis that both the degree of utility curvature and the degree of loss aversion increases with the size of the outcomes involved.

The remainder of this chapter is organized as follows. Section 3.2 briefly provides background information about the ongoing debate in the literature about the proper shape of the utility function. Section 3.3 discusses prospect theory, and section 3.4 provides an
explanation of the measurement techniques we used to obtain parameter-free measurements of utility curvature and loss aversion at the individual level. Section 3.5 presents the experimental method, followed by the presentation of the results of the experiment in section 3.6. Section 3.7 contains a discussion of the experimental method and the main results, and section 3.8 concludes. Finally, section 3.9 presents details of the experimental instructions, and a table with unweighted results can be found in the appendix to this chapter in section 3.9.

3.2 Background

The separation of risk attitudes into a utility-, a loss aversion- and a probability weighting-component is crucial from a policy perspective because choice behaviour based on diminishing marginal utility is considered to be rational by most economists in the sense that these choices satisfy the fundamental axioms of expected utility (in particular the independence axiom) whereas choice behaviour based on subjective probability weighting for example, does not agree with these normatively compelling axioms (Bleichrodt et al. 2001; Wakker 2005). For instance, consider the so-called Equal Sacrifice Principle first put forth by Mill (1848). According to this principle, tax rates should be set in such a way that all people paying tax lose the same amount of utility. Hence, information about the utility that people derive from money obtained in isolation, i.e. obtained in an environment where confounding effects such as probability weighting did not play a role, is necessary. This study provides this information on the basis of a large representative dataset.

Parametric studies that provide measurements and decompositions of risk attitudes into a utility- and a probability weighting-component are numerous and, consequently, there is an ongoing debate about the shape of the utility function. For gains, most studies have corroborated that the utility function is concave-shaped, reflecting the natural intuition that each new Euro brings less utility than the Euro before and implying diminishing marginal utility (Wakker and Deneffe 1996). The debate regarding the shape of the utility function for losses has not been settled, however.

First of all, there is no consensus at present about the fundamental question whether the utility function for losses is either convex- or concave-shaped. Although the majority of studies have found a convex utility function for losses (Currim and Sarin 1989; Tversky and Kahneman 1992; Abdellaoui 2000; Etchart-Vincent 2004; Abdellaoui et al. 2007b), some
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studies have found the opposite result (Davidson et al. 1957; Laury and Holt 2007 (for real incentives only), Abdellaoui et al. 2008). A second point of debate is whether utility curvature for losses is either more or less pronounced compared to utility curvature for gains. More pronounced convexity for losses than for gains was found by Fishburn and Kochenberger (1979), virtually no difference in the degree of utility curvature was found by Abdellaoui et al. (2007b), and Schunk and Betsch (2006), whereas less pronounced convexity for losses than concavity for gains has been reported by Fennema and van Assen (1999), Wakker et al. (2007), and Abdellaoui et al. (2005). Finally, there is no consensus on whether utility curvature is more (or less) pronounced for larger outcomes. Increasing relative risk aversion has been found, for example, by Kachelmeier and Shehata (1992), Holt and Laury (2002, 2005), and Harrison et al. (2005a), whereas the opposite result, i.e. a decreasing relative risk aversion coefficient, has been found, for example, by Friend and Blume (1979), and Blake (1996).

There are four possible confounding factors in the aforementioned studies that are not present in the current study, and that may explain the seemingly contradictory findings. First of all, some studies assume expected utility and, thus, ignore the important role of probability weighting in risk attitudes. Second, the functional form of the utility (and probability weighting-) function are sometimes assumed beforehand and, therefore, the estimations depend critically on the appropriateness of the assumed functional form: conclusions drawn on the basis of the parameter estimates need no longer be valid if the true functional form differs from the assumed functional form. Third, most of these studies use aggregate data to estimate the different assumed functional forms, ruling out heterogeneity of individual preferences. Finally, student populations are commonly used as subjects, making the external validity of the results questionable.

3.3 Prospect Theory

We consider decision under risk, with \( \mathbb{R} \) the set of possible monetary outcomes of gains and losses with respect to some wealth level or reference point. The reference point is assumed to be the status quo, i.e. the current wealth level. A prospect is a finite probability distribution over (monetary) outcomes. Thus, a prospect yielding outcome \( x_i \) with probability \( p_i \) (\( i = 1, \ldots, n \)) is denoted by \((p_1:x_1, \ldots, p_n:x_n)\). A two-outcome prospect \((p:x, 1-p:y)\) is denoted by \((p:x, \ldots, p_i:x_i, \ldots, p_n:x_n)\).
y) and the unit of payment for outcomes is one Euro. In this chapter and the following, *prospect theory* refers to the modern (cumulative) version of prospect theory introduced by Tversky and Kahneman (1992), that corrected the original '79 version for violations of stochastic dominance and, more importantly, can also deal with uncertainty, i.e. the case of unknown probabilities. Prospect theory entails that the value of a prospect with outcomes $x_1 \leq \ldots \leq x_k \leq 0 \leq x_{k+1} \leq \ldots \leq x_n$ is given by:

$$\sum_{i=1}^{k} \pi^+_i U(x_i) + \sum_{j=k+1}^{n} \pi^-_j U(x_j).$$

(3.3.1)

Here $U: \mathbb{R} \to \mathbb{R}$ is a continuous and strictly increasing utility function satisfying $U(0) = 0$, and $\pi^+$ and $\pi^-$ are the decision weights, for gains and losses respectively, defined by

$$\pi^+_i = w^+(p_1 + \ldots + p_i) - w^+(p_1 + \ldots + p_{i-1}) \quad \text{for } i \leq k,$n

and

$$\pi^-_j = w^-(p_j + \ldots + p_n) - w^-(p_{j+1} + \ldots + p_n) \quad \text{for } j > k.$$ (3.3.2)

Here $w^+$ is the probability weighting function for gains and $w^-$ is the probability weighting function for losses, satisfying $w^+(0) = w^-(0) = 0$ and $w^+(1) = w^-(1) = 1$, and both strictly increasing and continuous. Thus, the decision weight of a positive outcome $x_i$ is the marginal $w^+$ contribution of $p_i$ to the probability of receiving better outcomes, and the decision weight of a negative outcome $x_i$ is the marginal $w^-$ contribution of $p_i$ to the probability of receiving worse outcomes. Finally note that the decision weights do not necessarily sum to 1 and that prospect theory coincides with expected utility if people use a fixed reference point and do not distort probabilities, i.e. prospect theory coincides with expected utility if individuals use a fixed reference point in terms of wealth and $w^+$ and $w^-$ are the identity.

### 3.4 Measuring The Utility Function

This section provides an explanation of the measurement techniques used to obtain parameter-free measurements of utility curvature and loss aversion at the individual level.

#### 3.4.1 Measuring Utility Curvature: The Tradeoff Method

The (gamble-) tradeoff method, introduced by Wakker and Deneffe (1996), draws inferences from a series of indifferences between two-outcome prospects in order to obtain a so-called *standard sequence of outcomes*, i.e. a series of outcomes that is equally spaced in utility units.
Contrary to other elicitation techniques often used to measure individual utility functions such as the certainty equivalence method, the probability equivalence method, and the lottery equivalence method (McCord and de Neufville 1986), utilities obtained through the tradeoff method are robust to subjective probability distortion. Hence, besides being valid under expected utility, the tradeoff method retains validity under prospect theory, rank-dependent utility and cumulative prospect theory (Wakker and Dennehe 1996).

Consider an individual who is indifferent between the prospects \((p:x_1, g)\) and \((p:x_0, G)\) with \(0 \leq g \leq G \leq x_0 \leq x_1\). In most existing laboratory experiments employing the tradeoff method (as well as in our experiment) individual indifference is obtained by eliciting the value of outcome \(x_1\) that makes a person indifferent between these two prospects while fixing outcomes \(x_0, G, g\), and probability \(p\). Under prospect theory, indifference between these prospects implies that:

\[
\begin{align*}
  w^*(p)(U(x_1) - U(x_0)) &= (1 - w^*(p))(U(G) - U(g)).
\end{align*}
\]

Thus, under prospect theory, the weighted improvement in utility by obtaining outcome \(G\) instead of outcome \(g\) is equivalent to the weighted improvement in utility by obtaining outcome \(x_1\) instead of outcome \(x_0\). Now suppose that the same person is also indifferent between the prospects \((p:x_2, g)\) and \((p:x_1, G)\). If we apply the prospect theory formula to this indifference we find that:

\[
\begin{align*}
  w^*(p)(U(x_2) - U(x_1)) &= (1 - w^*(p))(U(G) - U(g)).
\end{align*}
\]

Combining equations (3.4.2) and (3.4.1) yields:

\[
\begin{align*}
  U(x_2) - U(x_1) &= U(x_1) - U(x_0) .
\end{align*}
\]

Thus, the tradeoff in utilities between receiving outcome \(x_2\) instead of outcome \(x_1\) is equivalent to the tradeoff in utilities between receiving outcome \(x_1\) instead of outcome \(x_0\). Or, put differently, \(x_1\) is the utility-midpoint between outcome \(x_0\) and outcome \(x_2\) and the sequence of outcomes \(x_0, x_1, x_2\) is equally spaced in terms of utility units. One can continue eliciting individual indifference between prospects \((p:x_0, g)\) and \((p:x_{n-1}, G)\) in order to obtain an increasing sequence \(x_0, \ldots, x_n\) of gains that are equally spaced in utility units. A similar process can be used to construct a decreasing sequence of equally spaced losses. More specifically, individual indifference between the prospects \((p:y_1, l)\) and \((p:y_{n-1}, L)\) with \(0 \geq l \geq L \geq y_0 \geq y_1 \geq \ldots \geq y_n\) implies that the resulting decreasing sequence of losses \(y_0, \ldots, y_n\) is equally spaced in utility units. In what follows, we will use the term utility increment (utility
decrement) to denote the equal utility difference between the elements of an increasing (decreasing) standard sequence of gains (losses).

### 3.4.2 Measuring Loss Aversion

The tradeoff method allows measuring utilities for either gains or losses. Without further information, these measurements cannot be combined, because they are not on the same scale. This requires the elicitation of additional indifferences that involve mixed prospects, i.e., prospects that involve both gains and losses. With the proper use of the obtained standard sequences, this can be done in a parameter-free way.

A full description of the utility function over gains and losses allows for the comparison of utility in the two domains and, hence, allows for the characterization of loss aversion. Unfortunately, a commonly accepted definition of loss aversion does not exist in the literature (Abdellaoui et al. 2007b). We define the loss aversion coefficient \( \lambda \) as follows:

\[
\lambda = \frac{U(y_0) x_0}{U(x_0) y_0}.
\] (3.4.4)

This definition approximates the definition proposed by Köbberling and Wakker (2005), who characterize loss aversion as the ratio between the left and right derivatives of the utility function at zero, i.e., \( \lambda_{KW} = U'_L(0) / U'_R(0) \). This “local” definition measures the kink of the utility function at the reference point. It closely resembles the definition of loss aversion of Tversky and Kahneman (1992), who implicitly used \( \lambda = U(-\$1)/U(\$1) \). Köbberling and Wakker’s definition, however, has the advantage that it does not depend on the unit of the outcomes, i.e., it is independent of the currency unit. Other definitions have also been proposed, such as Kahneman and Tversky’s (1979) original formulation of loss aversion as \( -U(-x) > U(x) \) for all \( x > 0 \), or a stronger version formulated by Wakker and Tversky (1993) given by \( U'(-x) > U'(x) \) for all \( x > 0 \). These definitions do not yield an index of loss aversion but formulate it as a property of the utility function over a whole range. An index can then be constructed by taking the mean or median value of the relevant values of \( x \). This is not an arbitrary choice, however, making comparison between measurements difficult. Hence, we have to be careful with comparing loss aversion estimates (see Abdellaoui et al. 2007b for a more extensive discussion).
Our method to measure loss aversion consists of three steps. First we determine the utility of \( x_0 \) in terms of utility increments. To do so, we elicit the value of outcome \( b \) that makes an agent indifferent between the prospects \((r:b, 0)\) and \((r:x_1, x_0)\), where \( r \) is some fixed probability. Under prospect theory, indifference between these prospects implies:

\[
\begin{align*}
U(x_0) &= \frac{w^+(r)}{1 - w^+(r)} \left( U(b) - U(x_1) \right) .
\end{align*}
\] (3.4.5)

For given probability weights this equation pins down the utility of outcome \( x_0 \) in terms of increments of the standard sequence for gains. Suppose for example that \( w^+(r) = 1 - w^+(r) \), and that \( b \) falls within the standard sequence for gains, say half-way between \( x_2 \) and \( x_3 \). Then, using linear interpolation to obtain the utility of \( b \), equation (3.4.5) implies that the utility of \( x_0 \) is equal to 1.5 times the utility increment for gains, i.e. \( U(x_0) = 1.5 \left( U(x_1) - U(x_0) \right) \).

The linear approximation of the utility of outcome \( b \) can be justified on the grounds that utility is often found to be linear over small monetary intervals (Wakker and Denneffe 1996). Graphically, equation (3.4.5) identifies the utility of outcome \( x_0 \) in terms of the amount of steps of the standard sequence, as illustrated by brace 1 in Figure 3.1.

In the second step, an analogous question for losses allows for the identification of the utility of outcome \( y_0 \) in terms of utility decrements. We obtain the outcome \( c \) that makes an agent indifferent between the prospects \((r:0, c)\) and \((r:y_0, y_1)\). Under prospect theory, indifference between these prospects implies:

\[
\begin{align*}
U(y_0) &= \frac{w^-(1-r)}{1 - w^-(1-r)} \left( U(c) - U(y_1) \right) .
\end{align*}
\] (3.4.6)

In similar spirit to equation (3.4.5) for gains, this equation identifies the utility of outcome \( y_0 \) in terms of utility decrements of the standard sequence for losses, which is illustrated by brace 2 in Figure 3.1 below. The outcome \( c \) must fall within the standard sequence for losses and its utility can be obtained by using (linear) interpolation again.

---

21 Linear interpolation to obtain the utility of outcome \( b \) is only possible if outcome \( b \) falls within the standard sequence, which is why we used \( x_0 \) and \( x_1 \) as outcomes for the second prospect.
The first two steps connect the standard sequence for gains and losses to the zero outcome, but do not determine their relative scale. In the third and final step, the size of the utility increment for gains in terms of the utility decrement for losses is determined by eliciting the outcome \( d > x_0 \) that makes the agent indifferent between the mixed prospects \((r:d, y_i)\) and \((r:x_0, y_0)\). Under prospect theory, indifference between these prospects implies:

\[
U(y_d) - U(y_i) = \frac{w(r)}{w(1-r)} (U(d) - U(x_0)).
\] (3.4.7)

From a measurement perspective this equation amounts to relating the utility decrement of the standard sequence of losses to the utility increment of the standard sequence of gains, as depicted by brace 3 in Figure 3.1. The utility of outcome \( d \) can again be approximated by using interpolation.

Equations (3.4.5) – (3.4.7), the fact that the standard sequences are equally spaced in utility units, and (linear) interpolation of the utility of indifference outcomes \( b, c \) and \( d \), determines the utilities of the outcomes \( \{y_0, \ldots, y_i, 0, x_0, \ldots, x_i\} \) up to scale. Setting, for
example, \( U(y_i) = -1 \) completely pins-down the utility function such that it can be depicted graphically.\(^{22}\)

In the above steps, the probability weights corresponding to the probabilities used in the elicitation procedure were assumed to be known, while in fact they are unknown a priori. Several parameter-free techniques to obtain these probability weights have been proposed in the literature (Abdellaoui 2000; Bleichrodt and Pinto 2000). Hence, if combined with these measurement methods, the three indifferences stated above can in principle be used to measure the utilities of the standard sequences of gains and losses on the same scale. In this chapter, we do not use additional questions to obtain the probability weights, and assume either linear probability weighting as in classical economic analyses or employ the empirical estimates of the probability weights found by Kahneman and Tversky (1992) in the analysis. A different method to measure loss aversion in a parameter-free way is in Abdellaoui et al. (2007b).

### 3.5 The Experiment: Method

**Participants.** \( N = 1935 \) Dutch participated in the experiment which was held in February 2006. We used the DNB Household survey which is a household panel that completes a questionnaire every week on the Internet or, if Internet is not available in the household, by a special box connected to the television. The household panel is a representative sample of the Dutch population; it consists of people from all income groups and age groups above 16 years (see second column of Table 3.2 for further details).

**Procedure.** The experiment consisted of two parts, I and II. The questions of the first part (Q1 – Q16) were designed to elicit utility, as described in section 3.4. The questions of the second part (Q17 – Q27) were designed to determine probability weighting for both the domain of gains and the domain of losses. A description and an analysis of these question is given in

---

\(^{22}\) The specific utilities for this normalization are \( U(y_i) = (i - n)\Delta U_y + 1 \) and \( U(x_j) = i\delta U_x + U(x_0) \) for \( i = 0, \ldots, n \), with \( \Delta U_y = -\frac{(1 - w^*(r))}{(w^*(r) - n)} \), \( \Delta U_x = \frac{(\Delta U_y w^*(r))}{(w^*(r) \delta)} \) and \( U(x_j) = \frac{(w^*(r) \hat{\delta}\Delta U_x)}{(1 - w^*(r))} \). The hat variables are continuous quantities that measure the utility distance between the corresponding outcome and the same ranked outcome of the other prospect, in terms of the amount of utility steps of the standard sequence of that domain. Under linear interpolation for example, we have \( \hat{b} = \frac{(b - x_i)}{(x_{i+1} - x_i)} + k - 1 \) with \( x_i < b < x_{i+1} \).
Respondents were thus simply asked to report the upper prize of the left prospect that would make them indifferent between both prospects. The wheel in the middle served to explain probabilities to respondents. Both the probabilities reported in the wheel and the colors of the wheel corresponded to the probabilities of the prospects. The prizes of the prospects used were hypothetical (for a discussion see section 3.7).

**Table 3.1: The Obtained Indifferences in Part I**

<table>
<thead>
<tr>
<th>Matching Question</th>
<th>Prospect L</th>
<th>Prospect R</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>(0.5: (g, 10))~</td>
<td>(0.5: (50, 20))</td>
</tr>
<tr>
<td>2</td>
<td>(0.5: (x, g)) ~</td>
<td>(0.5: (x, G))</td>
</tr>
<tr>
<td>:</td>
<td>:</td>
<td>:</td>
</tr>
<tr>
<td>7</td>
<td>(0.5: (x, g)) ~</td>
<td>(0.5: (x, G))</td>
</tr>
<tr>
<td>8</td>
<td>(0.5: (y, l)) ~</td>
<td>(0.5: (y, L))</td>
</tr>
<tr>
<td>:</td>
<td>:</td>
<td>:</td>
</tr>
<tr>
<td>13</td>
<td>(0.5: (y, l)) ~</td>
<td>(0.5: (y, L))</td>
</tr>
<tr>
<td>14*</td>
<td>(0.5: (b, 0)) ~</td>
<td>(0.5: (x, x))</td>
</tr>
<tr>
<td>15*</td>
<td>(0.5: (0, y)) ~</td>
<td>(0.5: (y, y))</td>
</tr>
<tr>
<td>16*</td>
<td>(0.5: (d, y)) ~</td>
<td>(0.5: (x, y))</td>
</tr>
</tbody>
</table>

**Notes:** Underlined outcomes are the matching outcomes and questions marked with an asterisk were presented in randomized order.
Stimuli. For each respondent we obtained a total of 16 indifferences; see Table 3.1. Following the first practice question, matching questions 2 to 7 served to obtain an increasing sequence of gains \(x_0, \ldots, x_6\) that are equally spaced in utility units, followed by six matching questions to obtain a decreasing sequence of losses \(y_0, \ldots, y_6\) that are equally spaced in terms of utility (see section 3.4.1). Matching questions Q14-Q16 served to obtain a parameter-free measurement of the degree of loss aversion at the individual level (see section 3.4.2). As can be seen in Table 3.1, the parameter values of \(p\) and \(r\) used throughout section 3.4 were set at 1/2, as in Bleichrodt and Pinto’s (2000) experiment.

Treatments. In order to be able to test whether utility curvature is more pronounced for larger monetary outcomes, respondents were randomly assigned to two different treatments. These treatments only differed in the parameter values used for \(G, g, x_0, L, l,\) and \(y_0\). In the low-stimuli treatment, these parameter values were set at \(G = 64, g = 12, x_0 = 100, L = -32, l = -6,\) and \(y_0 = -50\). In the high-stimuli treatment, all parameter values were scaled up by a factor 10, i.e. the parameter values were set at \(G = 640, g = 120, x_0 = 1000, L = -320, l = -60,\) and \(y_0 = -500\).

3.6 The Experiment: Results

This section presents both parametric and non-parametric results regarding the shape of the utility function for gains and losses (Section 3.6.2), and loss aversion (Section 3.6.4). Since the panel of respondents is a representative sample of the Dutch population, the raw sample means would provide unbiased estimates of the population means if we would observe answers from all individuals in the panel. Not surprisingly, there is non-response in the data which, if non-random, will bias the statistical inferences. We deal with this sample selection problem by constructing sampling weights. The sample selection process is described in the next subsection.

3.6.1 Sample Selection

Because we did not give financial incentives to participate in the experiment, we expected that some members of the panel would not respond, or would not provide answers to all questions. Indeed, about 20% of the panel members did not start the experiment or stopped
answering questions before reaching the end of the experiment. Non-response is the first of four types of sample selection that we observed in the dataset.

The second type of sample selection is the result of an imposed monotonicity condition: the obtained standard sequence of gains (losses) had to be strictly increasing (decreasing), which precludes violations of stochastic dominance. This is a natural requirement, since individuals that violate it either have a lack of understanding or make a mistake, indicating a lack of attention. A number of studies have shown that not-providing incentives not only increases the variance of subjects’ responses, but often also decreases performance (Camerer and Hogarth 1999; Hertwig and Ortmann 2001). We found that in our sample about 40% of the subjects displayed at least one inconsistency, the observed probability of which is heavily correlated with education (discussed below). This effect is also found by von Gaudecker et al. (2008), and it suggests that we should be cautious of sample selection with respect to education when implementing research designs targeted to the general population that involve cognitively demanding tasks.

The final two types of sample selection involve only a small fraction of respondents. Since estimated means are sensitive to outliers, we dropped extreme responses that would solely have a significant effect on the results. Observations were defined as outliers when the subjects’ answer belonged to the top or bottom percentile of the distribution of outcomes for individuals who answered all questions (including the inconsistent observations). This amounts to about 1% of the observations. Using sample medians to reduce the effect of outliers would be another way to mitigate their influence, but correcting this estimator for sample selection is not straightforward. Hence, we chose to drop a small fraction of extreme observations and focused our attention on estimating population means for the general public. The last type of sample selection involves the loss aversion questions, where we imposed the condition that the values of outcomes $b$, $c$, and $d$, had to lie in the interval of the obtained standard sequence of the individual, and, hence, dropped 12 observations. The absolute frequencies of the classification of the sample selection mechanism are reported at the bottom of Table 3.2. The samples for gains, losses and loss aversion differ because different consistency conditions have been imposed, as already mentioned.

Selection with respect to education (and other variables) may introduce a bias in the estimation if the outcome variable of interest is related to it. Then information on the
selection mechanism is needed to conduct proper statistical inference. Since we have background information on both in- and out-of-sample respondents we can check whether the answers of both groups of respondents differ systematically, and construct sampling

### Table 3.2: Sample Selection Probit and Classification

<table>
<thead>
<tr>
<th>Variable</th>
<th>Fraction</th>
<th>Gains</th>
<th>Losses</th>
<th>Loss Aversion</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low Amounts Treatment</td>
<td></td>
<td>0.144**</td>
<td>0.101*</td>
<td>0.088</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.058)</td>
<td>(0.059)</td>
<td>(0.065)</td>
</tr>
<tr>
<td>Female</td>
<td>46%</td>
<td>−0.052</td>
<td>−0.079</td>
<td>−0.116*</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.060)</td>
<td>(0.061)</td>
<td>(0.067)</td>
</tr>
<tr>
<td>Lower Secondary Education</td>
<td>26%</td>
<td>0.127</td>
<td>0.029</td>
<td>0.218</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.142)</td>
<td>(0.143)</td>
<td>(0.177)</td>
</tr>
<tr>
<td>Higher Secondary Education</td>
<td>14%</td>
<td>0.335**</td>
<td>0.148</td>
<td>0.507***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.151)</td>
<td>(0.152)</td>
<td>(0.182)</td>
</tr>
<tr>
<td>Intermediate Vocational Training</td>
<td>19%</td>
<td>0.046</td>
<td>−0.148</td>
<td>0.147</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.146)</td>
<td>(0.148)</td>
<td>(0.180)</td>
</tr>
<tr>
<td>Higher Vocational Training</td>
<td>25%</td>
<td>0.258*</td>
<td>0.039</td>
<td>0.394**</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.143)</td>
<td>(0.144)</td>
<td>(0.175)</td>
</tr>
<tr>
<td>Academic Education</td>
<td>11%</td>
<td>0.488***</td>
<td>0.305*</td>
<td>0.681***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.158)</td>
<td>(0.158)</td>
<td>(0.187)</td>
</tr>
<tr>
<td>Age 35-44</td>
<td>18%</td>
<td>−0.157*</td>
<td>−0.202**</td>
<td>−0.284***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.092)</td>
<td>(0.093)</td>
<td>(0.099)</td>
</tr>
<tr>
<td>Age 45-54</td>
<td>22%</td>
<td>−0.234***</td>
<td>−0.281***</td>
<td>−0.325***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.088)</td>
<td>(0.089)</td>
<td>(0.095)</td>
</tr>
<tr>
<td>Age 55-64</td>
<td>18%</td>
<td>−0.313***</td>
<td>−0.340***</td>
<td>−0.524***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.094)</td>
<td>(0.096)</td>
<td>(0.106)</td>
</tr>
<tr>
<td>Age 65+</td>
<td>19%</td>
<td>−0.462***</td>
<td>−0.428***</td>
<td>−0.632***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.095)</td>
<td>(0.096)</td>
<td>(0.108)</td>
</tr>
<tr>
<td>Income ≤ €1.150&lt;€1.800</td>
<td>25%</td>
<td>0.196*</td>
<td>0.269**</td>
<td>0.319**</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.118)</td>
<td>(0.122)</td>
<td>(0.146)</td>
</tr>
<tr>
<td>Income ≤ €1.800&lt;€2.600</td>
<td>31%</td>
<td>0.200*</td>
<td>0.253**</td>
<td>0.381***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.115)</td>
<td>(0.119)</td>
<td>(0.143)</td>
</tr>
<tr>
<td>Income ≥ €2.600</td>
<td>35%</td>
<td>0.344***</td>
<td>0.411***</td>
<td>0.526***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.115)</td>
<td>(0.119)</td>
<td>(0.142)</td>
</tr>
<tr>
<td>Catholic</td>
<td>30%</td>
<td>0.014</td>
<td>0.008</td>
<td>−0.007</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.068)</td>
<td>(0.069)</td>
<td>(0.077)</td>
</tr>
<tr>
<td>Protestant</td>
<td>20%</td>
<td>0.160**</td>
<td>0.126</td>
<td>0.215**</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.077)</td>
<td>(0.078)</td>
<td>(0.084)</td>
</tr>
<tr>
<td>Constant</td>
<td></td>
<td>−0.503***</td>
<td>−0.510***</td>
<td>−1.199***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.176)</td>
<td>(0.179)</td>
<td>(0.217)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>N</th>
<th>1935</th>
<th>1935</th>
<th>1935</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-response</td>
<td>375</td>
<td>422</td>
<td>1361*</td>
</tr>
<tr>
<td>Non-Monotone</td>
<td>728</td>
<td>811</td>
<td>123</td>
</tr>
<tr>
<td>Outside interpolation int.</td>
<td></td>
<td></td>
<td>12</td>
</tr>
<tr>
<td>Outlier</td>
<td>18</td>
<td>12</td>
<td>1</td>
</tr>
<tr>
<td>Sample</td>
<td>814</td>
<td>690</td>
<td>438</td>
</tr>
</tbody>
</table>

Log-likelihood: −1276.243 −1226.928 −978.2592

Notes: Standard errors allow for clustering within households. */**/*** significant at the 10/5/1% level. †: Combines non-response (2 cases) with not being in the union of the sample for gains and losses (1339 cases).
weights by calculating the inverse of the probability of being observed in the sample. Table 3.2 presents the results of probit regressions of appearance in the respective sub-samples with respect to gender, age, education, income and religion. All variables have been split up in categories such that the results can not driven by assumptions regarding the functional form.

As can be seen in the table, there appears to be selection on most variables. Since the loss aversion equation compounds the selection effects of the gain and the loss domains, it shows the most prominent effects. Generally, the probability that a given respondent is observed in the sample is increasing in income and education level, and decreasing in age. Women are less likely to answer our loss aversion questions, while individuals with a protestant background have a higher inclination to respond. These effects are interesting in their own right, and they are consistent with the findings of von Gaudecker et al. (2008) who specifically investigate sample selection in the same internet panel using risk aversion (choice) tasks. They find that non-response is related to education, gender and age, and that the amount of inconsistencies is more than twice as high in the cross section of the population compared to a sub-sample of young students, i.e. the typical subject pool used in laboratory experiments. Thus, respondents from the population appear to have more difficulty conducting the risk aversion choice tasks than the typical subject in the lab. We should note that since each question poses a new test for monotonicity, a random error model would predict the exclusion of a higher fraction of observations as the amount of questions rises.

For the purpose of this analysis it is important to acknowledge that there is sample selection with respect to demographic variables that, if related to utility curvature or loss aversion, will bias the population estimates if it is not accounted for. Hence, in what follows, the reported coefficients are estimates of the population means for the general public, obtained by weighting each observation by the inverse of the (predicted) probability of being included in the sample. These coefficients are unbiased estimates of the population means for the Dutch population under the assumption that non-response is random after conditioning on the selection variables that we observe. This rules out selection on the outcome variables of interest. Harrison et al. (2007) find that reducing show-up fees increases the likelihood of attracting risk-averse agents. We conjecture that this mechanism
is not at work in our setting because the panel participants are used to participating in the questionnaire without pay.

Generally, the weighting scheme slightly reduces the estimated means, but leaves the qualitative pattern unaffected. We will only comment on the weighted parameters, except when there are notable differences compared to the unweighted data.\footnote{Table 3.8 in the Appendix to chapter 3 provides summary statistics of the unweighted data.}

### 3.6.2 Utility Curvature: Non-Parametric Analysis

Table 3.3 summarizes the results regarding the obtained utility function for monetary gains and losses under the different treatments. As can be seen in the table, the difference between the successive elements of the average standard sequences is mostly increasing for both gains and losses and under both treatments. Also, at face value utility curvature seems to be more pronounced for lower monetary outcomes.

| i | xi | xi – xi-1 | yi | | yi – yi-1 | |
|---|---|---|---|---|---|
| 1 | 1984 | 984 | 204 | 104 | –849 | 349 | –87 | 37 |
| 2 | 2975 | 991 | 318 | 114* | –1242 | 393*** | –126 | 39* |
| 3 | 4017 | 1042** | 440 | 122*** | –1663 | 420*** | –168 | 42** |
| 4 | 5093 | 1076** | 577 | 137** | –2073 | 410 | –211 | 43* |
| 5 | 6179 | 1086 | 729 | 151** | –2488 | 415 | –255 | 43 |
| 6 | 7310 | 1131** | 892 | 164** | –2910 | 422 | –299 | 45 |

Notes: Estimated averages in euros. Standard deviations in parenthesis. */**/*** indicates that the predicted population mean is significantly higher than its predecessor at the 10/5/1% level, based on weighted t-tests.

We performed t-tests to check whether the differences between the successive elements of the standard sequence for gains and losses are indeed significantly increasing.\footnote{Non-parametric tests on the raw data yield similar results.} As can be seen in the table, a total of 8 differences between the obtained successive elements of the standard sequence appear to be significantly increasing for gains. In the loss domain there
are 5 significant differences. Only one mean difference is lower than its predecessor, but this difference is not significant. Overall, these results thus imply concave utility for gains and convex utility for losses, reflecting diminishing sensitivity toward outcomes: people are more sensitive to changes near the status quo than to changes remote from the status quo, as predicted by prospect theory but contrary to the classical prediction of universal concavity. This result is consistent with the findings of other parameter-free studies employing the tradeoff method to obtain utilities for gains (Wakker and Denef 1996; Abdellaoui 2000) and losses (Fennema and van Assen 1998; Etchart-Vincent 2004) as well as with results from studies using parametric fittings (Currim and Sarin 1989; Tversky and Kahneman 1992; Heath et al. 1999; Davies and Satchell 2003).

**Table 3.4: Classification of Respondents**

<table>
<thead>
<tr>
<th>GAINS</th>
<th>LOSSES</th>
<th>Convex</th>
<th>Linear</th>
<th>Convex</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Convex</td>
<td>50 (8.95%)</td>
<td>31 (5.22%)</td>
<td>77 (14.88%)</td>
<td>158 (29.06%)</td>
<td></td>
</tr>
<tr>
<td>Linear</td>
<td>25 (4.90%)</td>
<td>108 (17.54%)*</td>
<td>43 (6.78%)</td>
<td>176 (29.23%)</td>
<td></td>
</tr>
<tr>
<td>Concave</td>
<td>49 (8.61%)</td>
<td>44 (7.68%)</td>
<td>149 (25.42%)*</td>
<td>242 (41.72%)</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>124 (22.47%)</td>
<td>183 (30.44%)</td>
<td>269 (47.09%)</td>
<td>576 (100%)</td>
<td></td>
</tr>
</tbody>
</table>

*Note: Table reports absolute frequencies for individuals that gave consistent answers for both gains and losses. The estimated population fractions are in parenthesis.

* A test of equality of probability is rejected in favor of the hypothesis that the concave-convex shape is more prevalent than the linear-linear form (one-sided test, \( z = 2.84 \), p-value = 0.002).

Additionally, we analyzed the shape of the utility function at the individual level. For each respondent we normalized utility of gains such that it is exactly in the unit square, i.e. we rescaled \( z_i = (x_i - x_0) / x_0 \) and set \( u(z_i) = i / 6 \) for all \( i = 0, \ldots, 6 \). Then, we classified a respondent’s utility function as concave (convex; linear) if this area was larger than (smaller than; equal to) 1/2 for gains. Figure 3.3 illustrates the area measure for a typical standard sequence. Using a similar procedure for losses, a utility function was classified as concave (convex; linear) if the area was smaller than (larger than; equal to) 1/2. Table 3.4 gives the absolute sample frequencies and, in parenthesis, the predicted population fractions. There appears to be considerable variability in the elicited shapes of utility, with a significant amount of observations in all cells. The predominant pattern is a concave-convex shape of the utility function (25%), again implying diminishing sensitivity in both domains. If we look at unconditional probabilities, the case for diminishing sensitivity is stronger, with 42% of respondents being classified as concave for gains and 47% as convex for losses. These
results are somewhat below the relative frequencies reported by Abdellaoui (2000) and Abdellaoui et al. (2007b).

Figure 3.3: Area under a normalized utility function

3.6.3 Utility Curvature: Parametric Analysis

Although we obtained utilities in a parameter-free way using the trade-off method, we also used parametric methods to analyze the data. For each respondent, we estimated the power utility function with parameter $\rho$ for both treatments. Thus, for each respondent and for each separate domain (gains and losses) we estimated:

\[
U(x) = x^\rho \quad \text{for } \rho > 0 \tag{3.6.1}
\]
\[
U(x) = \ln(x) \quad \text{for } \rho = 0 \tag{3.6.2}
\]
\[
U(x) = -x^\rho \quad \text{for } \rho < 0 \tag{3.6.3}
\]

by minimizing the sum of squared residuals. For losses we first transformed the outcomes to the positive domain such that the power function is well defined. The power utility function with parameter $\rho$ is currently the most popular parametric family for fitting utility (Wakker 2008) and is also known as the family of constant relative risk aversion (CRRA) because the ratio $-xU''(x)/U'(x)$, i.e. the index of relative risk aversion, is constant and equal to $1 - \rho$. We also estimated the exponential utility function for both gains and losses which is defined by:

\[
U(x) = 1 - \exp(-\gamma x) \quad \text{for } \gamma > 0 \tag{3.6.4}
\]
\[ U(x) = z \quad \text{for } \gamma = 0 \]  
\[ U(x) = \exp(-\gamma z) - 1 \quad \text{for } \gamma < 0 \]  
where \( z = (x - x_0)/(x_6 - x_0) \). This family is also known as the family of constant absolute risk aversion (CARA) because the ratio \(-U''(x)/U'(x)\), i.e. the Pratt-Arrow measure of risk aversion, is constant and equal to \( \gamma \).

Finally, we estimated the \textit{expo-power utility function}, introduced by Abdellaoui et al. (2007a), which is a variation of the two-parameter family proposed by Saha (1993) and which is defined by:

\[ U(x) = -\exp(-z^{\delta} / \delta) \quad \text{for } \delta \neq 0 \]  
\[ U(x) = 1/z \quad \text{for } \delta = 0 \]  
where \( z = x / x_6 \). This particular specification allows for both concave and convex utility functions, and a subset of this specification allows for the combination of concave utility, a decreasing Pratt-Arrow measure of risk aversion \((1 - \delta)/x + x^{\delta+1}\) and an increasing index of relative risk aversion \((1 - \delta + x^{\delta})\), which is a desirable feature because these phenomena are often found empirically (Abdellaoui et al. 2007a). As mentioned in the introduction, the one-to-one relationship between utility curvature and risk attitudes is not valid under non-expected utility models such as prospect theory and, thus, we avoid the terms index of relative risk aversion and Pratt-Arrow measure of risk aversion in what follows.

<table>
<thead>
<tr>
<th>Table 3.5: Estimated mean utility curvature</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treatment</td>
</tr>
<tr>
<td>Gains, high</td>
</tr>
<tr>
<td>N = 378</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Gains, low</td>
</tr>
<tr>
<td>N = 428</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Losses, high</td>
</tr>
<tr>
<td>N = 326</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Losses, low</td>
</tr>
<tr>
<td>N = 356</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
</tbody>
</table>

\textit{Note:} Estimated standard deviations in parenthesis.

Table 3.5 below summarizes the average optimal parameter estimates for the different parametric specifications for each specific treatment, found by minimizing the sum of squared residuals. As can be seen in the table, the (weighted) average estimate of the power coefficient \( q \) for gains is 0.95 in the high- and 0.94 in the low-stimulus treatment. This result seems to be consistent with a mean estimate for gains of 0.91 found by Abdellaoui et al.
(2007b), based on a parameter-free analysis. A two-sided t-test, adjusted for the sampling weights (as are all t-tests reported in this section), does not reject the null hypothesis that the estimated mean $\rho$-parameters for gains are equal across the high- and the low-stimulus treatment ($t = 0.539$, p-value = 0.593).

Analysis of the individual $\rho$-parameters on the basis of one-sided t-tests does indicate that the $\rho$-coefficients for gains are significantly lower than 1 in both the high- and the low-stimulus treatment (low: $t = -3.04$, p-value = 0.001; high: $t = -2.105$, p-value = 0.018), which implies a significant overall degree of diminishing marginal utility for gains. For losses, the obtained parameter estimates are 0.92 for the high-stimulus treatment and 0.93 for the low stimulus treatment respectively, and we cannot reject the hypothesis that they are equal ($t = 0.100$, p-value = 0.918). In addition, the obtained $\rho$-coefficients for losses proved to be significantly lower than 1 in both the high and the low-stimulus treatment (low: $t = -2.414$, p-value = 0.008; high: $t = -2.256$, p-value = 0.012). In the parametric estimation, we thus again find that sensitivity with respect to losses diminishes, which is in line with previous findings using non-parametric data (Fennema and van Assen 1998; Abdellaoui 2000; Etchart-Vincent 2004; Abdellaoui et al. 2007b; Schunk and Betsch 2006).

Although respondents in the sample were significantly less risk averse in the gain domain (Wilcoxon rank sum test, $z = 2.159$, p-value = 0.031), we could not draw such a strong conclusion for the population ($t = 1.315$, p-value = 0.189), thus supporting the findings of Abdellaoui et al. (2007), and Schunk and Betsch (2006) who find no differences in curvature across domains. The parameter estimates of the exponential and expo-power utility functions are all highly correlated to the estimated power parameters and, hence, statistical tests based on these functional families give very similar results and will not be reported here.

The dataset allows us to relate the degree of utility curvature to socio-demographic variables. Therefore, we performed a simple (weighted) linear regression analysis with the individual estimates as dependent variables and a treatment dummy and several socio-demographic variables as independent variables.\(^{25}\) The results of this regression are reported in the first three columns of Table 3.6. As can be seen in the table, the estimated coefficients

\(^{25}\) We used several alternative (non-linear) functional forms, but this did not change the results.
for gains (\(\rho^+\)) and losses (\(\rho^-\)) appear largely idiosyncratic, with no apparent association with any of the included demographic variables except for a weak association with age. Because our method to obtain utilities is robust to subjective probability weighting and we treat gains and losses separately, our results suggest that the differences in measured risk attitudes by gender and education that are often observed stem from differences in probability weighting or loss aversion. With respect to gender, for example, our results are consistent with a recent study by Fehr-Duda et al. (2006), who do not find gender differences in the utility functions for both gains and losses based on parametric fittings and using students as subject. This result questions the validity of ascribing gender differences in risk taking behavior to differences in utility curvature, as is done in classical studies (Barsky et al. 1997; Hartog et al. 2002; Donkers et al. 2001). Other socio-demographic variables concerning profession, affinity with financial matters, being a house owner and religion were also not found to be a significant predictor of utility.

<table>
<thead>
<tr>
<th>Table 3.6: Regression Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variable</td>
</tr>
<tr>
<td>------------------</td>
</tr>
<tr>
<td>Low Amounts</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Female</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Age</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>High Education</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>In(Income+1)</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Constant</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>N</td>
</tr>
<tr>
<td>R²</td>
</tr>
</tbody>
</table>

Notes: Weighted linear regression. Standard errors allow for clustering within households. \(*/**/***: significant at the 10/5/1% level.
3.6.4 Loss Aversion

Table 3.7 presents the summary statistics and weighted means for the different indifference values of outcomes \( b, c, \) and \( d, \) and the resulting loss aversion coefficient. Loss aversion is calculated both on the assumption of expected utility, i.e. \( w(\frac{1}{2}) = \frac{1}{2} \), and prospect theory. For the latter we use the estimated subjective probability weighting function found by Kahneman and Tversky (1992), which implies \( w^{-}(\frac{1}{2}) = 0.4540 \) and \( w^{+}(\frac{1}{2}) = 0.4206 \). Table 3.7 shows there are significant differences in the loss aversion coefficient between the weighted and unweighted samples. The weighted mean value of \( \lambda \) under expected utility, denoted by \( \lambda_{EU} \), is 1.79 for the low- and 1.73 for the high-amounts treatment, while the sample averages are 1.64 and 1.69 respectively. This is caused by the fact that lower educated individuals are underrepresented in our sample, while they are more loss averse on average. Under prospect theory, the weighted mean value of \( \lambda \), denoted by \( \lambda_{PT} \), is equal to 1.84 for the high-stimuli treatment and 1.90 for the low-stimuli treatment. These results are suggestive of decreasing loss aversion which has been found in other studies (Abdellaoui et al. 2007b; Bleichrodt and Pinto 2002 (health)), but the standard errors are too high to draw any strong conclusions, i.e. we cannot reject the hypothesis that loss aversion is the same across treatments (\( t = 0.321, \ p-value = 0.747 \)).

<table>
<thead>
<tr>
<th>Table 3.7: Mean Results Loss Aversion</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td><strong>UNWEIGHTED</strong></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td><strong>WEIGHTED</strong></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td><strong>High</strong></td>
</tr>
<tr>
<td><strong>Low</strong></td>
</tr>
<tr>
<td><strong>High</strong></td>
</tr>
<tr>
<td><strong>Low</strong></td>
</tr>
<tr>
<td><strong>( b )</strong></td>
</tr>
<tr>
<td>4016</td>
</tr>
<tr>
<td>(1604)</td>
</tr>
<tr>
<td>386</td>
</tr>
<tr>
<td>(150)</td>
</tr>
<tr>
<td>3970</td>
</tr>
<tr>
<td>(1553)</td>
</tr>
<tr>
<td>391</td>
</tr>
<tr>
<td>(148)</td>
</tr>
<tr>
<td><strong>( c )</strong></td>
</tr>
<tr>
<td>–1569</td>
</tr>
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<tr>
<td>1.90</td>
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<td>(1.58)</td>
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</table>

*Note: Standard deviations in parenthesis.*

26 Given the values \( b, c \) and \( d, \) the loss aversion coefficient can be written as \( \lambda = (1 - w^{+}(r))\hat{c}d / (1 - w^{-}(r))\hat{b} \) (see footnote 22).
Under both assumptions the 95% confidence intervals of the loss aversion measure are [1.58, 1.94] and [1.68, 2.06] respectively. These intervals exclude the value of 1, meaning there is significant evidence of loss averse behavior for sample and also for Dutch population as a whole. Thus, generally, our result suggests that on average people weight a particular loss about 1.87 times as heavy as a corresponding gain when making decisions. The estimated loss aversion coefficient $\lambda$ is lower than the parametric estimate of $\lambda = 2.25$ obtained by Tversky and Kahneman (1992), and the non-parametric estimate of $\lambda = 2.15$ based on the definition of loss aversion proposed by Kahneman and Tversky (1979), found by Abdellaoui et al. (2007b). Our (weighted) mean estimate of $\lambda$ is however more consistent with a recent study by Gächter et al. (2007) who report an average (within-subject) $\lambda$ of 1.95 in a riskless setting, using WTA and WTP disparities of a miniature car, using a large sample of car buyers. The authors also measured loss aversion at the individual level using choices between mixed prospects and find that both measures of loss aversion correlate highly, which suggests that loss aversion is a constant trait that operates in different decision contexts in a similar way.

Interestingly, if we regress the obtained measurement of loss aversion on socio-demographic characteristics, we find that females are significantly more loss averse than males as the final column of Table 3.6 shows. Conditional on other covariates, females weight losses about 0.416 more heavily than males. The difference in the unconditional means is about the same, with an estimated loss aversion coefficient of 2.10 for women, and 1.66 for men. In addition, higher educated individuals, defined as having a higher vocational education or better, appear to have a much lower degree of loss aversion (−0.497), which is consistent with the unconditional effects found by Schmidt and Traub (2002) and Gächter et al. (2007). This provides evidence that, contrary to classical studies that ascribed gender differences in risk taking behavior solely to differences in the degree of utility curvature (Barsky et al. 1997; Halek and Eisenhauer 2001; Hartog et al. 2002), this phenomenon is to a large extent driven by loss aversion.
When conditioning on other covariates Gächter et al. (2007) do not find any significant gender differences, but find strong effects of age, income and education. We do not find a strong effect of either age or income, which may be caused by differences in the sample compositions, the correlation between the covariates, and also elicitation context. The fact that direction of effects is the same in both studies strengthens the case that loss aversion is a personal trait, but further research into these associations is needed, especially if we want to draw conclusions on the causal effect of education and income on loss aversion and vice-versa.

3.7 Discussion

3.7.1 Discussion of method

We used direct matching to obtain indifferences between prospects. There is evidence that using direct choice between prospects by using a bisection method (Abdellaoui 2000) or by using a multiple price list (Tversky and Kahneman 1992; Holt and Laury 2002) to obtain indifference between prospects yields more reliable results, with fewer choices that are inconsistent within subject (Bostic et al. 1990; Luce 2000). However, using such methods to obtain indifferences is fairly time consuming which was not tractable in this large-scale experiment with the general public.

We used hypothetical incentives in our experiment. There is an extensive debate in experimental methodology about whether real or hypothetical incentives yield better or more reliable data. Camerer and Hogarth (1999) and Hertwig and Ortmann (2001) provide excellent summaries of the ongoing debate. In general, real incentives do seem to reduce data variability (Camerer and Hogarth 1999) and increase risk aversion in choice (Holt and Laury 2002, 2005; Weber et al. 2004; Harrison 2006) and direct matching tasks (Kachelmeier and Shehata 1992). We did not use the incentive compatible Becker-DeGroot-Marschak (BDM) rewarding scheme to implement real incentives for the following reasons. First of all,

\[ \text{It could be argued that this is the case because females and males weight probabilities differently as chapter 4 and a recent study by Fehr-Duda et al. (2006) suggest. It can be shown, however, that our estimate of loss aversion depends proportionally on } (1 - w^{(\frac{1}{2}))}/(1 - w^{(\frac{1}{2}))}. \text{ This means that pessimism with respect to probabilities increases our estimate of loss aversion. This implies that our obtained gender difference in loss} \]
a large part of the experiment concerned substantial losses and, hence, real incentives could not be used for ethical reasons. Second, the BDM scheme is fairly complex (Braga and Starmer 2005) and the BDM scheme is prone to irrational auction strategies (Plott and Zeiler 2005, p. 537). For example, respondents might report a higher matching outcome thinking it is a clever bargaining strategy or respondents might fail to understand that it is a dominant strategy to report their true matching outcome. Because it is important to minimize the burden on respondents in a large-scale experiment, this was another reason for not implementing real incentives. Third, there is evidence that real incentives do not affect results in relatively simple tasks (Camerer and Hogarth 1999), and we conjecture that the trade-off method is less susceptible to hypothetical bias since it measures utility curvature through the changes in the changes in outcomes, not the levels. Hence, any bias of similar magnitude operating on all the answers will leave our measurements of utility curvature unchanged. The effect on the loss aversion questions is ambiguous.28 Fourth and finally, due to practical limitations it is virtually impossible to implement real incentives in a large-scale experiment (Donkers et al. 2001; Guiso and Paiella 2003), although Harrison et al. (2005b) did use real incentives in their study using a representative sample of 253 individuals taken from the Danish population, as did Dohmen et al. (2006) using a representative sample of 450 individuals taken from the German population.

3.7.2 Discussion of the main results

If we compare our findings to other measurements of risk attitudes using large representative datasets, we find that our estimated relative risk coefficient for gains of 0.06 (= 1 – 0.94) is relatively small. For example, Andersen et al. (2008) found a mean risk aversion coefficient of 0.74, and Barsky et al. (1997) found a mean risk tolerance (the reciprocal of the constant relative risk coefficient) of 0.24 which translates into a mean relative risk coefficient of 4.16. The smallest degree of relative risk aversion coefficient found aversion would become even stronger if we allow probabilities weights to differ between the sexes. Hence, the gender coefficient can be interpreted as a lower bound.

28 It is hard to speculate on the effect of hypothetical bias on our measurement of loss aversion. Assuming that individuals are more risk seeking in hypothetical settings (Weber et al. 2004; Harrison 2006), c will be upward biased while d and b will be downward biased. The effect on the resulting loss aversion coefficient, which is proportional to \( \frac{\hat{c}a}{\hat{b}} \), is ambiguous (see footnote 22 and 26).
by Hartog et al. (2002) was 20. Clearly, the difference between these studies and the present study is that all these studies assumed expected utility and hence ignored the important role of probability weighting in the analysis. Hence, our results give empirical support to the conjecture of Rabin (2000b, p.202) being that diminishing marginal utility is an “implausible explanation for appreciable risk aversion, except when the stakes are very large”: utility curvature is less pronounced than suggested by classical utility measurements. Hence, this suggests that the phenomenon probability weighting is valid outside the laboratory, that is, the results support the external validity of subjective probability weighting.

In addition, our results show that utility for money is concave for gains and convex for losses, supporting the presence of a reflection effect (i.e. risk attitudes for gains are the mirror image of risk attitudes for losses) as predicted by prospect theory, but contradicting the classical prediction of universal concavity. Further, we find that lower educated respondents are more loss averse which suggests that measurements of loss aversion based on (highly educated) student samples (e.g. Abdellaoui et al. 2007b) lead to an underestimation of the loss aversion coefficient. Also, our results confirm the common finding that females are more risk averse than males. Contrary to classical studies that ascribed this gender difference solely to differences in the degree of utility curvature (e.g. Barsky et al. 1997; Pålsson 1996; Hartog et al. 2002), our results suggest that this finding is to a large extent caused by gender differences in the degree loss aversion. Finally, we did not find evidence that the degree of utility curvature (e.g. Holt and Laury 2002, 2005; Friend and Blume 1979) or the degree of loss aversion (Abdellaoui et al. 2007b) de- or increased with the size of the gains and losses involved.

3.8 Conclusion

We have obtained parameter-free measurements of the utility component as well as the loss aversion component of risk attitudes using a representative sample from the Dutch population. The results suggest that utility is concave for gains and convex for losses, implying diminishing sensitivity towards outcomes, as predicted by prospect theory. In addition, our results suggest that classical utility measurements overestimate concavity, which can be explained by the ignoring of probability weighting and loss aversion in these measurements. In addition, we have obtained parameter-free measurements of loss aversion. The results show that respondents were significantly loss averse and weighted a
loss about 1.87 times as heavy as a commensurable gain. Interestingly, we have found evidence that males and higher educated persons are significantly less loss averse. The former result suggests that gender differences in risk attitudes are primarily driven by loss aversion and not by utility curvature as suggested by previous studies that assume the classical expected utility model. The latter result suggests that measurements of loss aversion based on relatively highly educated student samples lead to an underestimation of the loss aversion coefficient. Finally, we found that both the degree of utility curvature and the degree of loss aversion are not altered by scaling up the monetary outcomes involved.

3.9 Appendix to chapter 3

3.9.1 Unweighted results

<table>
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<th></th>
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<th>Low (N = 431)</th>
<th>High (N = 383)</th>
<th>LOSSES</th>
<th>Low (N = 360)</th>
<th>High (N = 330)</th>
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<td>(x_i - x_{i-1})</td>
<td>(y_i)</td>
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<td>y_i - y_{i-1}</td>
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<td>(424)</td>
<td>(1297)</td>
<td>(267)</td>
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</tbody>
</table>

Notes: standard deviations in parenthesis. */**/*** significantly higher than its predecessor at the 10/5/1% level (Wilcoxon signed-rank test).

3.9.2 Experimental Instructions (Part I)

[Instructions are translated from Dutch]

Welcome at this experiment on individual decision making. The experiment is about your risk attitude. Some people like to take risks while other people like to avoid risks. The goal of this experiment is gain additional insight into the risk attitude of people living in the Netherlands. This is very important for both scientists and policymakers. If we get a better understanding of how people react to situations involving risk, policy can be adjusted to take this into account (for example with information provision on insurance and pensions,
and advice for saving and investment decisions). Your cooperation at this experiment is thus very important and is highly appreciated.

The questions that will be posed to you during this experiment will not be easy. We therefore ask you to read the following explanation attentively. In this experiment, there are no right or wrong answers. It is exclusively about your own preferences. In those we are interested.

Probabilities (expressed in percentages) play an important role in this experiment. Probabilities indicate the likelihood of certain events. For example, you probably have once heard Erwin Krol say that the probability that it will rain tomorrow is equal to 20 percent (20%). He then means, that rain will fall on 20 out of 100 similar days. During this experiment, probabilities will be illustrated using a wheel, as depicted below.

Suppose that the wheel depicted in the picture above is a wheel consisting of 100 equal parts. Possibly you have seen such a wheel before in television shows such as The Wheel of Fortune. Now imagine that 25 out of 100 parts of the wheel are orange and that 75 out of 100 parts are blue. The probability that the black indicator on the top of the wheel points at an orange part after spinning the wheel is equal to 25% in that case. Similarly, the probability that the black indicator points at an blue part after spinning the wheel is equal to 75%, because 75 out of 100 parts of the wheel are blue. The size of the area of a color on the wheel thus determines the probability that the black indicator will end on a part with that color.

Besides probabilities, lotteries play an important role in this experiment. Perhaps you have participated in a lottery such as the National Postal Code Lottery yourself before. In this experiment, lotteries yield monetary prizes with certain probabilities, similar to the
National Postal Code Lottery. However, the prizes of the lotteries in this experiment can also be negative. If a lottery yields a negative prize, you should imagine yourself that you will have to pay the about amount of money. In the following explanation we will call a negative prize a loss and a positive prize a profit. During this experiment, lotteries will be presented like the example presented below:

In this case, the lottery yields a profit of 1000 Euro with probability 50%. However, with probability 50%, this lottery yields a loss of 200 Euro. You should image that if you participated in this lottery, you would get 1000 Euro with probability 50%, and with probability 50% you would have to pay 200 Euro.

During this experiment you will see two lotteries, named Lottery L (Left) and Lottery R (right), on the top of each page. Between these lotteries you will see a wheel that serves as an aid to illustrate the probabilities used. You will see an example of the layout of the screen on the next page.

In this example, Lottery R yields a profit of 500 Euro with probability 50% and with probability 50% it yields a loss of 200 Euro. You should imagine that, if we would spin the wheel once and the black indicator would point at the orange part of the wheel, Lottery R would yield a profit of 500 Euro. However, if the black marker would point at the blue part of the wheel, Lottery R would yield a loss of 200 Euro.

Similarly, Lottery L yields a loss of 300 Euro with probability 50%. However, as you can see, the upper prize of Lottery L is missing. During this experiment, we will repeatedly ask you for the upper prize of Lottery L (in Euro) that makes Lottery L and Lottery R equally good or bad for you. Thus, we will ask you for the upper prize of Lottery L for which you value both lotteries equally.

You could imagine that most people prefer Lottery L if the upper prize of Lottery L is very high, say 3000 Euro. However, if this prize is not so high, say 500 Euro, most people
would prefer Lottery R. Somewhere between these two prizes there is a “turnover point” for which you value both lotteries equally. For high prizes you will prefer Lottery L and for low prizes you will prefer Lottery R. The turnover point is different for everybody and is determined by your own feeling. To help you a little bit in the choice process, we will report the range of prizes in which the answer of most people lies approximately at each question. How this works precisely will become clear in the practice question that will start if you click on the CONTINUE button below. If something it not clear to you, you can read the explanation of this experiment again by pressing the BACK button below.

[Practice question]

The practice question is now over. The questions you will encounter during this experiment are very familiar to the practice question. If you click on the BEGIN button below, the experiment will start. If you want to go through the explanation of this experiment again, click on the EXPLANATION button. Good luck.
4 A Parametric Analysis of Prospect Theory’s Functionals

4.1 Introduction

After numerous studies systematically falsified the classical expected utility model as descriptive theory of decision making under risk (Allais 1953; Kahneman and Tversky 1979), various new descriptive theories of individual decision making under risk have been developed (Starmer 2000). The most prominent of these non-expected utility models is prospect theory (Kahneman and Tversky 1979; Tversky and Kahneman 1992). Prospect theory entails two fundamental breakaways from the classical model. Instead of defining preferences over wealth, preferences are defined over changes with respect to a flexible reference point, often taken as the status quo. Decision makers are assumed to be less sensitive to changes in outcomes further away from this reference point, which is called diminishing sensitivity, and it is assumed that negative changes (losses) hurt more than positive changes (gains), a phenomenon called loss aversion. This generalization helps explain phenomena such as the equity premium puzzle (Benartzy and Thaler 1995), downward-sloping labor supply (Goette et al. 2004), the End-of-the-day-Effect in horse race betting (McGlathlin 1956), and the co-existence of appreciable small stake- and moderate large stake- risk aversion (Rabin 2000a). Furthermore, linearity in probability is replaced by a subjective probability weighting function that is assumed to have an inverse-S shape, reflecting increased sensitivity toward changes in probabilities near 0 and 1. This accommodates anomalies of the classical model such as the Allais paradox (1953), the co-

* This chapter is based on Booij et al. (2007).
existence of gambling and insurance, betting on long-shots at horse races (Jullien and Salanié 2000), and the avoidance of probabilistic insurance (Wakker et al. 1997).29

The generalization that prospect theory entails breaks the one-to-one relationship between utility curvature and risk attitudes that holds under expected utility. Hence, in the prospect theory framework, risk attitudes are jointly determined by utility curvature, and subjective probability weighting, where outcomes are defined as changes with respect to the status quo. This adds complexity to the interpretation of the degree of risk aversion (preferring the expected value of a prospect to the prospect itself), as it can no longer be summarized into a single index of curvature (Wakker 1994), and it complicates the empirical determination of risk aversion, because of the simultaneous confounding effects of utility curvature and subjective probability weighting (Tversky and Kahneman 1992).

In order to test prospect theory’s hypotheses about the specific functional forms, and to quantify the sources of risk aversion, various authors have attempted to empirically determine the prevailing shape for the utility- and probability-weighting functions. These studies deal with the simultaneity problem by either assuming a parametric form for these functions (Tversky and Kahneman 1992; Camerer and Ho 1994; Tversky and Fox 1995; Donkers et al. 2001; Harrison and Rutström 2007; Abdellaoui et al. 2008) or by exploiting a particular design that permits them to be disentangled non-parametrically (Wakker and Denneffe 1996; Abdellaoui 2000; Bleichrodt and Pinto 2000; Abdellaoui et al. 2007b).

Both approaches have their advantages and drawbacks. The parametric approaches are easy to estimate and interpret, but they suffer from a contamination effect: a misspecification of the utility function will also bias the estimated probability weighting function and vice versa (Abdellaoui 2000). For instance, in the parametric estimation of prospect theory, Harrison and Rutström (2007) assume the one parameter probability weighting function introduced by Tversky and Kahneman (1992). This function may be a misspecification if the true weighting function exhibits underweighting for intermediate and large probabilities, and minimal overweighting of small probabilities. Moreover, the authors assume the probability weighting function for gains and losses to be equal. This assumption will directly affect the loss aversion measure if the degree of pessimism differs between both domains.

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29 For a survey of examples of field phenomena that prospect theory can and expected utility cannot explain, see
Donkers et al. (2001) impose the same restriction and use a one parameter weighting function due to Prelec (1998). Both studies find relatively much utility curvature and a low degree of loss aversion compared to the non-parametric approaches, which suggests that the probability weighting function may have been mis-specified. Another disadvantage of the parametric approach is that allowing for unobserved heterogeneity in the model is necessarily parametric which means the results may depend on the choice of the stochastic error process (Wilcox 2008, p. 265).

The non-parametric methods do not have these problems as no functional forms are assumed beforehand and estimation is conducted at the individual level allowing for full heterogeneity. This approach, however, requires data that have a chained nature which may introduce error propagation leading to less precise inference (Wakker and Deneffe 1996; Blavatskyy 2006) and, in theory, an incentive compatibility problem (Harrison and Rutström 2008).

This chapter aims at combining the best of both approaches by parametrically estimating the complete prospect theory model, thereby allowing for decision errors, using a rich dataset that permits the identification of prospect theory’s functionals without making stringent parametric assumptions. The results have relevance for the empirical issue of whether the utility for losses is convex (Currim and Sarin 1989; Tversky and Kahneman 1992; Abdellaoui 2000; Etchart-Vincent 2004) or concave (Davidson et al. 1957; Laury and Holt 2000 (for real incentives only); Fehr-Duhda et al. 2006; Abdellaoui et al. 2008) and also whether the prevailing shape of the probability weighting function in the population is inverse S-shaped (Kahneman and Tversky 1992; Wu and Gonzales 1996; Fehr-Duhda et al. 2006), linear (Hey and Orme 1994) or convex (Jullien and Salanié 2000; Goeree et al. 2002; van de Kuilen et al. 2006).

The data that are used in this study are obtained from the same representative internet survey that is used in chapter 3, which consists of 27 matching questions per individual. To reduce the dependence on functional form assumptions we use a three stage estimation procedure that exploits the (gamble-) trade-off method for the elicitation of utilities. This method is robust against subjective probability distortion (Wakker and Deneffe 1996) such

Camerer (2000).
that the measurement of utility does not depend on the estimates of the probability weights. Our stochastic specification allows for decision errors, and it naturally accommodates the propagation of errors that is introduced by the chaining of the questions that is at the heart the trade-off method (Blavatskyy 2006). Furthermore, the data contains background variables that can be linked to the obtained preference parameters to shed light on how the various components of risk attitudes vary in the population. Finally, a randomly assigned scaling-up of the outcomes by a factor 10 allows us to test whether utility curvature and probability weighting are sensitive to the magnitude of the stakes (Etchart-Vincent 2004).

The analysis confirms and complements the study in chapter 3 (Booij and van de Kuilen 2007) which presents non-parametric estimates of utility curvature and loss aversion obtained from a subset of the same data. The results reiterate the main finding that utility curvature is close to linear and much less pronounced than suggested by classical utility measurements that neglect probability weighting. Diminishing sensitivity is also found, as predicted by prospect theory but contrary to the classical prediction of universal concavity. Utility for gains and losses is found to be closer to linear compared to other parametric studies, suggesting these may be mis-specified, while the parametric results are a little more curved compared to the non-parametric estimates. This suggests that assuming homogeneity leads to a small downward bias, while providing evidence that error propagation is unlikely to greatly affect the results in the non-parametric analysis.

In addition to these results we find evidence of an inverted-S shaped probability weighting function that is more elevated for losses than for gains, suggesting pessimism in both domains. We do not find evidence that the shape or the degree of elevation of the probability weighting functions depend on the magnitude of the stakes, but the weighting function for gains varies with gender and age. The weighting function for losses seems unrelated to any background variables. These results confirm the common finding that females are more risk averse than males, but contrary to classical studies that ascribed this gender difference solely to differences in the degree of utility curvature, our results show that this finding is primarily driven by subjective probability weighting and loss aversion.

The remainder of this chapter is organized as follows. Section 4.2 discusses prospect theory and summarizes the parametric estimates found in the literature. Section 4.3 presents the experimental method and summary statistics of the data, followed by the presentation of
the econometric specification in section 4.4. The results are presented in section 4.5. Section 4.6 concludes, followed by the appendix to this chapter that provides tables of additional results and experimental instructions.

4.2 Prospect Theory

4.2.1 Parametric specifications

With prospect theory we refer to the modern (cumulative) version described in section 3.3. To make the model empirically tractable, several parametric shapes have been proposed for the utility- and probability weighting functions. The utility function determines individuals’ attitudes towards additional monetary gains and losses. The curvature of this function for gains is often modeled by a power function because of its simplicity and its good fit to (experimental) data (Wakker 2008). Tversky and Kahneman (1992) introduced this function for prospect theory, written as $U(x) = x^\alpha 1(x \geq 0) - \lambda (-x)^\beta 1(x < 0)$. Here the parameters $\alpha$ and $\beta$ determine the curvature of the utility for money gains and losses respectively. The psychological concept of diminishing sensitivity implies that both $\alpha < 1$ and $\beta < 1$, i.e. individuals are decreasingly sensitive to changes further away from the reference point. Less frequently used parametric specifications of the utility function are the exponential and the expo-power utility functions. These functions often have a slightly inferior fit. Their properties are described extensively in Abdellaoui et al. (2007a).

The parameter $\lambda$ determines the utility ratio between a gain of one Euro and a loss of one Euro:

$$\lambda = -\frac{U(-1)}{U(1)}. \quad (4.2.1)$$

30 In its traditional use in the expected utility model, power utility implies that the fraction of wealth that an agent is prepared to pay to forego a fair gamble over percentages of wealth, is constant. Therefore, the power function is commonly referred to as constant relative risk aversion (CRRA). Under non-expected utility models such as prospect theory this designation is no longer appropriate.
This definition of loss aversion is slightly different from that in (3.4.4). Both can be seen as an approximation of the definition proposed by Köbberling and Wakker (2005) 
\( \lambda^{kw} = \frac{U'_r(0)}{U'_s(0)} \). An individual is defined loss averse when \( \lambda > 1 \).

The probability weighting function captures the degree of sensitivity towards probabilities. Two distinct properties of this function have been put forward, that can be given a psychological interpretation. The first property refers to the degree of curvature of the probability weighting function, which reflects the degree of discriminability with respect to changes in probabilities. This property is closely linked to the notion of diminishing sensitivity, where the probability of 0 (impossibility) and 1 (certainty) serve as reference points. According to this psychological hypothesis, people’s behavior becomes less responsive to changes on the probability scale as they move further away from these reference points. This implies an inverse-S shaped weighting function, with relatively much curvature near the probability end points and a linear shape in between. The second property of the probability weighting function refers to its elevation, which determines the degree of attractiveness of gambling (Gonzalez and Wu 1999). For gains (losses), a highly elevated probability weighting function implies that individuals are optimistic (pessimistic), and overweight probabilities relative to the objective probabilities of winning (losing).

Several parametric functions have been proposed to describe the probably weighting function (see Stott 2006 for an overview). The most commonly used specification is the linear-in-log-odds specification, introduced by Goldstein and Einhorn (1987) (GE-87), and given by:

\[
\omega(p) = \frac{\delta p^\gamma}{(\delta p^\gamma + (1 - p)^\gamma)}. \\
\]

The popularity of this function stems from its empirical tractability and the fact that it has two parameters \( \gamma \) and \( \delta \), that separately control curvature and elevation respectively. Hence, both parameters can readily be given a psychological interpretation as indexes of discriminability and attractiveness. Another popular specification in which \( \gamma \) and \( \delta \) have a

---

31 Both measures will be almost identical if utility for gains is not significantly more curved over the interval \([1, x]\) than utility of losses over the interval \([y, -1]\). Given the approximate linearity of utility over these short intervals (Wakker and Denefle 1996), this is likely to hold approximately.
similar interpretation is the two parameter specification due to Prelec (1998) (Prelec-2), given by:

\[ w(p) = \exp(-\delta(-\ln p)^\gamma). \]

The GE-87 specification has an inverted-S shape when \( 0 < \gamma < 1 \). An additional (sufficient) condition for the Prelec-2 function is \( 0 < \delta < 1 \). One-parameter specifications have also been used to describe the probability weighting function, but these cannot set curvature and elevation independently. Estimates of these probability weighting functions will lead to biased inferences if curvature and elevation do not co-vary accordingly.

4.2.2 Empirical evidence

Table 4.1 gives the definition and estimates of the power utility function and some commonly used one- and two-parameter probability weighting functions. All the mentioned studies estimate prospect theory, albeit with varying (parametric) assumptions, incentives, tasks and samples. Although the table is not intended to be exhaustive, it covers most studies that somehow report a parametric measure of utility curvature, loss aversion or probability weighting under prospect theory. Studies that do not report such estimates are not included in the table, which means that not all studies mentioned in the introduction are listed. If multiple measures of loss aversion are reported we take the definition that most closely resembles that of Köbberling and Wakker (2005).

With respect to the shape of the utility function the table reveals four notable features. First of all, the utility for gains is much closer to linearity (a power equal to 1) than what is found in classical utility measurements that do not take probability weighting into account. In that literature estimates just below .5 (Cubitt et al. 2001; Holt and Laury 2002; Harrison et al. 2005b; Andersen et al. 2008) or lower (Barsky et al. 1997; Dohmen et al. 2006) are common. Second, in all studies that report utility curvature for gains and losses, losses are evaluated more linearly than gains, but utility for losses does display diminishing sensitivity \((\beta < 1)\) in most studies. This suggests that people become less sensitive towards additional gains more rapidly as compared to additional losses. Third, there is some variability in the estimates, but the power parameters for both domains are always quite close. This suggests that the differences in the estimates between studies most likely stem from differences in the
elicitation method and the method of analysis. Fourth, there is significant variation in the
coefficient of loss aversion, but it is always estimated to be higher than one.

Table 4.1: Empirical estimates of prospect theory using different parametric functionals

<table>
<thead>
<tr>
<th>Functional Form, name</th>
<th>Estimates</th>
<th>Properties**</th>
<th>Authors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Utility</td>
<td>$a$</td>
<td>$\beta$</td>
<td>$\lambda$</td>
</tr>
<tr>
<td>$U(x) = x^\alpha 1{x \geq 0} - \lambda (x^\beta 1{x &lt; 0})$</td>
<td>.88</td>
<td>.88</td>
<td>2.25</td>
</tr>
<tr>
<td></td>
<td>.22</td>
<td>ml</td>
<td>c</td>
</tr>
<tr>
<td></td>
<td>.50</td>
<td>ml</td>
<td>c</td>
</tr>
<tr>
<td></td>
<td>.59</td>
<td>md</td>
<td>c</td>
</tr>
<tr>
<td></td>
<td>.49</td>
<td>md</td>
<td>c</td>
</tr>
<tr>
<td></td>
<td>.89</td>
<td>md</td>
<td>c</td>
</tr>
<tr>
<td></td>
<td>.61</td>
<td>ml</td>
<td>b</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>.91</td>
<td>md</td>
<td>c</td>
</tr>
<tr>
<td></td>
<td>.68</td>
<td>ml</td>
<td>b</td>
</tr>
<tr>
<td></td>
<td>1.01</td>
<td>md</td>
<td>c</td>
</tr>
<tr>
<td></td>
<td>.72</td>
<td>md</td>
<td>c</td>
</tr>
<tr>
<td></td>
<td>.81</td>
<td>ml</td>
<td>c</td>
</tr>
<tr>
<td></td>
<td>.71</td>
<td>ml</td>
<td>c</td>
</tr>
<tr>
<td></td>
<td>.86</td>
<td>md</td>
<td>c</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Probability weights.</th>
<th>$\delta^*$</th>
<th>$\gamma^*$</th>
<th>$\delta^*$</th>
<th>$\gamma^*$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\omega(p) = \frac{p^\gamma}{\left[p^\gamma + (1-p)^\gamma\right]}$, TK-92.</td>
<td>.61</td>
<td>.69</td>
<td>c</td>
<td>n</td>
</tr>
<tr>
<td></td>
<td>.56</td>
<td></td>
<td>c</td>
<td>n</td>
</tr>
<tr>
<td></td>
<td>.71</td>
<td></td>
<td>c</td>
<td>n</td>
</tr>
<tr>
<td></td>
<td>.60</td>
<td>.70</td>
<td>c</td>
<td>y</td>
</tr>
<tr>
<td></td>
<td>.67</td>
<td></td>
<td>m</td>
<td>n</td>
</tr>
<tr>
<td></td>
<td>.76</td>
<td>.76</td>
<td>c</td>
<td>y</td>
</tr>
<tr>
<td></td>
<td>.91</td>
<td>.91</td>
<td>c</td>
<td>y</td>
</tr>
<tr>
<td></td>
<td>.84</td>
<td>.68</td>
<td>c</td>
<td>n</td>
</tr>
<tr>
<td></td>
<td>.77</td>
<td>.69</td>
<td>md</td>
<td>c</td>
</tr>
<tr>
<td></td>
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<td>y</td>
</tr>
<tr>
<td></td>
<td>.65</td>
<td>.60</td>
<td>.84</td>
<td>.65</td>
</tr>
<tr>
<td></td>
<td>.82</td>
<td>.55</td>
<td>m</td>
<td>n</td>
</tr>
<tr>
<td></td>
<td>.98</td>
<td>.83</td>
<td>1.35</td>
<td>.84</td>
</tr>
<tr>
<td></td>
<td>.41</td>
<td>1.24</td>
<td>c</td>
<td>y</td>
</tr>
<tr>
<td></td>
<td>.87</td>
<td>.51</td>
<td>1.07</td>
<td>.53</td>
</tr>
<tr>
<td></td>
<td>.74</td>
<td>.74</td>
<td>c</td>
<td>n</td>
</tr>
<tr>
<td></td>
<td>.53</td>
<td>.53</td>
<td>m</td>
<td>n</td>
</tr>
<tr>
<td></td>
<td>.413</td>
<td>.413</td>
<td>b</td>
<td>n</td>
</tr>
<tr>
<td></td>
<td>1.00</td>
<td>.77</td>
<td>b</td>
<td>n</td>
</tr>
<tr>
<td></td>
<td>1.08</td>
<td>.53</td>
<td>m</td>
<td>n</td>
</tr>
<tr>
<td></td>
<td>2.12</td>
<td>.96</td>
<td>ml</td>
<td>m</td>
</tr>
</tbody>
</table>

Notes: Adopted names and notations do not form a convention, and are used for convenience. As reported in the text, $\gamma$ mainly controls curvature (sensitivity) and $\delta$ mainly controls elevation (attractiveness) of the probability weighting function. $+/−$ denote gains/losses.

* The utility functional is specified on the complete real axis, where $\lambda$ represents the loss aversion coefficient which creates a kink in utility at the status quo. The displayed utility function is based on the assumption $a > 0$ and $\beta > 0$, which is mostly found empirically. The function has a different specification for other parameter values (Wakker 2008).

** Properties: E( estimator); m: mean; md: median; ml: maximum likelihood; T(task); c: choice; m: matching; b: both; I(incentives): yes (random lottery incentive scheme/Becker de Groot-Marschak procedure; no (fixed or no payment).
The table conveys three other notable features with respect to the estimated shape of the probability weighting function. The predominant shape is inverse-S, with few studies reporting \( \gamma > 1 \). Also, for studies that report estimates of both domains, elevation is higher in the loss domain. This is intuitively plausible because it suggests that in both domains individuals display pessimism, i.e. they dislike gambling. Finally, the estimates of elevation show a little less variability than those of curvature, suggesting that curvature is harder to identify empirically.

The coefficients of loss aversion reported in Table 4.1 range from 1.07 to 3.2. Hence, all studies find evidence of loss aversion, albeit to varying degrees. This may be caused by differing definitions of loss aversion and different elicitation contexts. Figure 4.1 plots a power utility function and a GE-87 probability weighting function for gains and losses corresponding to the average of the estimates found in Table 4.1. The next section describes the data that will enable us to identify utility curvature and probability weighting for a representative sample.

**Figure 4.1**: Utility and probability weighting functions for average estimates

![Utility and probability weighting functions](image)

Note: Figure based on the average of the estimates from Table 4.1. \((a, \beta, \gamma) = (0.69, 0.86, 2.07)\) and 
\((\delta', \gamma', \gamma') = (0.76, 0.69, 1.09, 0.72)\).

### 4.3 The Data

#### 4.3.1 Survey design

*Participants.* For the elicitation of both utility curvature and subjective probability weighting we used the same internet questionnaire that was used in chapter 3. There, only the first part of the questionnaire (Q1 – Q16) is used to non-parametrically identify utility for a representative sample of the Dutch population (see section 3.5 for details). The second part
of the questionnaire (Q17 – Q27) consists of questions that, in conjunction with the first part, allow for the determination of the probability weighting function for gains and losses, which is the aim of this chapter.

Procedure. After completion of the first part, respondents first read experimental instructions for the second part (section 4.7.2), followed by a practice question. In this part indifference was obtained through probability matching, i.e. in Figure 4.2 subjects were asked to report the (missing) probability that would make them indifferent between two particular lotteries, where the parameters \((L_2, R_1, R_2)\) differed between questions. After filling in a specific number the areas in the wheel were filled accordingly and the respondent was asked to confirm his choice or reconsider.

Figure 4.2: The Framing of the Prospect Pairs in Part II

![Figure 4.2](image)

Note: The specific parameter values varied between the questions, see Table 4.2.

Table 4.2 gives a full description of the parameter values of the questions of the second part. The ten main questions Q18 – Q27 re-used the answers \(x_0, \ldots, x_6, y_0, \ldots, y_6\) given in the first part, and asked the respondents to give the probability that would make them indifferent between the two prospects (Figure 4.2). For example, if an individual responded with \(x_2=€180\) and \(x_6=€800\) in the first part, then Q18 would elicit the probability \(p_1\) that made him indifferent between prospects (€180) and \((p_2: €800, €100)\).

The questions of the second part allow for the non-parametric determination of the subjective probability weighting functions at the individual level if one assumes that no stochastic errors have been made in the elicitation of the indifference outcomes \((x_0, \ldots, x_6, y_0, \ldots, y_6)\) in the first part. To see this, consider the domain of gains and assume that there is no stochastic error component in the subjects’ responses. Then, under prospect theory, the
reported probabilities $p_i$ satisfy $w(p_i) = ((U(x_i) - U(x_0)) / ((U(x_0) - U(x_o)))$. Given that the outcomes $x_0, \ldots, x_6$ comprise a standard sequence of outcomes, there holds $U(x_i) - U(x_j) = U(x_{i+1}) - U(x_i)$ for $i = 1, \ldots, 5$. This implies that $((U(x_i) - U(x_0)) / ((U(x_0) - U(x_o))) = i / 6$, and hence $w(p_i) = i / 6$ (Abdellaoui 2000). However, in the presence of error this correspondence need no longer hold because the outcomes $x_0, \ldots, x_6$ are then, in general, not equally spaced in utility units. The econometric specification we use explicitly accounts for this in the analysis of the responses to these questions.

4.3.2 Summary statistics

For the estimation of utility curvature and loss aversion we use the questions from the first part of the experiment (see section 3.5) for the same sample as in chapter 3, i.e. we use only individuals that gave monotonous responses in the first part. The order of the probability matching questions that were posed in the second part was completely random, meaning that subjects could not have an easy comparison with questions that had outcomes close in magnitude. This increases the likelihood of an inconsistent answer. Moreover, these questions are likely to be more cognitively demanding for respondents. Hence, in the second part we allowed for one mistake (meaning a violation of dominance) in the subjects’ answers before classifying them as inconsistent. Furthermore, we only considered individuals in the

<table>
<thead>
<tr>
<th>Matching Question</th>
<th>Prospect L ($p_i$)</th>
<th>Prospect R ($p$: $R_1, R_2$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>17 (practice)</td>
<td>(250)</td>
<td>($p$: $R_1, R_2$)</td>
</tr>
<tr>
<td>18*</td>
<td>($x_i$)</td>
<td>($p$: $x_0, x_0$)</td>
</tr>
<tr>
<td>19*</td>
<td>($y_i$)</td>
<td>($p$: $y_0, y_0$)</td>
</tr>
<tr>
<td>20*</td>
<td>($x_i$)</td>
<td>($p$: $x_0, x_0$)</td>
</tr>
<tr>
<td>21*</td>
<td>($y_i$)</td>
<td>($p$: $y_0, y_0$)</td>
</tr>
<tr>
<td>22*</td>
<td>($x_i$)</td>
<td>($p$: $x_0, x_0$)</td>
</tr>
<tr>
<td>23*</td>
<td>($y_i$)</td>
<td>($p$: $y_0, y_0$)</td>
</tr>
<tr>
<td>24*</td>
<td>($x_i$)</td>
<td>($p$: $x_0, x_0$)</td>
</tr>
<tr>
<td>25*</td>
<td>($y_i$)</td>
<td>($p$: $y_0, y_0$)</td>
</tr>
<tr>
<td>26*</td>
<td>($x_i$)</td>
<td>($p$: $x_0, x_0$)</td>
</tr>
<tr>
<td>27*</td>
<td>($y_i$)</td>
<td>($p$: $y_0, y_0$)</td>
</tr>
</tbody>
</table>

Note: Underlined outcomes are the matching probabilities and questions marked with an asterisk were presented in randomized order. The specific values $x_i$ and $y_i$ are obtained in the first part.
second part if they had been classified consistent in the first, because the questions in the second part were determined by the first. Of the remaining data we removed some outlying answers that clearly indicated either a mistake or lack of understanding (denoted by Outlier). As in chapter 3, we estimated a sample-selection equation and used the inverse of the predicted probabilities as weights in the econometric analysis to control for a potential bias due to sample selectivity (see section 4.7.1). This procedure yields unbiased estimates if sample selection is random conditional on the selection variables. Most coefficients were not greatly affected by this procedure, except for the measure of loss aversion, which is adjusted upwards as in chapter 3 because men and higher educated people are over-represented in the sample. The sample selection process was already discussed in more detail in section 3.6.1. Table 4.3 gives the summary statistics of the selected sample.

Table 4.3: Summary Statistics (unweighted)

<table>
<thead>
<tr>
<th></th>
<th>$x_1$</th>
<th>$y_i$</th>
<th>$p_i$</th>
<th>$q_i$</th>
<th>$b$</th>
</tr>
</thead>
<tbody>
<tr>
<td>i</td>
<td>High</td>
<td>Low</td>
<td>High</td>
<td>Low</td>
<td>High</td>
</tr>
<tr>
<td>1</td>
<td>€1993</td>
<td>€205</td>
<td>€−851</td>
<td>€−86</td>
<td>27.3%</td>
</tr>
<tr>
<td></td>
<td>(602)</td>
<td>(94)</td>
<td>(231)</td>
<td>(36)</td>
<td>(15.3)</td>
</tr>
<tr>
<td>2</td>
<td>€3000</td>
<td>€319</td>
<td>€−1243</td>
<td>€−126</td>
<td>41.4%</td>
</tr>
<tr>
<td></td>
<td>(1131)</td>
<td>(184)</td>
<td>(431)</td>
<td>(59)</td>
<td>(17.5)</td>
</tr>
<tr>
<td>3</td>
<td>€4060</td>
<td>€441</td>
<td>€−1664</td>
<td>€−168</td>
<td>51.6%</td>
</tr>
<tr>
<td></td>
<td>(1692)</td>
<td>(313)</td>
<td>(634)</td>
<td>(83)</td>
<td>(17.4)</td>
</tr>
<tr>
<td>4</td>
<td>€5161</td>
<td>€576</td>
<td>€−2075</td>
<td>€−211</td>
<td>62.5%</td>
</tr>
<tr>
<td></td>
<td>(2311)</td>
<td>(561)</td>
<td>(856)</td>
<td>(106)</td>
<td>(18.7)</td>
</tr>
<tr>
<td>5</td>
<td>€6283</td>
<td>€727</td>
<td>€−2494</td>
<td>€−254</td>
<td>75.9%</td>
</tr>
<tr>
<td></td>
<td>(2980)</td>
<td>(865)</td>
<td>(1069)</td>
<td>(130)</td>
<td>(19.2)</td>
</tr>
<tr>
<td>6</td>
<td>€7447</td>
<td>€893</td>
<td>€−2920</td>
<td>€−298</td>
<td>89.3%</td>
</tr>
<tr>
<td></td>
<td>(3713)</td>
<td>(1244)</td>
<td>(1297)</td>
<td>(156)</td>
<td>&quot;&quot;</td>
</tr>
<tr>
<td>N</td>
<td>383</td>
<td>431</td>
<td>330</td>
<td>360</td>
<td>184</td>
</tr>
<tr>
<td>Non-R.</td>
<td>187</td>
<td>188</td>
<td>210</td>
<td>212</td>
<td>126</td>
</tr>
<tr>
<td>Non-M.</td>
<td>388</td>
<td>340</td>
<td>422</td>
<td>389</td>
<td>73</td>
</tr>
<tr>
<td>Outlier</td>
<td>13</td>
<td>5</td>
<td>9</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>Total</td>
<td>971</td>
<td>964</td>
<td>971</td>
<td>964</td>
<td>383</td>
</tr>
</tbody>
</table>

Note: Standard deviations in parentheses.

The table readily shows some apparent features of the data. The differences between subsequent outcomes of the standard sequence are gradually increasing, suggesting mild concavity in the utility for gains and mild convexity for losses. Also, the probabilities reported in the gain domain are all uniformly higher than the ones in the loss domain suggesting more elevation in the probability weighting function for losses. This is consistent with pessimism with respect to gambling in both domains. Finally, the outcomes between the high and the low treatments are mostly close to a scaling up by a factor 10, suggesting no difference between treatments.
4.4 The econometric model

Following Wakker and Deneffe (1996) and Abdellaoui (2000), Booij and van de Kuilen (2007, chapter 3) exploit the sequential nature of the questions to analyze the shape of the utility function non-parametrically. This approach has the advantage of being robust against probability weighting and allowing for full heterogeneity in preferences, i.e. they estimate the shape of the utility curve for each individual without making any prior parametric assumption. The disadvantage of this approach is that individual error is not explicitly accounted for statistically, and potential error propagation is not modeled. Also, for the second part, errors generating monotonicity violations would yield uninterpretable weighting functions (recall that we allow for one monotonicity violation in the second part) if errors are not modeled in the analysis. Moreover, Wilcox (2008, pp. 264-265) shows that individual level estimation can suffer from a finite-sample bias leading to biased predictions. By smoothing out errors a parametric approach can alleviate these problems (Currim and Sarin 1989), albeit at the cost of having to make auxiliary assumptions.

Under prospect theory, as described in section 3.3, the questions in the experiment yield the following equations

\begin{align*}
\omega^+ \left( \frac{1}{2} \right) (U(x_{i,n}) - U(x_{i-1,n})) &= (1 - \omega^+ \left( \frac{1}{2} \right)) (U(G_n) - U(g_n)) \cdot e_{i,n}^+ \cdot \eta_n^+ \quad i = 1, \ldots, 6, \\
\omega^- \left( \frac{1}{2} \right) (U(y_{i,n}) - U(y_{i-1,n})) &= (1 - \omega^- \left( \frac{1}{2} \right)) (U(L_n) - U(l_n)) \cdot e_{i,n}^- \cdot \eta_n^- \quad i = 1, \ldots, 6, \\
U(x_{i,n}) - U(x_{0,n}) &= \omega^+ \left( p_{i,n} \right) \left( U(x_{0,n}) - U(x_{i,n}) \right) \cdot e_{i,n}^+ \quad i = 1, \ldots, 5, \\
U(y_{i,n}) - U(y_{0,n}) &= \omega^- \left( p_{i,n} \right) \left( U(y_{0,n}) - U(y_{i,n}) \right) \cdot e_{i,n}^- \quad i = 1, \ldots, 5, \\
w^+ \left( \frac{1}{2} \right) \left( U(b_n) - U(x_{i,n}) \right) &= \left( 1 - w^+ \left( \frac{1}{2} \right) \right) U(x_{0,n}) \cdot e_n^b, \\
w^- \left( \frac{1}{2} \right) \left( U(c_n) - U(y_{i,n}) \right) &= \left( 1 - w^- \left( \frac{1}{2} \right) \right) U(y_{0,n}) \cdot e_n^c, \\
w^+ \left( \frac{1}{2} \right) \left( U(d_n) - U(x_{0,n}) \right) &= w^+ \left( \frac{1}{2} \right) \left( U(y_{0,n}) - U(y_{i,n}) \right) \cdot e_n^d, \\
\end{align*}

where we allow for a multiplicative stochastic error \( e_{i,n}^r \), including individual specific effects \( \eta_n^r \) that capture differences in probability weighting between individuals \( n \). In the superscripts, \( o \) and \( p \) denote outcomes and probabilities respectively, and the + and – signs denote the gain and the loss domain. The letters \( b, c, d \), refer to the corresponding loss aversion questions (see section 3.5).
The errors are assumed to be independently log-normally distributed with different variances, i.e. \( \epsilon'_{i,n} \sim LN\left(0, \sigma_i^2\right) \). This is a Fechner model on the log of the value scale, similar to the model employed by Donkers et al. (2001). We chose a multiplicative specification over an additive one (e.g. Blavatskyy 2006) because it naturally satisfies monotonicity. An additive specification would require a truncated error distribution to satisfy monotonicity (Blavatskyy 2007), which is numerically much more involved. Also, we chose the common Fechner structure over a random preference specification or a “trembling hand” specification, two other popular stochastic models (Wilcox 2008). In the first stochastic framework it would be hard to eliminate individual effects, while it is unclear how to implement the second in a continuous outcome context. The consequences of different error specifications in models of decision making under risk has attracted increased attention since the seminal paper by Hey and Orme (1994). There is, however, currently no consensus in the literature on what error structure to use (Hey 1995; Loomes and Sugden 1995; Carbone and Hey 2000; Blavatskyy 2007).

In order to eliminate the probability weighting terms and potential individual specific effects, subsequent outcome equations can be divided by one another. To make the current study consistent with chapter 3, loss aversion is estimated using all questions around the zero outcome. Taking logarithms then gives

\[
\begin{align*}
\epsilon_{i,n}^o &\equiv \ln \left(\frac{e_{i,n}^o}{e_{i,n}^i}\right) = \ln \left(\frac{U(x_{i+1,n}) - U(x_{i,n})}{U(x_{i,n}) - U(x_{i-1,n})}\right) \quad i = 1,\ldots,5, \\ \epsilon_{i,n}^p &\equiv \ln \left(\frac{e_{i,n}^o}{e_{i,n}^i}\right) = \ln \left(\frac{U(y_{i+1,n}) - U(y_{i,n})}{U(y_{i,n}) - U(y_{i-1,n})}\right) \quad i = 1,\ldots,5, \\ \epsilon_{i,n}^r &\equiv \ln \left(\frac{\epsilon_{i,n}^o}{\epsilon_{i,n}^p}\right) = \ln \left(\frac{w^*(p_i)U(x_{0,n}) - U(x_{0,n})}{U(x_{i,n}) - U(x_{0,n})}\right) \quad i = 1,\ldots,5, \\ \epsilon_{i,n}^{LA} &\equiv \ln \left(\frac{\epsilon_{i,n}^d / \epsilon_{i,n}^c}{\epsilon_{i,n}^o}\right) = \ln \left(\frac{(1-w^* \left(\frac{1}{2}\right)) \left(\frac{U(d) - U(x_{0,n})}{U(c) - U(x_{0,n})}\right) \left(\frac{U(y_{1,n}) - U(y_{0,n})}{U(y_{0,n}) - U(y_{1,n})}\right)}{(1-w^* \left(\frac{1}{2}\right)) \left(\frac{U(b_n) - U(x_{1,n})}{U(c_n) - U(x_{1,n})}\right) \left(\frac{U(y_{0,n}) - U(y_{1,n})}{U(y_{0,n}) - U(y_{1,n})}\right)}\right), \quad (4.4.8)
\end{align*}
\]

where LA, denotes loss aversion. Under the assumptions of (4.4.1)-(4.4.7), the transformed error terms, collected in \( \epsilon_n = (\epsilon_{1,n}^o, \epsilon_{2,n}^o, \ldots, \epsilon_{5,n}^o, \epsilon_{1,n}^p, \ldots, \epsilon_{5,n}^p, \epsilon_{1,n}^{LA}, \ldots, \epsilon_{5,n}^{LA}) \),
Prospect Theory’s Functionals

\( \varepsilon_{1,n^\prime}, \varepsilon_{2,n^\prime}, \varepsilon_{3,n^\prime} \), are normally distributed with zero mean and covariance matrix \( \Sigma \). This matrix has off-diagonal elements equal to zero, except for the outcome equations (4.4.1) and (4.4.2). The first differencing applied to these equations generates a correlation between the subsequent error terms. For example, assuming constant error variance, the covariance matrix for positive outcomes is a tridiagonal matrix equal to

\[
\Sigma^+ = \text{cov} \left[ \varepsilon_{1,n^\prime}, \varepsilon_{2,n^\prime}, \varepsilon_{3,n^\prime} \right] = 2\sigma^2 \begin{pmatrix} 1 & -\frac{1}{2} & 0 & \cdots & 0 \\ -\frac{1}{2} & 1 & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & 0 \\ 0 & \cdots & 1 & -\frac{1}{2} \\ 0 & \cdots & 0 & -\frac{1}{2} & 1 \end{pmatrix}.
\]

(4.4.13)

In this example the correlation between each subsequent error is \(-\frac{1}{2}\). In general the first off-diagonal elements will vary. Hence, we will assume the covariance matrices of the outcome domains \( (\Sigma^+, \Sigma^-) \) to be fully flexible in the empirical analysis. Because the questions of the second part are not chained we simply assume the matrixes \( \Sigma^+, \Sigma^- \) to have equal (non-zero) diagonal and off-diagonal elements. By assuming non-zero off diagonal elements, within-subject correlation in the answers is accounted for. The mean of the diagonal and off-diagonal elements are given by \( \bar{\sigma} \) and \( \bar{\rho} \) respectively.

To estimate the model we assume two popular parametric specifications. For utility we take the common power specification, with a loss aversion factor \( \lambda \), as specified by Kahneman and Tversky (1979). For the subjective weighting of cumulative probabilities we take the frequently used linear-in-log-odds specification as first employed by Goltstein and Einhorn (1987). These parametric families have been shown to have a good fit to experimental data (Gonzalez and Wu 1999; Abdellaoui 2008). The probability weighting functions of both domains are allowed to differ as is assumed in the modern version of prospect theory. We have

---

32 To see this, consider the covariance of two subsequent errors in the gain domain:

\[
\text{cov} \left[ \varepsilon_{1,n^\prime}, \varepsilon_{2,n^\prime} \right] = \text{cov} \left[ \ln \varepsilon_{1,n^\prime}, \ln \varepsilon_{2,n^\prime} - \ln \varepsilon_{1,n^\prime} \right] = \text{cov} \left[ \ln \varepsilon_{1,n^\prime}, \ln \varepsilon_{2,n^\prime} \right] - \text{cov} \left[ \ln \varepsilon_{1,n^\prime}, \ln \varepsilon_{1,n^\prime} \right] - \text{cov} \left[ \ln \varepsilon_{2,n^\prime}, \ln \varepsilon_{2,n^\prime} \right]
\]

\[+ \text{cov} \left[ \ln \varepsilon_{1,n^\prime}, \ln \varepsilon_{2,n^\prime} \right] = 0 - \sigma^2 - 0 + 0 = -\sigma^2.\]

The correlation then becomes:

\[
\text{corr} \left[ \varepsilon_{1,n^\prime}, \varepsilon_{2,n^\prime} \right] = \frac{\text{cov} \left[ \varepsilon_{1,n^\prime}, \varepsilon_{2,n^\prime} \right]}{\sqrt{\text{var} \left[ \varepsilon_{1,n^\prime} \right] \cdot \text{var} \left[ \varepsilon_{2,n^\prime} \right]}} = -\sigma^2 \sqrt{2\sigma^2 \cdot 2\sigma^2} = -\frac{1}{2}.
\]

33 In the context of discrete choice Stott (2006) shows that the more parsimonious one parameter specifications often provide a sufficient fit in terms of the Akaike information criterion.
\[
U(x; \alpha, \beta, \lambda) = \begin{cases} 
  x^\alpha & x \geq 0 \\
-\lambda(-x)^\beta & x < 0 
\end{cases} \tag{4.4.14}
\]

\[
w^+(p; \delta^+, \gamma^+) = \frac{\delta^+ p^{\gamma^+}}{\delta^+ p^{\gamma^+} + (1 - p)^{\gamma^+}} \tag{4.4.15}
\]

\[
w^-(p; \delta^-, \gamma^-) = \frac{\delta^- p^{\gamma^-}}{\delta^- p^{\gamma^-} + (1 - p)^{\gamma^-}}. \tag{4.4.16}
\]

This gives the log-likelihood function:

\[
\ell(\alpha, \beta, \lambda, \delta^+, \gamma^+, \delta^-, \gamma^-) = \sum_{n=1}^N \left\{ \ln 2\pi + 2\ln |\Sigma| + e_n^T \Sigma^{-1} e_n \right\}. \tag{4.4.16}
\]

To estimate the model we split up the likelihood and use a three stage procedure (limited-information maximum likelihood, LIML) to estimate utilities, and subsequently the probability weighting function and loss aversion. This has two advantages. First of all, it will ensure that the estimated utility curve will not suffer from a functional-form misspecification bias due to misspecification of the probability weighting function. This is precisely what Wakker and Deneffe’s (1996) trade-off method is designed for. Using full-information maximum likelihood would eliminate this advantage by re-introducing an interaction between the estimation of probability weighting and utility curvature. Also, the outcome matching questions (Part I) are generally believed to be easier to respond to and give higher quality data. Hence we base the estimate of utility only on the questions from the first part. In the second stage the probability weighting functions are estimated using the estimates of utility from the first stage. Loss aversion is estimated in the final stage, taking the estimated utility and probability weighting functions as given. Table 4.4 summarizes the estimation strategy.

<table>
<thead>
<tr>
<th>Table 4.4: Estimation Strategy</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>1ST STAGE</strong></td>
</tr>
<tr>
<td>(OUTCOMES)</td>
</tr>
<tr>
<td>Gains</td>
</tr>
<tr>
<td>Losses</td>
</tr>
<tr>
<td>( \text{cov} )</td>
</tr>
</tbody>
</table>

By splitting up the estimation we cannot determine the correlations between the errors of the different question modules, i.e. utilities and probabilities, gains and losses. This is
unfortunate since it would be interesting to know whether there is unobserved heterogeneity that affects the answers in both domains in a structural way, but it does bias the results. The standard errors in the second and third stages are corrected for the uncertainty in the first stage estimates by using the adjustment specified by Murphy and Topel (1979).

4.5 Results

The model as such assumes homogeneity in preferences. A certain degree of heterogeneity can be implemented, however, by parameterizing the preference parameters \( \phi = (\alpha, \beta, \lambda, \delta', \gamma^*, \delta', \gamma^-) \)' by a linear combination of regressors, i.e. \( \phi = B'X \). Hence, apart from estimating the average shape of utility and probability weighting we can test whether there are significant differences in these preferences with respect to variables such as age, gender, education and income. The first row of estimates in Table 4.5 gives the results of the model with only a constant, while the second gives the model with the set of demographic variables that appear to be associated with prospect theory’s parameters.

---

34 Note that for the same reason we would not be able to estimate any correlation between random coefficients if they were specified. This is done in Tu (2005), who is unable to identify most correlations, but the ones he does indicate a negative correlation in risk aversion caused by the outcome and probability domain. However, Tu’s model is not non-parametrically identified, so it is unclear whether this correlation is genuine or stems from non-linearity.

35 The correction specified by Murphy and Topel (1979) amounts to calculating

\[
\hat{V}_{2}^{\text{HT}} = \hat{V}_{1} + \hat{V}_{1}'[\hat{C}_{1} \hat{C}' - \hat{R}_{1} \hat{R}' \hat{R}_{1}] \hat{V}_{1}
\]

where \( \hat{V}_{1} \) and \( \hat{V}_{1} \) are the respective first- and second-stage covariance estimates, and \( C = \sum_{i=1}^{n} \left( \frac{\partial u_{1}(a)}{\partial x_{i}} \right) \left( \frac{\partial u_{2}(a)}{\partial x_{i}} \right) \) and \( R = \sum_{i=1}^{n} \left( \frac{\partial u_{1}(a)}{\partial x_{i}} \right) \left( \frac{\partial u_{2}(a)}{\partial x_{i}} \right) \).
Table 4.5: Maximum likelihood estimates

<table>
<thead>
<tr>
<th>Preference parameter</th>
<th>Gains</th>
<th>Losses</th>
<th>Loss. Av.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\alpha$</td>
<td>$\delta^*$</td>
<td>$\gamma^*$</td>
</tr>
<tr>
<td><strong>Constant only</strong></td>
<td>0.859***</td>
<td>0.772***</td>
<td>0.618***</td>
</tr>
<tr>
<td></td>
<td>(0.018)</td>
<td>(0.051)</td>
<td>(0.038)</td>
</tr>
<tr>
<td><strong>Low Amounts</strong></td>
<td>0.003***</td>
<td>0.004***</td>
<td>0.006***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.004)</td>
<td>(0.002)</td>
</tr>
<tr>
<td><strong>High Education</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>In(Income+1)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Weighted Average</strong></td>
<td>0.863</td>
<td>0.779</td>
<td>0.608</td>
</tr>
<tr>
<td>$\bar{\sigma}$</td>
<td>0.188***</td>
<td>0.267***</td>
<td>0.302***</td>
</tr>
<tr>
<td>$\bar{p}$</td>
<td>-0.354***</td>
<td>0.133***</td>
<td>-0.062</td>
</tr>
<tr>
<td>$t$</td>
<td>-13870.9</td>
<td>-16080.7</td>
<td>-14431.0</td>
</tr>
<tr>
<td>$N$</td>
<td>814</td>
<td>366</td>
<td>690</td>
</tr>
</tbody>
</table>

Note: Murphy-Topel standard errors in parenthesis. Significance levels (one-sided tests): *: 10%; **: 5%; ***: 1%.

4.5.1 Utility curvature

The estimated power for gains ($\hat{\alpha} = 0.859$) and for losses ($\hat{\beta} = 0.826$) are displayed in the first row of Table 4.5. Both parameters are significantly below one ($z = 8.04$, $p$-value = 0.000 and $z = 9.87$, $p$-value = 0.000), and they are not significantly different from one another ($z = 1.39$, $p$-value = 0.166). Our estimates are closer to linearity as compared to the parametric studies of Harrison and Rutström (2007) and Donkers et al. (2001), who find $(\hat{\alpha}, \hat{\beta}) = (.71, .72)$ and (.61, .61) respectively, which suggests that their parametric specifications may be inappropriate for separating utility from probability weighting. The estimates confirm diminishing sensitivity, both with respect to losses and to gains (Tversky and Kahneman 1992; Abdellaoui 2000; Abdellaoui et al. 2007b), and we cannot reject equal curvature in both domains in favor of the more recent hypothesis of partial reflection (Wakker et al. 2007).

These results are qualitatively similar to those obtained in chapter 3. Those estimates, based on fitting a power function to individual level data, are somewhat closer to linearity ($\hat{\alpha} = 0.94$ and $\hat{\beta} = 0.92$ is found), but still significantly below one, and not significantly different from each other. This suggests that assuming homogeneity in utility curvature may
lead to a small downward bias in the estimate of the average, while also providing evidence that any potential bias in the non-parametric analysis due to error propagation is unlikely to be of high magnitude.

If we compare the coefficients to the average estimates of the literature reported in Table 4.1 ($\tilde{a} = 0.69$ and $\tilde{\beta} = 0.86$ respectively), we find that the estimated power coefficient for gains is significantly higher ($z = 9.61$, $p$-value $= 0.000$) while that of losses is significantly different at the 10% level only ($z = 1.94$, $p$-value $= 0.053$). It should be noted that most recent estimates of utility curvature are much closer to linearity (Abdellaoui 2000; Etchart-Vincent 2004; Abdellaoui et al. 2005; Fehr-Duda et al. 2006; Abdellaoui et al. 2007b; Andersen et al. 2006; Abdellaoui et al. 2008) than what is suggested by the average estimate calculated from Table 4.1. Hence our estimates fall within the range of contemporaneous estimates that find the power of value function to be between .8 and 1. Figure 4.3 plots the estimated utility function (dashed line) and the average found in the literature (solid line). Indeed the estimated utility curve for losses is very close to the literature average, while that of gains is a little more linear.

Table 4.5 also shows a significant treatment effect for gains. The low amounts treatment for gains (Low Amounts) is associated with a power coefficient that is .071 lower than for outcomes that are scaled up by a factor ten, suggesting that utility is more pronounced for low outcomes. This is not often found in the literature, though Cohn et al. (1975) and Blake (1996) report similar results. The effect is driven by the fact that, for gains, the last two mean elements of the standard sequence for low amounts are a bit higher than those in the high-amount treatment divided by 10 (see Table 4.3). However, it should be noted that no significant difference was found in the non-parametric estimates. Because both approaches diverge, we will not draw strong conclusions with respect to this result.

---

36 Effectively the non parametric-estimates of chapter 3 allow for full heterogeneity in preferences, while the pooled estimation conducted in this paper, does not. It is a priori not evident which method of analysis would yield the highest estimates, but it is clear that, because the model is non-linear, taking the average of estimates will yield a different result from estimating the average directly.
Figure 4.3: Estimated utility and probability weighting functions

(A) u(x) vs. x

(B) w^+(p) vs. w^-(p)

Note: The parameters of the solid lines are based on the averages of the estimates in Table 4.1. Dashed lines depict the current estimates. The loss aversion parameter is assumed to equal to the average estimate of $\lambda = 2.09$ from Table 4.1.

4.5.2 Loss Aversion

Table 4.5 shows a loss aversion coefficient of $\hat{\lambda} = 1.58$, which is lower than the parametric estimate of $\lambda = 2.25$ obtained by Tversky and Kahneman (1992), and the non-parametric estimate of $\lambda = 2.54$ that was found by Abdellaoui et al. (2007b), based on Köbberling and Wakker’s (2005) definition (they find values below 2 for the other, global, definitions). Also, the obtained loss aversion parameter is lower than the average (non-parametric) estimate of $\hat{\lambda} = 1.87$ obtained in chapter 3, where estimation is conducted at the individual level. A similar effect is reported by Abdellaoui et al (2008, p. 259) who find a pooled estimate of loss aversion that is lower than the average of the individual estimates. The obtained loss aversion is significantly larger than one ($z = 5.88$, $p$-value = 0.000), and it is consistent with the recent estimates of Schmidt and Traub (2002), Johnson et al. (2006), Harrison and Rutström (2007) and Abdellaoui et al. (2008, pooled estimate) who find values of 1.43, 1.85, 1.38 and 1.60 respectively. These and our results provide evidence that people weight a particular loss less than twice as heavy as a commensurable gain when making decisions. This is an interesting finding because Tversky and Kahneman’s (1992) original estimate of 2.25 seems to serve as the focal point estimate of loss aversion for many researchers, while many recent estimates find values below two.

Some studies have reported a decrease in the degree of loss aversion with the size of outcomes (Bleichrodt and Pinto 2002 (health); Abdellaoui 2007b). Our point estimate of .004 for the Low Amount treatment (Table 4.5) does not provide additional support for this result.
4.5.3 Probability weighting

For both domains we estimated the elevation parameter $\delta$, and the curvature parameter $\gamma$ of the GE-87 probability weighting function specified in (4.4.15). The estimated elevation parameters point at pessimism with respect to gambling in both domains. For gains we find $\hat{\delta}^g = 0.772$, which is significantly lower than 1 ($z = 4.46, p$-value = 0.000). This implies that a probability of a half is weighted by $\hat{w}^g(\gamma) = 0.436$, which points to sizeable underweighting. The estimated weight is close to Tversky and Kahneman’s (1992) original estimate of $\hat{w}^g(\gamma) = 0.421$ and it is not significantly different from the average estimate in the literature ($z = .23, p$-value = 0.818). For losses the point estimate is $\hat{\delta}^l = 1.022$ which is higher than one, suggesting pessimism also in the loss domain ($\hat{w}^l(\gamma) = 0.505 > .5$), but we cannot reject the hypothesis that $\delta = 1$ ($z = 0.27, p$-value = 0.787). The elevation of the weighting function for losses is significantly higher than that of gains ($z = 4.54, p$-value = 0.000) as was also found by Abdellaoui (2000), Abdellaoui et al. (2005) and Fehr-Duda et al. (2006), and we cannot reject the hypothesis that the elevation parameter is different from the literature average (Table 4.1) of $\bar{\delta}^l = 1.09$ ($z = .81, p$-value = 0.418). Contrary to Etchart-Vincent (2004), who find more elevation for losses with higher stakes, we did not find any effect of the magnitude of the stakes on the degree of pessimism of the respondents.

The shape of the probability weighting function is primarily determined by $\gamma$, with $\gamma < 1$ generating an inverse-S shape, and $\gamma > 1$ a convex shape. Most studies that report a parametric estimate of the GE-87 weighting function find evidence of an inverse-S shaped weighting function but, as mentioned in the introduction, some studies have found a convex shaped weighting function. Interestingly, the point estimates for the degree of curvature in both domains are very similar, $\hat{\gamma}^g = 0.618$ and $\hat{\gamma}^l = 0.592$, and we cannot reject the hypothesis that both are equal ($z = .12, p$-value = 0.907). Linearity, which requires $\gamma = 1$, is clearly rejected in favor of the hypotheses that both parameters are below one ($z = 10.02, p$-value = 0.000 and $z = 6.65, p$-value = 0.000), which means that we have found significant evidence for an inversely-S shaped weighting function in both domains. The degree of curvature we find is slightly higher than the average estimate in the literature. For gains the estimate is about .07 lower than the literature average ($\bar{\gamma}^g = 0.69$), which is significant at the
10% level \((z = 1.90, p\text{-value} = 0.058)\). The estimate for losses is about .13 lower than the literature average \(\hat{\gamma} = 0.72\), which is significant at the 5% level \((z = 2.09, p\text{-value} = 0.037)\). These results are illustrated graphically by the plot in Figure 4.3, where the estimated weighting functions are slightly more pronounced than the literature averages for probabilities near 0 and 1, while they are hardly distinguishable from the literature averages for intermediate probabilities.

### 4.5.4 Demographics

The dataset also contains background characteristics of the respondents such as their age, gender, education and income. Table 4.5 gives the results of including regressors into the model, where most of the insignificant variables have been removed. The significance levels are reported for one-sided tests. Most of the variation in the behavioral parameters appears idiosyncratic, in particular for the domain of losses, where we do not find a significant effect for any variables. In the gain domain, we find a mild associations of age (+0.003) with utility curvature, and a substantial gender effect on the elevation \((-0.103)\) of the probability weighting function. This last result is interesting because traditionally gender differences in risk taking behavior have been ascribed to differences in utility curvature (e.g. Barsky et al. 1997). The analysis of chapter 3 already showed that loss aversion may explain much of the gender differences in risk attitudes, which is also found here (+0.251) and in other studies (e.g. Schmidt and Traub 2002). The current analysis further refines this by showing that part of this effect is also caused by differences in probability weighting. This is consistent with a recent study of Fehr-Duda et al. (2006), who report a significant gender difference in the elevation parameter of the GE-87 probability weighting function for gains but not for losses. These authors also find curvature to differ between the sexes, which we do not.

Older people seem to value money more linearly, with a 50 year age difference being associated with a power that is .15 higher. This effect works to reduce risk aversion, but it is countered by more non-linear weighting of probabilities \((-0.30)\) that, in general, work to increase risk aversion. The total effect of these estimates depends on the prospects under study. For prospects that entail a small probability of a large gain one may find risk aversion to decrease with age, while in those that do not, increasing risk aversion is more likely,
which is what is usually found (Pålsson 1996; Donkers and van Soest 1999; Halek and Eisenhauer 2001; Hartog et al. 2002).

Education, defined as having a higher vocational or academic education, does not affect utility curvature, nor is it associated with a more linear weighting of probabilities. This latter effect is surprising if we view expected utility as the rational model of choice under risk. From that perspective one may expect higher educated individuals to weight probabilities more linearly, which is not what we find. Education is associated with a lower degree of loss aversion (−.318), which suggest that the reduction in risk aversion with years of schooling that is often observed (Donkers et al. 2001; Hartog et al. 2002; Dohmen et al. 2006) stems mainly from lower sensitivity to losses (e.g. Gächter et al. 2007).

Finally, the included (log) income variable showed a mild negative association with loss aversion, which is consistent with Gächter et al. 2007. Hence, we conjecture that mainly the loss aversion component of risk attitudes is driving the decrease in (absolute) risk aversion with income that is often found (Donkers et al. 2001; Hartog et al. 2002). The non-parametric analysis of chapter 3 does not reveal such an association, however, so this statement remains speculative.

The (weighted) average predictions $B'\bar{X}$ are very close to the estimated parameters in the model with only a constant, except for loss aversion. The average prediction of $\bar{\lambda} = 1.75$ there is higher than the estimated 1.58 in the model with only a constant, again suggesting that assuming homogeneity lowers the estimated loss aversion.

### 4.5.5 Stochastics

Table 4.3 shows considerable variability in the answers to the questions, which is picked up by the estimated error variances. The estimated covariance-correlation matrices for the outcome equations are given in Table 4.6, where the diagonal elements correspond to the estimated variances, and the off-diagonal elements correspond to the estimated correlations between the error terms. The average variance $\bar{\sigma}^2$ is 0.188 for gains and 0.219 for losses. This means that the probability that a given utility difference is twice as high (low) as the next one is about 5% (5%). This may not seem very much, but it implies that in a standard sequence of six elements, there is about a 40% probability that there will be at least two subsequent utility increments that differ by a factor two. Although part of this variability is
driven by between subject heterogeneity, this result suggests that the assumption of a standard sequence without error is questionable.

Both estimated matrices have a tridiagonal structure, with the one off-diagonal correlation coefficients on average equal to \( \bar{\rho} \approx -0.35 \) (Table 4.3) and the other correlations equal to zero. The negative correlations are a little weaker than the predicted correlation of \(-\frac{1}{2}\) that follows under the assumption of equal variance, which means that not all underlying variances \( \sigma_i \) are equal. There does not appear to be much difference in the average variability of the answers for losses and for gains. The variances of the probability weighting questions are a little higher, 0.267 and 0.302 for gains and losses respectively, which confirms that these questions are more demanding for respondents. For gains there appears to be some positive correlation between the individual answers (\( \bar{\rho} = 0.133 \)), but not for losses.

Table 4.6: Estimated Variance-Correlation Matrices of outcome sequences

<table>
<thead>
<tr>
<th></th>
<th>Gains</th>
<th></th>
<th>Losses</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>( \varepsilon_1 )</td>
<td>( \varepsilon_2 )</td>
<td>( \varepsilon_3 )</td>
<td>( \varepsilon_4 )</td>
<td>( \varepsilon_5 )</td>
</tr>
<tr>
<td>( \varepsilon_1 )</td>
<td>0.194***</td>
<td></td>
<td>( \varepsilon_7 )</td>
<td>0.328***</td>
</tr>
<tr>
<td></td>
<td>(0.017)</td>
<td></td>
<td></td>
<td>(0.035)</td>
</tr>
<tr>
<td>( \varepsilon_2 )</td>
<td>-0.258***</td>
<td>0.207***</td>
<td>( \varepsilon_8 )</td>
<td>-0.281***</td>
</tr>
<tr>
<td></td>
<td>(0.045)</td>
<td>(0.022)</td>
<td></td>
<td>(0.045)</td>
</tr>
<tr>
<td>( \varepsilon_3 )</td>
<td>-0.006</td>
<td>-0.375***</td>
<td>0.203***</td>
<td>( \varepsilon_9 )</td>
</tr>
<tr>
<td></td>
<td>(0.016)</td>
<td>(0.064)</td>
<td>(0.027)</td>
<td></td>
</tr>
<tr>
<td>( \varepsilon_4 )</td>
<td>-0.006</td>
<td>-0.006</td>
<td>-0.408***</td>
<td>0.188***</td>
</tr>
<tr>
<td></td>
<td>(0.016)</td>
<td>(0.016)</td>
<td>(0.075)</td>
<td>(0.026)</td>
</tr>
<tr>
<td>( \varepsilon_5 )</td>
<td>-0.006</td>
<td>-0.006</td>
<td>-0.006</td>
<td>-0.373***</td>
</tr>
<tr>
<td></td>
<td>(0.016)</td>
<td>(0.016)</td>
<td>(0.057)</td>
<td>(0.015)</td>
</tr>
</tbody>
</table>

Note: The off-diagonal elements are correlation coefficients. Standard errors in parenthesis and significance levels */**/***: 10/5/1%. Test on equality of diagonal elements is rejected for both gains (\( z = 3.15, p\text{-value} = 0.042 \)) and losses (\( z = 4.67, p\text{-value} = 0.000 \)). Equality of the one-off diagonal elements is not rejected for gains (\( z = 1.98, p\text{-value} = 0.272 \)), but is rejected for losses (\( z = 3.09, p\text{-value} = 0.023 \)).

4.6 Summary and Conclusion

This study presents the first, representative, large-scale parametric estimation of prospect theory’s functionals, the utility function of money gains and losses, and the subjective probability weighting functions. Unlike previous large scale parametric studies, the richness
of the questionnaire allows for estimation of these curves without making too restrictive parametric assumptions, while allowing for response error in the individual answers. The results qualitatively confirm the non-parametric results of chapter 3 and suggest that utility is mildly concave for gains and mildly convex for losses, implying diminishing sensitivity and suggesting that classical utility measurements that neglect probability weighting, are overly concave.

A direct comparison with the non-parametric measures suggests that assuming homogeneity leads to a small downward bias, while providing evidence that a potential bias in a non-parametric analysis due to error propagation is unlikely to be large. Also our estimates are closer to linearity as compared to parametric studies that impose more stringent parametric assumptions (e.g. Donkers et al. 2001; Harrison and Rutström 2007), suggesting the utilities obtained in these studies may suffer from a contamination bias. Further, we find evidence that probabilities are weighted non-linearly, with an inverse-S shape, and that both functions display pessimism (low elevation for gains, high elevation for losses). Hence, these results externally validate probability weighting that was found in a laboratory context (Wu and Gonzalez 1996; Abdellaoui 2000). The obtained degree of loss aversion, as operationalized by Tversky and Kahneman (1992), is 1.6. This is somewhat lower than their estimate of 2.25, but consistent with contemporaneous evidence (Schmidt and Traub 2002; Johnson et al. 2006, Abdellaoui 2008). Furthermore, we found that neither the degree of utility curvature, nor the degree of loss aversion, is altered by scaling up monetary outcomes. The same holds for the probability weighting functions, that do not appear to be affected by the magnitude of the stakes, contrary to what Etchart-Vincent (2004) finds for the loss domain.

By including background characteristics our estimation procedure gives more background as to what causes risk aversion differences between groups in the population. This analysis suggests that the common finding that women are more risk averse than males (Byrnes and Miller 1999) stems from differences in probability weighting and loss aversion, and not from differences in utility curvature. Also, the reduction of risk aversion that is associated with a higher level of education (Donkers et al. 2001; Dohmen et al. 2006) does not derive from utility curvature but from differences in loss aversion. The robustness of
these results should be confirmed by further research, but they are indicative of the different channels through which risk taking behavior is associated with background variables.

Two disadvantages of the study are the lack of real incentives and the use of matching tasks in stead of choice tasks. Hypothetical tasks have been found, in some settings, to prime more erratic, and sometimes different behavior, than similar tasks involving real stakes (Camerer and Hogarth 1999; Holt and Laury 2002). Moreover, matching tasks have been found to increase the number of inconsistent answers, suggesting that these tasks are more cognitively demanding (Luce 2000, Hertwig and Ortmann 2001). This is confirmed by our data where for gains 37% of all individuals gave one or more inconsistent answer. These individuals were excluded from the analysis, leading to sample selection. To correct for this the analysis were conducted by using the inverse of the probability of appearing in the sample as weight. Given that our results blend in well with the results from laboratory experiments, providing evidence for diminishing sensitivity both with respect to outcomes and to probabilities, and also producing plausible relationships with demographic variables, we are confident that the obtained measures give a good representation of the average curvature of prospect theory’s functionals.
4.7 Appendix to chapter 4

4.7.1 Sample selection probit-equation

Table 4.7: Sample Selection Equations

<table>
<thead>
<tr>
<th>Variable</th>
<th>Frac.</th>
<th>Outcomes</th>
<th>Probabilities</th>
<th>Loss Aversion</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Gains</td>
<td>Losses</td>
<td>Gains</td>
</tr>
<tr>
<td>Low Amounts Treatment</td>
<td>50%</td>
<td>0.144***</td>
<td>0.101*</td>
<td>0.0123</td>
</tr>
<tr>
<td>Female</td>
<td>46%</td>
<td>-0.052</td>
<td>-0.079</td>
<td>-0.188**</td>
</tr>
<tr>
<td>Lower Secondary Education</td>
<td>26%</td>
<td>0.127</td>
<td>0.029</td>
<td>-0.264</td>
</tr>
<tr>
<td>Higher Secondary Education</td>
<td>14%</td>
<td>0.335**</td>
<td>0.148</td>
<td>0.169</td>
</tr>
<tr>
<td>Intermediate Vocational Training</td>
<td>19%</td>
<td>0.046</td>
<td>-0.148</td>
<td>-0.127</td>
</tr>
<tr>
<td>Higher Vocational Training</td>
<td>25%</td>
<td>0.258*</td>
<td>0.039</td>
<td>0.205</td>
</tr>
<tr>
<td>Academic Education</td>
<td>11%</td>
<td>0.488***</td>
<td>0.305*</td>
<td>0.568**</td>
</tr>
<tr>
<td>Age 35-44</td>
<td>18%</td>
<td>-0.157*</td>
<td>-0.202**</td>
<td>-0.0621</td>
</tr>
<tr>
<td>Age 45-54</td>
<td>22%</td>
<td>-0.234***</td>
<td>-0.281***</td>
<td>-0.258*</td>
</tr>
<tr>
<td>Age 55-64</td>
<td>18%</td>
<td>-0.313***</td>
<td>-0.340***</td>
<td>-0.273*</td>
</tr>
<tr>
<td>Age 65+</td>
<td>19%</td>
<td>-0.462***</td>
<td>-0.428***</td>
<td>-0.638***</td>
</tr>
<tr>
<td>€ 1.150&lt;Income≤€ 1.800</td>
<td>25%</td>
<td>0.196*</td>
<td>0.269**</td>
<td>0.298</td>
</tr>
<tr>
<td>€ 1.800&lt;Income≤€ 2.600</td>
<td>31%</td>
<td>0.200*</td>
<td>0.253**</td>
<td>0.325*</td>
</tr>
<tr>
<td>Income&gt;€ 2.600</td>
<td>35%</td>
<td>0.344***</td>
<td>0.411***</td>
<td>0.418**</td>
</tr>
<tr>
<td>Catholic</td>
<td>30%</td>
<td>0.014</td>
<td>0.008</td>
<td>0.0128</td>
</tr>
<tr>
<td>Protestant</td>
<td>20%</td>
<td>0.160**</td>
<td>0.126</td>
<td>0.136</td>
</tr>
<tr>
<td>Constant</td>
<td></td>
<td>-0.503***</td>
<td>-0.510***</td>
<td>-1.024***</td>
</tr>
</tbody>
</table>

Notes: Standard errors allow for clustering within households. *,**/***: significant at the 10/5/1% level.

4.7.2 Experimental instructions (Part II)

The first part of this experiment has now finished. In the second part of this experiment each question will again be presented on a separate page, with two lotteries Lottery L (Left) and Lottery R (Right) presented at the top. In between the two lotteries you will again be presented with a wheel to illustrate the probabilities. In this part of the experiment, however, Lottery L will always yield a fixed amount with certainty. Below the illustrated
lotteries, there will again be text explaining the question. The next screen will show you an example of a question that you could get in the second part of this experiment.

As you can see, in this example Lottery L always yields 500 euros. Lottery R on the other hand, gives with probability 25% a profit of 1000 Euro, and with a probability of 75% a loss of 300 Euro. You should again imagine that, if we were to turn the wheel and the black pointer would be in the orange area, Lottery R would yield 1000 euros. In case the black pointer would be in the blue area, Lottery R would yield a loss of 300 euros.

In the previous example you may have preferred Lottery L to Lottery R or the other way around. In the second part of this experiment, however, the probabilities of the prizes in lottery L will be missing, such as in the example given above.

In the second part of this experiment we will ask you in each question to state the value of the missing probability (in whole percentages, from 0% to 100%) for the upper prize of Lottery R that would make you value both equally.
Imagine that the probability of the upper prize of lottery R is equal to 100%. This would give the lotteries presented above. Lottery L will thus always give a profit of 500 Euro, while Lottery R will always give a 1000 euros. Given that Lottery L will always yield less than Lottery R, most people will prefer Lottery R to Lottery R.

Imagine now, however, that the probability of the upper prize of lottery R is equal to 0%. This would give the lotteries presented above. Lottery L will thus always give a profit of 500 Euro, while Lottery R will always give a loss of 300 euros. Given that Lottery L will always yield more than Lottery R, most people will now prefer Lottery L to Lottery R.

Hence, there is a value of the missing probability somewhere between 0% and 100% for which you would value both lotteries equally. In the questions that follow we will ask you for which value of the missing probability you value Lottery L and Lottery R equally. This missing probability can be different for everybody and is your own preference. How this
works precisely will become clear in the practice question that will start if you click on the CONTINUE button below. If something it not clear to you, you can read the explanation of this experiment again by pressing the BACK button below.

[Practice question]

The practice question is now over. The questions you will encounter during this experiment are very familiar to the practice question. If you click on the BEGIN button below, the experiment will start. If you want to go through the explanation of the second part of this experiment again, click on the EXPLANATION button. Good luck.
II Measuring causal effects in Education
5 The role of information in the take-up of student loans*

5.1 Introduction

Most developed countries substantially subsidize college enrollment through financial aid and subsidies to public institutions. When individuals seek to finance their education they will find it difficult to take out a commercial loan because of the absence of collateral and the presence of moral hazard. Financial aid in the form of grants or attractive loans are aimed at lifting credit constraints. There is, however, evidence that students underutilize financing possibilities in the forms of loans. Some have suggested that this is due to debt aversion which occurs when having a debt lowers utility over and above its impact on life-time consumption patterns (e.g. Field 2006; Oosterbeek and van den Broek 2008). Put differently, debt aversion arises when individuals not only care about their consumption profile, but also assign negative weight to having debt at a certain point in time, which decreases borrowing.

Another barrier to student loan take-up is information. If students are imperfectly or incorrectly informed about loan conditions, take-up rates on student loans will be suboptimal and may reduce investment in post-secondary education. In defense of a shift towards a more prominent role for loans, the former Dutch (vice-) minister responsible for higher education, Mark Rutte, argued that instead of debt aversion, the key factor explaining the low take-up rate in the Netherlands (35%) is the uninformedness of students about the generous loan conditions. He based this view on a study showing that students who are well informed about the loan conditions are also significantly more likely to have a student loan.

* This paper is based on Booij et al. (2008).
Figure 5.1: Knowledge about loan conditions and loan take-up rates

The top panel of Figure 5.1 shows the strong correlation between informedness and borrowing based on the data used in this chapter. For every correct answer about the loan conditions the take-up rate increases by roughly ten percentage points. At the same time the bottom panel shows that indeed many students are rather poorly informed about the loan conditions (over 70% gives a correct answer to not more than one out of five questions). This suggests that by better informing students the overall take-up rate will increase. This will obviously not happen if the relation in Figure 5.1 arises because students who are more interested in taking a loan also gather more information about the loan conditions, or that those who have taken out such a loan receive information about the loan conditions.

We conducted a randomized experiment to estimate the causal effect of better knowledge about loan conditions on loan take-up. Randomly fifty percent of the students who responded to an Internet questionnaire were given factual information about loan
Information and the take-up of student loans

Half a year later, the respondents were interviewed again. Those who were exposed to treatment turn out to have significantly more accurate knowledge about loan conditions, thereby indicating that the supply of information has an impact on knowledge six months later. At the same time, exposure to the information treatment and possessing more accurate knowledge appears to have no impact on the loan take-up rate, thereby rendering the claim of the higher education (vice-) minister invalid.

This chapter proceeds as follows. The next section provides more details of the student financial aid scheme in the Netherlands and the recent policy discussion related to that. Section 5.3 describes the experimental design and the empirical approach based on it. Section 5.4 introduces the data and section 5.5 presents and discusses the empirical results. Section 5.6 summarizes and concludes.

5.2 Background

The student financial aid system run by the Dutch government consists of three components: (i) a basic grant provided to all students; (ii) an additional grant for students from low income families; and (iii) a student loan scheme with a mortgage type repayment. Although the system changed several times after its introduction in 1986 (Belot et al. 2004), these three components have been part of the loan scheme since the start.

In 2007, the year of this study, the basic grant equaled € 290 per month, with an additional means-tested supplementary grant of € 250 per month at maximum. Additionally, all students were allowed to borrow an additional amount until their total financial aid from the government equaled € 790 at maximum. Hence, for students that do not receive the supplementary grant, the maximum loan amount was € 500. The basic and supplementary grants are given for 4 or for 5 years, depending on the length of the curriculum. After this period there is an extended loan period of three years in which students can borrow a maximum of € 790 per month.

37 Another study which manipulates the amount of information in an experimental setting is Duflo and Saez (2003). They, however, focus on the role of social interactions which do not play a role in this study since treated and controls are not connected.
If the student does not obtain a diploma within ten years, the received grants are transformed into a loan. The interest rate on the loan is equal to that of long term government bonds (3.7% in 2007), which is well below individual borrowing rates in the Netherlands.\footnote{Before 1992 government student loans were interest free. This was changed to prevent students making a} Repayment of the total debt starts after a grace period of 2 years. The monthly repayment amount is calculated as an annuity such that the total debt is repaid in exactly 15 years. However, the monthly installments are € 45 at minimum. In months when monthly income is below a certain threshold the installment is forgiven. This implies that students with low future incomes will not repay their entire debt.

Compared to financial aid schemes in other countries, the Dutch scheme is rather generous. Few other countries provide basic grants to all students, and if they do the amounts are smaller (Usher and Cervenan 2005). Also, only about half of the governments of OECD countries offer loan schemes to students, most of which contain no provision in case of low future incomes (Usher 2005). Not surprisingly, the Dutch higher education system was ranked in the top three in terms of affordability in an international comparative study of 16 countries conducted by Usher and Cervenan (2005).

While the grant given to students in the Netherlands is large in comparison with grants given elsewhere, it is insufficient to cover living costs and education expenditures. Hence it could be expected that students would make use of the loans scheme to supplement their income, as is observed in other countries. In Sweden for example, where the government offers a basic grant of similar magnitude as in the Netherlands, more than 85% of students take a loan. Similar take-up rates are observed in other countries (Norway: 78%, U.K.: 85%, US: 50%; see Vossensteyn, 2004; Usher, 2005). This figure has consistently been much lower in the Netherlands, where the take-up rate is around 35% (Biermans et al. 2003; van den Broek and Van de Wiel 2005).

The low take-up rate is viewed as a problem in the Netherlands because students seem to work next to their study to avoid debt. Studies have found that on average Dutch students spend about 10 hours per week working in a job on the side (Biermans et al. 2003; van den Broek et al. 2006). This is not desirable from the government’s perspective because it is likely to lead to an increased study length. Kalenkoski and Pabilonia (2008), Oettinger (2005), and
Stinebrickner and Stinebrickner (2003) provide evidence that work during college has detrimental effects on study performance. Indeed the Netherlands has a poor record in this respect, with an average study duration of 6 years (excluding drop-outs, CBS 2007) whereas the nominal duration of most higher education programs is 4 years. Since each student-year is heavily subsidized (Jongbloed et al. 2003), this is costly for the government.

To investigate the observed reluctance to borrow, the Dutch (vice-)minister of education called for research into students’ attitudes and knowledge with respect to the loan scheme. A subsequent study found that, not only did students prefer working to supplement their income over borrowing, they also appeared to be only moderately informed about the loan scheme (van den Broek and Van de Wiel 2005). Moreover, students who were actually borrowing appeared to be better informed about the borrowing conditions than students who were not taking a loan. The same pattern was found in a similar study on borrowing of students in the UK (Callender 2003). The policy recommendation in the Dutch report, that increasing student awareness of the loan conditions may increase borrowing, was soon echoed by the minister (Ministry of Education 2006). However, it is not a priori clear that this association reflects the causal link implied by this recommendation. It may well be that taking a loan increases students’ knowledge about the conditions but not vice versa.

5.3 Experimental design and empirical strategy

To isolate the causal impact of accurate knowledge about loan conditions on the loan take-up rate, we conducted a randomized experiment. A representative sample of Dutch higher education students were invited by E-mail to take part in two consecutive Internet surveys, with half a year in between (the first invitation did not announce the second questionnaire). The E-mail addresses were obtained from the Dutch agency that administers students’ university enrollment, grants and loans. This agency also possesses respondents’ background information on variables such as age, gender and Socio-Economic Status (SES).

The first questionnaire, sent out in February 2007, came in two versions. The entire sample of students received questions about their opinions concerning student loans and past borrowing. In addition, (a randomly assigned) half of the sample received factual
information about five loan conditions. This information was presented in the form of questions that asked respondents how favorable they thought each condition was. More specifically, these students were asked how favorable they perceived the following conditions:

1. The maximum loan amount during the grant period (which equals €500)
2. The maximum loan period after the grant period (which equals 36 months)
3. The grace period (which equals 2 years)
4. The maximum length of the repay period (which equals 15 years)
5. The interest rate on student loans (which equals 3.7%)

The main reason to present the factual information in the form of questions was to give respondents a reason to read and think about the information. The respondents that received the version with the factual information about the loan conditions are in the treatment group, while the respondents that received the version without the factual information constitute the control group.

The follow-up survey, administered six months later in August 2007, asked the respondents to the first questionnaire again to fill in an Internet questionnaire. This questionnaire was identical for the treatment and control groups. Questions were asked about respondents’ current study situation, their perceptions on job prospects, their attitudes towards borrowing, risk taking attitudes and the amount they borrowed in each of the months following the first survey.

Furthermore, questions were asked to measure respondents’ knowledge about the loan conditions. In particular, they were asked what they thought were the true values of the five conditions about which the treatment group received information in the first questionnaire. It was stated explicitly that they should not search for this information on the Internet or elsewhere, stressing that giving a wrong answer would be without any consequence and that we were only interested in getting a picture of students’ overall awareness about the loan conditions. We consider the fact that only a handful of respondents answered all five questions correctly (3 in the control group, 2 in the treatment group) as evidence that (almost) no one searched for the correct answers.

The intention behind this research design is that the random assignment of the information treatment generates exogenous variation in respondents’ knowledge about the
loan conditions and that this variation can then be used to estimate the impact of more accurate knowledge of loan conditions on the loan take-up rate using an instrumental variable approach, where the treatment is used as an instrument for the accuracy of knowledge about the loan conditions.

The outcome variable of interest is a binary variable (denoted by $y_{i}$) that equals 1 if student $i$ took a loan in the four months after the first survey, and 0 otherwise. This variable is related to characteristics such as family background, type of study, previous loan experience, and most importantly, the student’s knowledge about the loan conditions. This last variable, written as $K_{i}$, is operationalized as the number of questions about loan conditions the student answered correctly in the follow-up survey. Imposing a linear relationship, we can write:

$$y_{i} = \alpha K_{i} + x_{i}'\beta + u_{i}$$  \hspace{1cm} (5.3.1)

where $x_{i}$ collects control variables and $u_{i}$ denotes an error term. The effect of interest is $\alpha$. Estimation of this parameter using OLS will be biased if $K_{i}$ is correlated with $u_{i}$, which would for instance be the case if students who are more interested in taking up a loan also collect more information, or acquire more knowledge because they borrow (in which case $\alpha$ picks up a reverse causality).

To estimate the causal impact of $K_{i}$ on $y_{i}$ we instrument $K_{i}$ with the treatment dummy $T_{i}$, which equals 1 for students who were exposed to the information treatment and 0 for students who were assigned to the control group. To this end we estimate the following first stage equation:

$$K_{i} = \gamma T_{i} + x_{i}'\delta + \eta_{i}$$  \hspace{1cm} (5.3.2)

where $\eta_{i}$ is an error term. The idea here is that the treatment $T_{i}$ creates variation in knowledge $K_{i}$ that is independent of other factors that determine loan take-up. By looking only at the response in loan take-up with respect to this variation, the effect of knowledge on loan take-up can be estimated consistently. To do this, the reduced form equation

$$y_{i} = \tilde{\alpha} T_{i} + \tilde{x}_{i}'\tilde{\beta} + \tilde{u}_{i}$$  \hspace{1cm} (5.3.3)

is estimated in the second stage. The instrumental variable estimator of the causal effect $\frac{\partial y}{\partial K}$ is then given by \( \hat{\alpha} = \frac{\tilde{\gamma}}{\tilde{\delta}} = \frac{\tilde{\gamma}}{\tilde{\delta}} / \frac{\tilde{\gamma}}{\tilde{\delta}} = \hat{\alpha} / \hat{\gamma} \).
The standard conditions that need to be fulfilled in order to use the treatment indicator $T_i$ as an instrumental variable for knowledge $K_i$ are: (i) that $T_i$ has an impact on $K_i$ ($\gamma \neq 0$), and (ii) that $T_i$ is uncorrelated with $u_i$ conditional on $x_i$. The first condition can be tested, and our first stage estimations of equation (5.3.2) show that it is indeed fulfilled. In general the second condition cannot be tested, but since the information treatment was assigned randomly, we can be confident that this condition also holds. To support this, the next section presents results showing that treatment status is uncorrelated with observable characteristics.

5.4 Data

A total of 3,812 students responded to the first questionnaire in which they were asked about their field and level of study, and about their attitudes towards borrowing (see section 5.7.2). About half of this sample ($N=1,914$) randomly received information about the properties of student loans provided by the government. All students that completed the first survey were contacted again for the follow-up survey (see section 5.7.3). The response rate for this second survey was 61%, which is comparable to other studies that target this sample, and quite reasonable considering that it was conducted at the end of the summer holiday. Response rates were virtually identical for the treatment and control groups (61% and 60% respectively). Hence, there is no indication of selective non-response with respect to treatment.

Table 5.1 reports descriptive statistics of the background variables that will be used as control variables. These descriptives are reported separately for the treatment and control groups. The important result in this table is that there are no significant differences between the groups for any of the variables. This indicates - as we claimed above - that the randomization worked.
Table 5.1: Descriptive Statistics

<table>
<thead>
<tr>
<th></th>
<th>Controls Mean</th>
<th>s.d.</th>
<th>Treated Mean</th>
<th>s.d.</th>
<th>Difference</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Female</td>
<td>0.67</td>
<td>0.47</td>
<td>0.65</td>
<td>0.48</td>
<td>-0.018</td>
<td>0.386</td>
</tr>
<tr>
<td>Age</td>
<td>21.07</td>
<td>1.81</td>
<td>21.04</td>
<td>1.72</td>
<td>-0.031</td>
<td>0.684</td>
</tr>
<tr>
<td>Ethnic minority</td>
<td>0.05</td>
<td>0.21</td>
<td>0.04</td>
<td>0.20</td>
<td>-0.004</td>
<td>0.653</td>
</tr>
<tr>
<td>SES</td>
<td>2.52</td>
<td>1.39</td>
<td>2.53</td>
<td>1.38</td>
<td>0.004</td>
<td>0.941</td>
</tr>
<tr>
<td>Discount rate</td>
<td>0.21</td>
<td>0.19</td>
<td>0.21</td>
<td>0.19</td>
<td>-0.002</td>
<td>0.824</td>
</tr>
<tr>
<td>Risk tolerance</td>
<td>5.67</td>
<td>2.05</td>
<td>5.65</td>
<td>2.10</td>
<td>-0.016</td>
<td>0.859</td>
</tr>
<tr>
<td>Academic track</td>
<td>0.60</td>
<td>0.49</td>
<td>0.62</td>
<td>0.49</td>
<td>0.014</td>
<td>0.508</td>
</tr>
<tr>
<td>Loan experience</td>
<td>0.30</td>
<td>0.46</td>
<td>0.30</td>
<td>0.46</td>
<td>-0.004</td>
<td>0.838</td>
</tr>
<tr>
<td>N</td>
<td>1,090</td>
<td></td>
<td>1,098</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: Mean values with standard deviations in parentheses. p-values are based on t-tests.

The mean values for age, social background and ethnicity are comparable to those in the population of higher education students. Two preference parameters that play a central role in economic models of investment decisions under uncertainty are risk aversion and the subjective discount rate. Risk aversion is measured by a subjective self-evaluating measure of risk attitudes on a 1 to 10 scale that increases in risk tolerance (see Q25 on p.124). A series of hypothetical intertemporal choices pin down individuals’ subjective discount rate (see Q26-Q31 on p.124). The students are, on average, moderately risk tolerant (6/10) and also moderately impatient (20%). These numbers are comparable with Dohmen et al. (2006) and Harrison et al. (2002), who find 5/10 and 28% for the German and Danish populations, respectively.

The variable “loan experience” indicates whether the student had taken up a student loan prior to the first survey. In both groups this fraction equals 30%, which is similar to what is reported in other studies (Biermans et al. 2003; van den Broek et al. 2006). Hence, the sample reflects the observation that loan take-up is low in the Netherlands compared to other western countries (Usher 2005).

As discussed above, we operationalized students’ knowledge about the loan conditions by the number of questions the student answered correctly (Q14-Q19, p.123). To compare the answers to the true value, we rounded them to the unit which seemed to match the response scale for most respondents. The maximum loan amount (€ 500) for example was rounded to hundreds of euros, and the other questions were rounded to appropriate scales.
in a similar way. This rounding clarifies our graphical analyses (below) and does not affect the results since the correlation between the true and the rounded value is never below 0.99.

To better understand which students make use of student loans, the first column of Table 5.2 presents estimates from a linear probability model where loan experience is regressed on student characteristics. There are no differences between boys and girls, and older students are more likely to borrow. Interestingly, students who are more at risk of being liquidity constrained, that is students with an ethnic minority background and students from lower socio-economic backgrounds, are not more likely to have taken out a student loan. One explanation is that the means tested component of the Dutch grant scheme adequately compensates students for their financial background. Finally, the most important determinants of loan experience seem to be students’ discount rate and risk attitude.

It is also useful to consider how well different students are informed about the loan conditions. In the second column of Table 5.2 the number of correct answers on the five questions on loan conditions were regressed on the same student characteristics as in column (1). Students in the academic track are better informed, as are older and more

39The maximum loan period after the grant period (36 months) was rounded to years, the maximum length of the repay period (15 years) was rounded to 5 years, and the interest rate (3.7 percent) was rounded to half a percentage point around the true value. The grace period was not rounded since all respondents answered in whole years.

### Table 5.2: Student characteristics, loan experience and loan knowledge (OLS)

<table>
<thead>
<tr>
<th></th>
<th>Loan Experience</th>
<th>Loan Knowledge</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Female</td>
<td>0.003 (0.021)</td>
<td>-0.010 (0.049)</td>
</tr>
<tr>
<td>Age</td>
<td>0.040*** (0.007)</td>
<td>0.031* (0.015)*</td>
</tr>
<tr>
<td>Ethnic minority</td>
<td>-0.006 (0.047)</td>
<td>-0.113 (0.101)</td>
</tr>
<tr>
<td>Socio-Economic Status</td>
<td></td>
<td></td>
</tr>
<tr>
<td>-Level2</td>
<td>0.026 (0.025)</td>
<td>-0.047 (0.059)</td>
</tr>
<tr>
<td>-Level3</td>
<td>-0.034 (0.031)</td>
<td>-0.058 (0.079)</td>
</tr>
<tr>
<td>-Level4</td>
<td>0.072** (0.033)</td>
<td>0.009 (0.077)</td>
</tr>
<tr>
<td>-Level5</td>
<td>-0.004 (0.032)</td>
<td>0.078 (0.077)</td>
</tr>
<tr>
<td>Academic track</td>
<td>0.049** (0.021)</td>
<td>0.286*** (0.049)</td>
</tr>
<tr>
<td>Study duration(months)</td>
<td>0.011 (0.011)</td>
<td>0.123*** (0.027)</td>
</tr>
<tr>
<td>Discount rate</td>
<td>0.194*** (0.054)</td>
<td>0.145 (0.126)</td>
</tr>
<tr>
<td>Risk tolerance</td>
<td>0.016*** (0.005)</td>
<td>0.019* (0.011)</td>
</tr>
<tr>
<td>Intercept</td>
<td>-0.710*** (0.128)</td>
<td>-0.058 (0.304)</td>
</tr>
</tbody>
</table>

**Note:** Robust standard errors in parentheses. ***/** denote significance at a 10/5/1% confidence level.
experienced students. Risk averse students are also better informed. Again there is no relation between both socio-economic status and ethnicity, and loan knowledge.

Table 5.2 shows that the most important determinants of borrowing are students’ discount rates and risk attitudes. There is no indication that liquidity constrained students are more likely to borrow. The results in the table suggest that this could be due to the fact that these students are not better informed about the loan conditions in the Netherlands than students from more favorable backgrounds, an explanation we will investigate in the next section.

5.5 Results

This section presents the empirical results of our experiment. It starts with reporting the impact of the information treatment on knowledge about loan conditions. It then presents results from OLS regressions of borrowing behavior on knowledge about loan-conditions, the (reduced form) effect of exposure to the information treatment on borrowing behavior, and finally the IV-estimates of the impact of more accurate knowledge about loan conditions on borrowing behavior.

5.5.1 The impact of the information treatment on knowledge about loan conditions

Before turning to our discussion of the impact of knowledge about loan conditions on loan take-up we need to assure that exposure to the information treatment has an impact on students’ knowledge. The follow-up survey asked students about their knowledge about five loan conditions, and Table 5.3 reports for each condition the mean responses of the students in the treatment and control groups, and their differences.

| Table 5.3: Mean responses to questions about loan conditions, by treatment status |
|-------------------------------|------------------|------------------|------------------|------------------|------------------|------------------|
|                               | Controls         | Treated          | Difference       | p-value          |
|                               | Mean             | s.d.             | Mean             | s.d.             |                   |                   |
| Max loan                      | 422.8            | 213.6            | 448.2            | 210.8            | 25.4              | 0.005            |
| Max loan period               | 21.2             | 19.4             | 23.3             | 18.8             | 2.1               | 0.012            |
| Grace period                  | 4.9              | 3.4              | 5.0              | 3.4              | 0.1               | 0.597            |
| Repay period                  | 14.5             | 10.5             | 13.8             | 7.5              | −0.7              | 0.057            |
| Interest rate                 | 2.6              | 1.8              | 2.7              | 1.8              | 0.1               | 0.083            |
| N                             | 1,090            | 1,098            |                   |                   |                   |                   |

Note: Mean values with standard deviations in parentheses. p-values are based on t-tests.
The results in column (1) show that Dutch higher education students (represented by the control group) are indeed poorly informed about the loan conditions. They underestimate the size of the maximum loan by over 75 euros (by more than 15%), underestimate the maximum loan period by over one year (by more than a third), overestimate the maximum grace period by almost 3 years (150%), underestimate the maximum repayment period by less than half a year (less than 4%), and underestimate the interest rate by more than 1 percentage point (almost 30%).

Notice that the poor information of students in the control group is not always in the direction of regarding the loan conditions as less generous than they actually are, as illustrated by the fact that students both overestimate the grace period and underestimate the interest rate.

Comparing the results in column (1) to those in column (2) shows that students who were exposed to the information treatment have on average more accurate knowledge about the size of the maximum loan, about the maximum loan period and about the interest rate than students in the control group. Students in the control group have, however, on average more accurate knowledge regarding the maximum grace period and the maximum repayment period. This mixed picture casts some doubt on the effectiveness of the information treatment.

Comparing the averages to the true values is misleading however, because that does not properly account for the full difference in the distribution. Figure 5.2 displays histograms of the perceptions of both the treated (vertical bars) and controls (connected points) for all conditions. The bars of the treated are “hanging” from the line spanned by the controls, such that the bars crossing the x-axis at zero indicate a higher concentration among the treated at that value.
**Figure 5.2:** Students’ perceptions of loan conditions

Since the bars of the true values are shaded it is easy to see that there is a higher concentration of answers close to the correct value for the treated than the controls. For all conditions the treated bars are sticking out at the true value, meaning that the treated have better perceptions. This does not follow from the shifts in the averages because the distribution relocation is asymmetric around the true value. Hence it is possible for the average to move in the wrong direction while the fraction of informed people, the shaded column, increases.

The effects of the treatment on correctly answering the questions about the loan conditions are displayed in Table 5.4. For most conditions the treatment increases the group of correctly informed students by about 4 percentage points. The effect is strongest for the grace period (5.1%), and weakest for the interest rate (2.4%). Judging from Figure 5.2 however, it is clear that also for the latter condition the probability mass shifts to values closer to the true value. In total the controls answer on average 1.07 questions correctly, while the treated manage 1.26. Hence knowledge increases by about 18%, a moderate but significant change.
The information treatment has the strongest bearing on (total) knowledge. Effectively, all the variation in the treatment response of the different loan-conditions is collected by this measure, generating an F-statistic of 15.1. This number satisfies the rule of thumb of F>10 that is often used to gauge the risk of small sample bias caused by a weak instrument (Staiger and Stock 1997). However, the (partial) explanatory power of the instrument, given by the partial R-squared measure equals 0.007, which is not very high. This will further inflate the IV standard errors compared to those of OLS. The precision of the estimates may be increased if we select a sub-group for which the instrument has more power (see, for example, Black et al. 2005). In particular, it seems likely that the effect of information will be smaller for students who have prior loan experience. These students have already encountered the loan scheme, and may thus be expected to have some knowledge about it. Hence, there may be less scope for improvement for this group of students. To investigate this, we break down the first stage by prior loan experience. The results are presented in the middle and bottom panels in Table 5.4.

<table>
<thead>
<tr>
<th>Table 5.4: Effect of information on knowledge, all and by loan experience</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
</tr>
<tr>
<td>All (N=2,188)</td>
</tr>
<tr>
<td></td>
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<tr>
<td></td>
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<td></td>
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<td></td>
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<tr>
<td></td>
</tr>
<tr>
<td>Without loan experience (N=1,536)</td>
</tr>
<tr>
<td></td>
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<tr>
<td></td>
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</tr>
<tr>
<td></td>
</tr>
<tr>
<td>With loan experience (N=652)</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
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<tr>
<td></td>
</tr>
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<td></td>
</tr>
</tbody>
</table>

Each estimate comes from a separate regression that includes controls for age, gender, ethnicity, SES, discount rate, risk attitude, academic track, field of study and (in the top panel) loan experience. Robust standard errors in parentheses. */**/*** denote significance at a 10/5/1% confidence level.

For the aggregate measure of “Correct answers”, the point estimate drops from 0.18 to 0.12 and turns insignificant for the group of students that have prior loan experience. The partial F-statistic is only 1.76. This is partly caused by the reduction in sample-size, but if we look at the explained variance we find the same: the power of the instrument is severely reduced, from 0.007 to 0.002, if the sample is restricted to students with prior loan experience. In
contrast, for the group of students without loan experience the point estimate is now 0.21 and the explanatory power increases to 0.01. Apparently, inexperienced students are particularly affected by the treatment, which is the group of students that would be specifically targeted by an information campaign and for whom we may hope for the largest effects. Hence, in what follows we will show a break down by loan experience.

5.5.2 Borrowing behavior and knowledge about loan conditions

Column (1) in Table 5.5 reports the OLS estimates of the relation between borrowing behavior and knowledge about the loan conditions for the full sample, and for the groups with and without prior loan experience. The coefficients of the covariates have been suppressed in this table, they are reported in the appendix to this chapter (section 5.7.1). In all three cases, we observe a substantial and significant relation. Each additional correct answer is associated with an increase in the probability that a student has a loan of 8 to 9 percentage points. This result reiterates the pattern observed in Figure 1. But as in Figure 1, this relation need not be causal.

<table>
<thead>
<tr>
<th>Table 5.5: The effects of treatment and knowledge on borrowing behavior - OLS, Reduced Form (RF) and IV</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>(1)</td>
</tr>
<tr>
<td>All</td>
</tr>
<tr>
<td>(0.008)</td>
</tr>
<tr>
<td>No Loan Experience</td>
</tr>
<tr>
<td>(0.010)</td>
</tr>
<tr>
<td>Loan Experience</td>
</tr>
<tr>
<td>(0.016)</td>
</tr>
</tbody>
</table>

Note: Each estimate comes from a separate regression that includes controls for age, gender, ethnicity, SES, discount rate, risk attitude, academic track, field of study and (in the first three columns) loan experience. Robust standard errors in parentheses. */**/*** denote significance at a 10/5/1% confidence level.

Exposure to the information treatment has a significant effect on knowledge, especially for the target group of students without loan experience. Whether exposure to the information treatment also translates into an increase in borrowing is displayed in column (2) in Table 5.5. For the whole sample the estimated effect is 0.004, and not significantly different from zero. Interestingly, there is a divide in the effect if we consider the break down by loan experience. The point estimate is negative for the inexperienced borrowers (~0.015) and
positive for those that have encountered loans before (0.037). This difference is not significant, but it suggests that the effect may even be negative for the target group.

The ratio of the reduced form and the first stage estimates gives the instrumental variable estimate of the causal effect of knowledge on borrowing behavior. The estimates are presented in column (3) in Table 5.5. For the whole sample the IV estimate equals 0.022, which is not significantly different from zero. Unfortunately, the standard error of 0.092 is so large that we can also not reject that the IV estimate is equal to the OLS estimate. For the group of students without prior loan experience the IV-estimate equals ~0.071 which, with a standard error of 0.089, is not significantly different from zero. We reject equality of the OLS and IV-estimates; the IV-estimate is significantly below the OLS estimate (p-value = 0.042). For completeness the table also reports the IV-estimate for the group of students with prior loan experience, but since we have a weak instrument for this group the design is not informative here.

We have estimated the effect of being correctly informed about student loan conditions on their take up. Although our estimates are relatively imprecise they suggest that informing students about loan conditions may even lower take up rates. The explanation may lie in the fact that the treatment may result in positive or negative information updates. That is, the treatment may lead to more or less favorable perceptions of the actual loan conditions. The estimated effect of the treatment will therefore be an average of these two possibly offsetting effects which can explain the negative point estimates in Table 5.5.

5.6 Summary and discussion

The effectiveness of public policies is limited by the extent to which agents are correctly informed about them. Several studies document that students are poorly informed about the conditions of the government student loan scheme in the Netherlands. Students who are better informed have higher take-up rates. This suggests that governments can stimulate borrowing and thereby increase efficiency by providing more information about the supposedly favorable - conditions of their loan schemes. This is actually what the Dutch government has recently been considering.

To investigate whether there really exists a causal impact of better knowledge about loan conditions on borrowing behavior, we conducted a randomized experiment where half of the participants were exposed to an information treatment. Six months later we find that
students who received information have better knowledge about the loan conditions. While for students with prior loan experience our treatment has no effect, for students without prior loan experience - which is the main target group of an information campaign - our design is informative.

Naive OLS estimates reveal a significantly positive association between knowledge about loan conditions and borrowing. This is consistent with the findings of earlier studies. Our instrumental variable estimates suggest, however, that there is no causal impact of better knowledge on borrowing, thereby indicating that information provision is an ineffective method to increase the loan take-up rate. Although this may imply that the loan scheme is effective in lifting liquidity constraints, the results of our experiment do not answer the question why Dutch higher education students have low take-up rates on study loans. They merely reject uninformedness about the favorable loan condition as a valid explanation. Although the results suggest that the information constraint is not binding, other constraints may be, and subsequent studies should therefore focus on alternative explanations for low take-up rates such as debt aversion or the low returns to studying hard. The results of such studies can only be satisfactory if they also explain why borrowing rates are lower in the Netherlands than elsewhere.

5.7 Appendix to chapter 5

5.7.1 Regressions with covariates reported

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<th>OLS (1)</th>
<th>RF (2)</th>
<th>IV (3)</th>
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<td><strong>K</strong></td>
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<td>0.022</td>
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</tr>
<tr>
<td></td>
<td>(10.17)</td>
<td>(0.24)</td>
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<tr>
<td>Treatment</td>
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<td>0.012</td>
<td>0.012</td>
</tr>
<tr>
<td></td>
<td>(0.23)</td>
<td>(0.64)</td>
<td>(0.66)</td>
</tr>
<tr>
<td>Female</td>
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<td>0.012</td>
<td>0.012</td>
</tr>
<tr>
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<td>(0.71)</td>
<td>(0.64)</td>
<td>(0.66)</td>
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<td>0.027***</td>
<td>0.027***</td>
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<tr>
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<td>(3.85)</td>
<td>(3.87)</td>
<td>(3.80)</td>
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<td>Ethnic Minority</td>
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<td>0.093*</td>
<td>0.095*</td>
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<td></td>
<td>(2.22)</td>
<td>(1.97)</td>
<td>(2.00)</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>- Level 2</td>
<td>−0.025</td>
<td>−0.030</td>
<td>−0.028</td>
</tr>
<tr>
<td></td>
<td>(1.21)</td>
<td>(1.39)</td>
<td>(1.32)</td>
</tr>
<tr>
<td>- Level 3</td>
<td>0.000</td>
<td>−0.004</td>
<td>−0.003</td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(0.13)</td>
<td>(0.09)</td>
</tr>
<tr>
<td>- Level 4</td>
<td>0.008</td>
<td>0.007</td>
<td>0.007</td>
</tr>
<tr>
<td></td>
<td>(0.28)</td>
<td>(0.23)</td>
<td>(0.25)</td>
</tr>
<tr>
<td>--------------------------</td>
<td>--------</td>
<td>--------</td>
<td>--------</td>
</tr>
<tr>
<td>- Level 5</td>
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<td>-0.001</td>
<td>-0.002</td>
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<td>(0.29)</td>
<td>(0.02)</td>
<td>(0.08)</td>
</tr>
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<td>Discount rate</td>
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<td>0.18***</td>
<td>0.18***</td>
</tr>
<tr>
<td></td>
<td>(3.73)</td>
<td>(3.77)</td>
<td>(3.75)</td>
</tr>
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<td>Risk tolerance</td>
<td>0.021***</td>
<td>0.022***</td>
<td>0.022***</td>
</tr>
<tr>
<td></td>
<td>(5.35)</td>
<td>(5.55)</td>
<td>(5.26)</td>
</tr>
<tr>
<td>Academic track</td>
<td>0.053**</td>
<td>0.077***</td>
<td>0.071*</td>
</tr>
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</tr>
<tr>
<td>- Natural sciences</td>
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<td>0.005</td>
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<td></td>
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<td>(0.13)</td>
<td>(0.08)</td>
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<td>(1.94)</td>
<td>(1.94)</td>
<td>(1.95)</td>
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<td>- Economics</td>
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<td>0.035</td>
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<tr>
<td></td>
<td>(0.74)</td>
<td>(1.06)</td>
<td>(0.94)</td>
</tr>
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<td>- Law</td>
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<td>0.072</td>
<td>0.074</td>
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<tr>
<td></td>
<td>(1.73)</td>
<td>(1.48)</td>
<td>(1.53)</td>
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<td>- Humanities</td>
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<td>0.021</td>
<td>0.019</td>
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<td>(0.62)</td>
<td>(0.56)</td>
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<td>- Language and culture</td>
<td>0.071</td>
<td>0.081*</td>
<td>0.078*</td>
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<tr>
<td></td>
<td>(1.95)</td>
<td>(2.16)</td>
<td>(2.04)</td>
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<td>- Education</td>
<td>0.035</td>
<td>0.039</td>
<td>0.038</td>
</tr>
<tr>
<td></td>
<td>(0.79)</td>
<td>(0.84)</td>
<td>(0.83)</td>
</tr>
<tr>
<td>Study Duration</td>
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<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(0.69)</td>
<td>(0.39)</td>
<td>(0.09)</td>
</tr>
<tr>
<td>Loan Experience</td>
<td>0.36***</td>
<td>0.39***</td>
<td>0.38***</td>
</tr>
<tr>
<td></td>
<td>(16.71)</td>
<td>(17.82)</td>
<td>(11.12)</td>
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<td>-0.69***</td>
<td>-0.69***</td>
</tr>
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<td>(5.14)</td>
<td>(4.86)</td>
<td>(4.96)</td>
</tr>
<tr>
<td>N</td>
<td>2188</td>
<td>2188</td>
<td>2188</td>
</tr>
</tbody>
</table>

Note: Regressions on full sample. Robust standard errors in parentheses. */**/*** denote significance at a 10/5/1% confidence level.

5.7.2 Survey February 2007

Welcome to this short survey concerning student loans. Completing the questionnaire will only take a couple of minutes. One of the respondents of the survey will win an iPod Nano! You will be notified whether you are the winner directly after completing the questionnaire. The name of the winner will also be published on the www.HetStudentenpanel.nl website.

1 Do you still follow higher education?
   - yes, at an academic university
   - yes, at a higher vocational school
   - no, mean while I have obtained my degree <go to Q17>
   - no, I have quit studying prematurely <go to Q17>

2 What phase of studying are you in?
   - begin phase
   - middle phase
   - end phase
Information and the take-up of student loans

3 Does the IB-Groep [student financial aid organization] currently supply you with: (multiple answers possible)
   - basic grant
   - supplementary grant
   - interest bearing loan
   - no, I don’t receive any of these types of student financial aid

4 Did you in the passed (also) receive a student loan from the IB-Groep?  
   - yes  
   - no <treated go to Q6; controls go to Q12>

5 For how many months have you taken-up a student loan with the IB-Groep during your (current) studies? <only if Q3=3 or Q4=1> <open question: …months>

Controls go to Q12.

<RoleNote>Randomized questions on separate pages</RoleNote>

Students that receive a basic grant can (depending on the size of their supplementary grant) borrow a maximum of € 500 per month. Students who do not receive a basic grant can, for another 36 months, borrow a total of € 790 per month.

6 Do you think this is an attractive property?  
   - yes  
   - no  
   - neutral/no opinion

You can borrow while you receive a basic and/or a supplementary grant (the nominal study period): the normal period of your curriculum. When your eligibility for a basic grant ends you can take up a loan for another 36 months.

7 Do you think this is an attractive property?  
   - yes  
   - no  
   - neutral/no opinion

Students start repaying their debt on the first of January two years after they have quit or finished their studies (grace period). It is also possible to start repaying earlier.

8 Do you think this is an attractive property?  
   - yes  
   - no  
   - neutral/no opinion

You have to repay the debt in fixed monthly installments within 15 years. You do not have to pay the full monthly installment in case you have insufficient income in a particular year. After 15 years, any remaining debt will be forgiven.

9 Do you think this is an attractive property?  
   - yes  
   - no  
   - neutral/no opinion

The interest levied on the student loan is 3.7 in 2007. For comparison: a normal savings account will give you roughly the same return or more.

10 Do you think this is an attractive property?
You can choose the loan amount yourself. Temporary financial hardship? You can flexibly take a loan for two months and stop borrowing when it is no longer necessary.

11 Do you think this is an attractive property?
- yes
- no
- neutral/no opinion

12 Which statement comes to your mind first when thinking of student loans?
   a  I first think of:
     - Necessary evil
     - Gives the possibility to completely focus on studying
   b  I first think of:
     - Later I will earn enough to repay the debt.
     - I am afraid of having a large debt.
   c  I first think of:
     - Borrowing stresses the individual responsibility for studying.
     - I think borrowing is a risk
   d  I first think of:
     - Favorable conditions
     - Unfavorable conditions
   e  I first think of:
     - Study faster and start working
     - Afford extra luxury
   f  I first think of
     - Borrowing is better than working
     - Working is better than borrowing
   g  I first think of
     - Borrow more > work less > more spare time
     - Borrow more > work less > study more
   h  I first think of
     - Loans are a blessing
     - Loans are a curse
   i  I first think of
     - I feel guilty if I borrow in stead of taking a job
     - I can work the rest of my live.
   j  I first think of:
     - Borrowing is not done if it is nor necessary
     - Borrowing makes life more pleasurable
   k  I first think of:
     - The high rate of interest makes borrowing unattractive
Information and the take-up of student loans

1. The low rate of interest makes borrowing attractive

1. I first think of:
   - I would rather eat dry bread than take a loan.
   - Eat and drink well.

13. What is your attitude towards borrowing for your studies?
   - very negative
   - predominantly negative
   - mildly negative
   - neutral
   - mildly positive
   - predominantly positive
   - very positive

14. What is your parents’ opinion about student borrowing?
   - very negative
   - predominantly negative
   - mildly negative
   - neutral
   - mildly positive
   - predominantly positive
   - very positive
   - not applicable / I don’t know

This was the final question of the survey. Click on the button below to send it. Thank you very much for your cooperation.

5.7.3 Survey August 2007

Dear student. In February of this year you participated in an internet survey about student borrowing behavior. This survey is used to investigate attitudes towards borrowing by students. This research is conducted by ResearchNed from Nijmegen and the University of Amsterdam commissioned by the Ministry of Education, Culture and Sciences. At the end of this survey we will ask you about your study progress and your financial situation. You can also answer to the questionnaire if you have quit or finished studying. If you complete this second survey, you have a chance to win one out of five iPod MP3 players with 4GB!

1. Do you still follow higher education? <single response>
   - yes, at an academic university
   - yes, at a higher vocational school
   - no, meanwhile I have obtained my degree <go to Q3>
   - no, I have quit studying prematurely <go to Q5>

2. For how many months have you been studying? <number 1-120>
   
   ............months

3. When did you finish your studies? (we do not mean the date of the graduation ceremony, but we mean the formal completion date.)?
   
   ............months ............year

4. How many months did you need to complete your studies? <number 1-120> <go to Q8>
   
   ............months
5 When did you quit studying?

...........months ...........year

6 After how many months did you quit studying (counted from the exact date you started)? <number 1-120> <go to Q8>

...........months

7 Does the IB-Groep currently provide you a : <multiple response><if Q1=1 or 2>

☐ basic grant
☐ supplementary grant
☐ interest bearing loan
☐ no, I don’t receive any of these types of student financial aid

8 Have you ever taken out a student loan from the IB-Groep in the past? <single response><all>

☐ yes
☐ no

9 Have you taken out a student loan with the IB-Groep in the past four months and if so, what was the amount of the loan? <all>

a In April I borrowed:

☐ € ...........
☐ I did not borrow

b In May I borrowed:

☐ € ...........
☐ I did not borrow

c In June I borrowed:

☐ € ...........
☐ I did not borrow

d In July I borrowed:

☐ € ...........
☐ I did not borrow

10 How many credit points did you obtain in the past few months? <all>

a April ...............ECTS ☐ n.a.

b May ...............ECTS ☐ n.a.

c June ...............ECTS ☐ n.a.

d July ...............ECTS ☐ n.a.

11 How many credit points did you obtain in total in the last academic year? <all>

12 Next to your study how many hours did you, on average, work per week the past months (paid labor)?

a April ...............average hours per week ☐ n.a.

b May ...............average hours per week ☐ n.a.

c June ...............average hours per week ☐ n.a.

d July ...............average hours per week ☐ n.a.

13 Are you planning to borrow from the IB-Groep in August? <if Q1=1 or 2>

☐ yes: how much: € ......................
☐ no
The next questions concern your familiarity with the conditions of student loans. You do not have to give the correct answers to these questions. Our only interest is how familiar you are with the conditions of student loans.

14 What is the maximum amount that you can borrow from the IB-Groep while you receive a basic grant?

...........Euro

15 For how many months can you take out a student loan with the IB-Groep after you are no longer eligible for a basic?

...........months

16 How many months after finishing your study do you, at the latest, have to start repaying your debt with the IB-Groep?

...........years

17 In how many years do you have to payoff your debt?

...........years

18 What is the interest rate on student loans?

...........percent <1 decimal>

19 What is your attitude towards borrowing to finance your studies? <single response>

- very negative
- predominantly negative
- mildly negative
- neutral
- mildly positive
- predominantly positive
- very positive

20 What is the attitude of your parents about borrowing to finance your studies? <single response>

- very negative
- predominantly negative
- mildly negative
- neutral
- mildly positive
- predominantly positive
- very positive
- not applicable / I don’t know

21 Do you think you will attain the diploma of your current curriculum.? <single response> <if Q1=1 or 2>

- I don not think so
- probably will not
- probably will
- I am sure

22 Say you finish your current studies. How likely do you think it is that you find a job that corresponds to your education? <single response> <if Q1=1 or 2>

- I don not think so
- probably will not
- probably will
- I am sure

23 What net monthly income do you think you will earn 2 years after you have graduated? <single response> <if Q1=1, 2 or 3>

- less than € 1000
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24 What net monthly income do you think you will earn 5 years after you have graduated? <single response> <if Q1=1, 2 or 3>

- less than €1000
- approximately €1000
- approximately €1250
- approximately €1500
- approximately €1750
- approximately €2000
- approximately €2250
- approximately €2500
- approximately €2750
- approximately €3000
- approximately €3250
- approximately €3500
- approximately €3750
- approximately €4000
- more than €4000

25 How do you judge yourself: Are you in general prepared to take risks, or do you try to avoid risks? Evaluate yourself on a left to right scale, where the box on the far left means ‘not prepared to take risks’ and the box on the far right means ‘prepared to take risks’. <single response> <all>

prepared to take risks   not prepared to take risks

26 Say you have to choose between receiving €1.000 today or €1.050 in one year. Which of these two options would you prefer? <single response> <all>

- prefer €1.000 today
- prefer €1.050 in one year

27 Say you have to choose between receiving €1.000 today or €1.100 in one year. Which of these two options would you prefer? <single response> <all>

- prefer €1.000 today
- prefer €1.100 in one year

28 Say you have to choose between receiving €1.000 today or €1.200 in one year. Which of these two options would you prefer? <single response> <all>

- prefer €1.000 today
- prefer €1.200 in one year

29 Say you have to choose between receiving €1.000 today or €1.300 in one year. Which of these two options would you prefer? <single response> <all>
Information and the take-up of student loans

- prefer € 1.000 today
- prefer € 1.300 in one year

30 Say you have to choose between receiving € 1.000 today or € 1.400 in one year. Which of these two options would you prefer? <grid 1-5: does not apply to me at all – applies to me very well: randomized>
- prefer € 1.000 today
- prefer € 1.400 in one year

31 Say you have to choose between receiving € 1.000 today or € 1.500 in one year. Which of these two options would you prefer? <grid 1-5: does not apply to me at all – applies to me very well: randomized>
- prefer € 1.000 today
- prefer € 1.500 in one year

32 Finally we would like to ask you by how far the below statements apply to you. <grid 1-5: does not apply to me at all – applies to me very well: randomized>
   a I have purposefully chosen to follow higher education because I want to, in the future, be able to help others.
   b By following a higher education I will be able to contribute more to society.
   c Studying enables me to help others.
   d If you get the opportunity to follow higher education, I think it is important to reciprocate to society/others.
   e In my future employment I think it is more important to do something useful for society than to earn a high salary.
   f I have consciously chosen to follow higher education because of passion of my subject
   g To me, studying means acquiring knowledge and insight into the subject that interest me and that I would like to put into practice in my future career.
   h I have been interested in this subject from when I was young. To continue higher education in this field of subject is a logical step.
   i I also spend much time on my subject of interest outside of the curriculum.
   j Continuing in higher education is important because it creates an opportunity to develop more broadly.
   k Following higher education is a goal in itself.
   l I study to develop myself.
   m To expand myself is my main motivation to follow higher education. The professional perspective plays a minor role.
   n Studying is a necessary evil.
   o The main reason I went on to do higher education is that it was expected of me.
   p I am looking forward to finish studying.
   q I want my studies to take as little from my free time as possible.
   r I have consciously chosen an education that gives me a well paid job.
   s Higher education will provide me with a job with status.
   t It is important to me that my subject topic is in high regard.

33 How would you describe your financial situation in the past four months (March - June)?
- very bad
- bad
- reasonable
- good
- very good

34 How would you describe your current financial situation?
- Very bad
- bad
- reasonable
- good
- very good
This was the last question of the survey. You can press the button below to send it. Thank you very much for your cooperation! You will be notified if you have won the iPod nano after the survey research is completed (in September). The winners will be made public on the website www.studentenpanel.nl.
Conclusion

This thesis has presented four studies that investigate the measurement sensitivity of different micro economic quantities. The first and major part of the thesis consists of three papers that concern the sensitivity of measurements of risk attitudes with respect to departures from the classical expected utility model. In this model risk aversion is solely determined by curvature of the utility function and it is assumed that every decision problem is fully integrated into wealth. Measures of utility are important for equitable taxation, the composition of efficient public insurance, prescriptive decisions in health care and welfare analysis in structural economic models. In the second part we consider an empirical application in education economics where we investigate the measurement sensitivity of the causal effect of student’s knowledge about loan conditions on their borrowing behavior with respect to the classical (empirical) assumption of exogeneity. This measure is informative for policies that aim to increase student’s borrowing through increased information provision.

The first part starts with chapter 2, where we consider what happens to the obtained measure of utility curvature if it is assumed that individuals can not borrow from future income, which is implicitly assumed in the classical expected utility model. In that model it is assumed that individuals can borrow freely, such that they will smooth their consumption over time, borrowing money when income is relatively low, and saving money when income is relatively high. In this case the individuals’ consumption profile will be smooth and the consumption of a windfall gain will be spread over the entire lifetime, i.e. it will be fully integrated into lifetime wealth. When borrowing is constrained and this is binding, however, a windfall gain will be consumed quickly. In this case the consumption of the additional income is spread over a finite period that is endogenously determined and depends on time preferences. Hence, in this setting, the windfall gain is not fully integrated
into lifetime wealth and its relative impact depends on the length of the affected consumption period. A given amount of additional income has a larger relative impact when it is consumed in a day compared to when it is spread over the entire lifetime.

The effect of intertemporal constraints on the measure of utility curvature is illustrated using an empirical application where risk aversion is measured using the hypothetical valuation of a series of lotteries by a representative sample of individuals. It is shown how, in this context, the standard model can be extended to accommodate for the additional time dimension by formulating a simple discounted expected utility model. Here we allow for the opportunity that individuals have to spread consumption optimally over time, while making the plausible assumption that individuals are borrowing constrained. This model forms an intermediate case between the expected utility model defined over wealth (the standard model) and defined over income (the immediate model). The average coefficient of relative risk aversion was estimated to be 82. If consumption is assumed to be immediate, the inferred relative risk aversion is 2, while we find an estimate of 338 if full asset integration is assumed. This shows that the degree of utility curvature is estimated overly concave by the classical model if individuals are borrowing constrained and also that we can get lower estimates while retaining the plausible assumption that consumption is not immediate.

In chapter 3 we take a different departure from the classical expected utility model. There we assume people’s behavior is better described by prospect theory, which states that people evaluate outcomes with respect to a flexible reference point, and that they weight probabilities non-linearly. Using a non-parametric measurement method that is robust to these departures from the classical model, we find utility curvature to be close to linearity for a representative sample of the Dutch population. This result externally validates results from the laboratory that suggest that classical utility measurements overestimate concavity, which can be explained by the ignoring of probability weighting and loss aversion in these measurements. Further, the results suggest that utility is concave for gains and convex for losses, implying diminishing sensitivity towards outcomes, as predicted by prospect theory but contrary to the classical prediction of universal concavity. In the study we also obtain parameter-free measurements of loss aversion. The results show that on average people are
Conclusion

significantly loss averse and weight a loss about 1.87 times as much as a commensurable gain. Interestingly, we find evidence that males and higher educated persons are significantly less loss averse. The former result suggests that gender differences in risk attitudes are primarily driven by loss aversion and not by utility curvature as suggested by previous studies that assume the classical expected utility model. The latter result suggests that measurements of loss aversion based on relatively highly educated student samples lead to an underestimation of the loss aversion coefficient.

In chapter 4 we stay in the realm of prospect theory and, again, consider loss aversion and the non-linear weighting as departures from the classical theory. The approach in this chapter, however, is more parametric which allows for the econometric modeling of decision errors. Furthermore, we use a larger part of the dataset that allows for the estimation of subjective probability weighting as well. The results qualitatively confirm the non-parametric results of chapter 3 and suggest that utility is mildly concave for gains and mildly convex for losses, implying diminishing sensitivity and suggesting that classical utility measurements that neglect probability weighting are overly concave.

A direct comparison with the non-parametric measures suggests that assuming homogeneity leads to a small downward bias. Interestingly, the estimates are closer to linearity compared to parametric studies that impose more stringent parametric assumptions (e.g. Donkers et al. 2001; Harrison and Rutström 2007), suggesting the utilities obtained in these studies may suffer from a contamination bias: a misspecification of the probability weighting function will bias the estimated concavity of the utility function.

In addition to these results, we find evidence that probabilities are weighted non-linearly, with an inverse-S shape, and that both functions display pessimism (low elevation for gains, high elevation for losses). These results externally validate probability weighting that was found in a laboratory context. The obtained degree of loss aversion of 1.58, as operationalized by Tversky and Kahneman (1992), is somewhat lower than the non-parametric estimate of 1.87 in chapter 3, again suggesting that assuming homogeneity may lead to a small bias. The estimate is still consistent with contemporaneous studies (Schmidt and Traub 2002; Johnson et al. 2006, Abdellaoui 2008), however, that find loss aversion below 2. Finally the parametric analysis refines the result of chapter 3 that shows that
gender differences in risk aversion can not be ascribed to utility curvature, as is done in classical studies, but to loss aversion. This chapter adds differences in probability weighting for gains to this explanation.

In the second part of this thesis (chapter 5) we consider an empirical application in education economics where we investigate the measurement sensitivity of the causal effect of student’s knowledge about loan conditions on their borrowing, with respect to the classical empirical assumption of exogeneity. Several studies document that students are poorly informed about the conditions of the government student loan scheme in the Netherlands. Students who are better informed have higher take-up rates. This suggests that governments can stimulate borrowing and thereby increase efficiency by providing more information about the - supposedly favorable - conditions of their loan schemes. This interpretation, however, implicitly assumes that the knowledge students have about the loan conditions is independent of other (unobserved) factors that determine borrowing, i.e. it assumes that knowledge is exogenous. To investigate whether there really exists a causal impact of better knowledge about loan conditions on borrowing behavior, we conducted a randomized experiment where half of the participants were exposed to an information treatment. Using the information treatment as instrumental variable for knowledge we find that there is no causal impact of better knowledge on borrowing, thereby indicating that the exogeneity assumption invalid. The policy implication is that information provision is an ineffective method to increase the loan take-up rate.

This thesis has presented four studies that investigate departures from classical measurement assumptions in microeconomics. In the first part it was investigated how measures of utility are affected by departures from the classical assumption of expected utility. While applying prospect theory’s deviations from expected utility to the measurement of utility is not novel, introducing a time dimension to the model is a new approach that deserves consideration, especially for large stakes. A combination of the two models, by including a time dimension in prospect theory, could also be a fruitful approach to separate utility curvature from probability weighting, loss aversion and impatience. Including a time dimension by modeling optimal smoothing behavior is necessary
parametric, however, and depends heavily on the intertemporal constraints facing the agent. This may make the results from such an approach less convincing.

Careful thinking about identification assumption(s) is at the heart of good empirical research. The second part of this thesis makes clear that students’ loan take-up will not increase by information provision, even though there is a clear positive association between knowledge about loan conditions and borrowing. This means uninformedness about the favorable loan conditions cannot explain why borrowing rates are lower in the Netherlands than elsewhere, which remains an important puzzle that deserves further research. As higher education financing is under continuous pressure due to increased participation, future policy decisions may benefit from such an investigation.


