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Analysing risk preferences among insurance customers

Expected utility theory versus disappointment aversion theory

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Abstract

In this thesis we analyse risk preferences among insurance customers using two different theories, namely expected utility theory (EUT) and disappointment aversion theory (DAT). The goal is to find out which of these theories that best can explain the choices the customers made under risk. The analysis is based on a survey submitted to Norwegian insurance customers in the fall of 2011. The respondents were asked to choose between hypothetical income lotteries, and the answers are used to establish an interval of risk aversion for each respondent. We estimate an interval regression model and investigate the relationship between risk aversion and socioeconomic characteristics. We find that risk aversion is significantly negatively correlated with income and number of children, and that those who are married are significantly more risk averse than others. Next, we derive a cardinal measure of risk aversion for each respondent and find significant correlations between this measure and the likelihood of engaging in various risky activities. Assuming constant relative risk aversion, we find that the average coefficient of relative risk aversion is 7.930 under EUT, indicating that our sample is very risk averse. Next, we use simulation to derive the parameters of DAT. As far as we know, this is the first study where hypothetical income gambles of this type are used to estimate parameters of disappointment aversion. We find that the insurance customers appear to have a significant degree of disappointment aversion, and we reject a hypothesis that the customers adhere to the predictions of EUT on average.

Preface

This thesis was written as the concluding part of our major in Economic Analysis at the Norwegian School of Economics (NHH).

The topic was suggested to us by our supervisor, Fred Schroyen, who also provided us with the results from the survey used in the analysis. We would like to thank him for guiding us along the way, while continuously providing us with fruitful insight and interesting suggestions.

This has been a highly educational process, as we had to learn several advanced statistical models and methods during the course of the semester. Moreover, the complexity of the tasks at hand motivated us to learn programming in Maple. We are convinced that the accumulated knowledge will be useful to us in the future.

Bergen, June 2016.

Emil Haga and André Waage Rivenæs.

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1 Introduction

A vast majority of the decisions made in life involve some kind of risk. While certain people appreciate risky prospects, others avoid them at all cost. The manner in which individuals react to risk reveals something about their risk preferences. Attempting to model and analyse risk preferences has been a major focus in economics and finance for an extended period of time, as being able to quantify the effect of risk on welfare can be important for numerous applications. For instance, if a pension fund were to manage a portfolio optimally, it would be beneficial to know the risk preferences of its members. However, there still exists uncertainty as to which theory is the most adequate when it comes to analysing behaviour under risk.

In this paper, we will analyse risk preferences among Norwegian insurance customers using two different theories. The purpose is to investigate which of these theories that is best suited to explain the customers' choices under risk. The first theory is the traditional expected utility theory (EUT), suggested by Bernoulli (1738/1954) and further developed by Von Neumann & Morgenstern (1944) (hereafter, vNM). This theory is a natural benchmark, as it is by far the most used model when it comes to analysing risky behaviour. However, it builds upon a very controversial assumption, the independence axiom, which says that the choice between two lotteries should be independent of outcomes they have in common.

The second theory is disappointment aversion theory (DAT), proposed by Gul (1991). This theory is based on the idea that individuals get additional disutility from a gamble if a disappointing outcome occurs, compared to the utility gained from a corresponding good outcome. This theory is an extension of EUT, but the independence axiom is replaced by a weaker assumption. The fact that EUT is a special case of DAT makes it analytically convenient, as it makes it simpler to compare predictions across theories.

Our analysis is based on a survey submitted to Norwegian insurance customers in the fall of 2011. It is inspired by Barsky, Juster, Kimball & Shapiro (1997) (hereafter, BJKS), who developed a method to estimate relative risk aversion through a set of questions where the respondents were asked to choose between hypothetical income gambles. In each question, the respondents could choose between either keeping their current income, or participating in a gamble in which there was a 50 per cent probability of doubling one's income, and 50 per cent probability of reducing it by a certain factor.

Using such hypothetical questions is convenient, as it makes it possible to measure risk aversion with respect to arbitrarily large risk, but it comes at the cost of potential survey response-error. We will follow the methodology of BJKS to estimate relative risk aversion under EUT, and supplement with a new set of hypothetical gambles in order to make it possible to estimate parameters of DAT. To the best of our knowledge, this is the first study that uses hypothetical income gambles of the BJKS-type to estimate parameters of disappointment aversion.

In the following section, we will cover traditional expected utility theory and define measures of risk aversion. Section 3 presents extensions of expected utility theory. First, we describe Gul's theory of disappointment aversion, and look at how the theory can be applied to different problems. Secondly, we discuss a few alternative models that resemble DAT, and look at how these models compare to each other in empirical tests. In section 4, we review the literature on hypothetical income gambles of the BJKS-type. Section 5 describes the design of our survey, and discusses the pros and cons of using a questionnaire compared to a real-life experiment. In section 6, we describe the data collection-process. In section 7 we perform ordered probit and interval regressions to investigate the relationship between risk aversion and socioeconomic factors. Section 8 estimates two different cardinal measures of risk aversion for each respondent, and converts these measures to parameters of risk aversion under EUT. In section 9, we estimate the parameters of disappointment aversion and look at the connection between the estimated parameters and socioeconomic characteristics. Section 10 investigates if the estimates from DAT and EUT result in different predictions of risky behaviour. Section 11 concludes.

2 Traditional utility theory

2.1 The expected utility hypothesis

In his expected utility hypothesis, Bernoulli (1738/1954) pointed out that two people facing the same lottery might value it differently due to differences in their psychology. These differences can be represented by the concept of utility, which is a subjective measure of satisfaction for a given individual. This concept was contrary to the idea at that time, which was that the value of a lottery, for all individuals, should equal its mathematical expectation (Eeckhoudt, Gollier & Schlesinger, 2005, p. 3).

The expected utility hypothesis states that the utility (u) of a lottery (L) is best represented by the weighted average of all possible levels of utility. The possible outcomes (x), typically measured in monetary units, are ordered into N different states (s). A given outcome equals the individual's initial wealth (w) plus the risky payoff in that state. The level of utility the individual will obtain in each particular state represents the value of this state. The expected utility of the lottery, denoted $V(L)$, is the weighted average of these values, with the weights equal to the probability (p_s) that the given state is realized.

$$E[u(L)] \coloneqq V(L) = \sum_{s=1}^{N} p_s u(x_s) \tag{1}$$

When comparing alternatives, the individual is predicted to prefer the alternative with the highest expected utility. Even though individuals may not truly compute this value explicitly, the idea is that they are predicted to act as if they did.

Mathematically, the relationship between a monetary outcome and the degree of satisfaction can be characterized by a utility function, $u: x \to \mathbb{R}$. Let $u(x)$ be a twice differentiable, continuous function. Although utility is subjective, the utility function is assumed to exhibit some basic properties of realistic behaviour. First of all, the utility function should be increasing in wealth, so that $u'(x) > 0$. For a given individual, a higher level of wealth should induce a higher level of utility.

The main reason people will value lotteries differently, is due to differences in risk preferences. In general, most people can be described as risk averse. A risk averse individual can be defined as someone who dislikes a zero-mean risk at all levels of wealth, so that $u(w) > E[u(w+Z)]$, where Z is a risky gamble with $E[Z] = 0$ (Eeckhoudt et al., 2005, p. 7). Correspondingly, an individual for whom $u(w) = E[u(w+Z)]$ is said to be risk neutral, whilst an individual for whom $u(w) < E[u(w+Z)]$ is said to be risk loving. However, risk neutrality and risk loving with respect to large risks is seldom observed in practice.

Risk preferences are modelled by allowing for a non-linear relationship between utility and wealth. Risk aversion is incorporated by assuming that the utility function is concave with respect to wealth, so that $u''(x) < 0$. It follows from Jensen's inequality that any individual with a concave utility function will dislike zero mean risks, and thus having a concave utility function is a necessary and sufficient condition for being risk averse.[1] Accordingly, risk neutrality would imply that $u''(x) = 0$, while risk loving would imply that $u''(x) > 0$.

However, if an individual's preferences are to be represented by expected utility, some restrictions must hold.

2.2 The von Neumann-Morgenstern axioms

Von Neumann & Morgenstern (1944) presented an axiomatic characterization of expected utility. They listed several axioms that need to hold if an individual's preferences are to be represented by expected utility. These axioms have since become standard in the economic literature.

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[1] Let z be a random variable and let f be a twice-differentiable function. Jensen's inequality states that $E[f(Z)] \leq f(\mathrm{E}[Z])$ for all Z if and only if f is concave. For an individual who dislikes zero mean risks at all levels of wealth, we must have: $E[u(w+Z)] \leq u(w)$, where Z is a zero mean risk. If we let $Z' \coloneqq w + Z$, this is equivalent to $E[u(Z')] \leq u(\mathrm{E}[Z'])$. Thus, Jensen's inequality implies that $u(x)$ must be concave for this individual.

Let $\mathcal{L}$ denote the set of lotteries over the space of all possible outcomes. A binary preference relation will represent the preferences an individual has with respect to the different lotteries. Let L_1 and L_2 be lotteries where $L_1, L_2 \in \mathcal{L}$. Then $L_1 \succcurlyeq L_2$ indicates that L_1 is weakly preferred over L_2, $\succ$ indicates strict preference and $\sim$ indicates indifference.

The following system of axioms puts restrictions on an individual's preferences on $\mathcal{L}$.

Axiom 1: Completeness

For every L_1 and L_2, either $L_1 \succcurlyeq L_2$ is true, or $L_2 \succcurlyeq L_1$ is true, or both.

Completeness means that people have well defined preferences and are able to make a choice between alternatives. It also implies that ties are possible.

Axiom 2: Transitivity

For every L_1, L_2 and L_3, if both $L_1 \succcurlyeq L_2$ and $L_2 \succcurlyeq L_3$, then $L_1 \succcurlyeq L_3$.

The transitivity axiom is necessary to ensure that a respondent's choices are internally consistent. Intuitively, if someone prefers apples to oranges, and prefers oranges to bananas, he or she should also prefer apples to bananas. Together with completeness, the axiom makes it possible to order all lotteries on a single scale, instead of merely comparing two and two lotteries.

Axiom 3: Independence

Let L_1, L_2 and L_3 be three lotteries where $L_1 \succcurlyeq L_2$ and let $a \in [0,1]$, then $aL_1 + (1-a)L_3 \succcurlyeq aL_2 + (1-a)L_3$.

The independence axiom states that the preference ordering of two lotteries is unchanged if mixed with a third lottery in an identical manner. This axiom is by far the most controversial (see e.g. Allais, 1979).

Axiom 4: Continuity

Let L_1, L_2 and L_3 be lotteries such that $L_1 \succcurlyeq L_2 \succcurlyeq L_3$, then there exists some $a \in [0,1]$, such that $L_2 \sim aL_1 + (1-a)L_3$.

This axiom implies that if L_1 is preferred to L_2, then there exists a lottery in the region near L_1 that also will be preferred to L_2 (Levin, 2006). Hence, a is strictly below 1 when L_1 is strictly preferred to L_2.

Axiom 5: Monotonicity

Let L_1 and L_2 be lotteries over the possible outcomes x_1 and x_2, where $x_1 \succcurlyeq x_2$, and let p and q be probabilities such that $1 \geq p \geq q \geq 0$. If L_1 assigns the probability p to x_1 and $(1-p)$ to x_2, and L_2 assigns the probability q to x_1 and $(1-q)$ to x_2, then $L_1 \succcurlyeq L_2$.

Monotonicity implies that the player would prefer the lottery that assigns a higher probability to the preferred outcome, i.e., more of a good thing is always better.

The vNM-theorem says that if the axioms (1-5) hold, then there exists a continuous utility function of the expected utility form, $V: \mathcal{L} \to \mathbb{R}$ such that $V(L_1) \geq V(L_2)$ if and only if $L_1 \succcurlyeq L_2$, $\forall\, L_1, L_2 \in \mathcal{L}$ (Levin, 2006).[2]

2.3 Measures of risk aversion

In order to be able to compare the levels of risk aversion different individuals exhibit; several measures have frequently been applied in the literature.[3]

[2] Note that two utility functions of the expected utility form $U(L)$ and $V(L) = a + bU(L)$, where a and b are scalars with $b > 0$, have the same preferences.
[3] We will present these measures under expected utility theory, but note that all of the following measures also are relevant for disappointment aversion theory, although the calculation is slightly different.

2.3.1 Certainty equivalent and risk premium

The *certainty equivalent* is the minimum amount of wealth an individual would accept with certainty instead of taking a gamble (Copeland, Weston & Shastri, 2014, p. 52). Accordingly, the certainty equivalent (c) can be defined as the value that satisfies the following equality

$$u(c) = E[u(w + Z)] \quad (2)$$

where Z is a risky payoff related to the gamble. Hence, the individual is indifferent between receiving the certainty equivalent for sure, and accepting the gamble. For a risk averter, the certainty equivalent is always lower than the expected final wealth of taking the gamble.[4] When facing a gamble, an individual has a lower certainty equivalent the more risk averse he is.

The maximum amount of wealth an individual would be willing to give up in order to avoid a zero-mean gamble is called the *risk premium* (Eeckhoudt et al., 2005, p. 10). The risk premium is always nonnegative for a risk averse individual.

The risk premium, denoted as π, is the value that satisfies

$$E[u(w + Z)] = u\big(w + E[Z] - \pi(w, Z)\big) \quad (3)$$

where $E[Z] = 0$. The individual ends up with the same utility either by accepting the risk or by paying the risk premium.[5] When comparing two individuals, if agent 1 is more risk averse than agent 2, then $\pi_1(w, Z) > \pi_2(w, Z)$ for a given gamble (Pratt, 1964).

The risk premium can also be measured in relative terms. The *relative risk premium,* $\hat{\pi}$, is

[4] To see this, note that $u(c) = E[u(W + Z)] < u(E[W + Z])$ by Jensen's inequality, as $u''(x) < 0$ for a risk averse individual. Since $u(c) < u(E[W + Z])$, and u is a strictly increasing function, we must have $c < E[W + Z]$.

[5] Remark that the risk premium is related to the certainty equivalent. The risk premium equals the expected final wealth, minus the certainty equivalent, so that $\pi = E[w + Z] - c$.

referred to as the share of initial wealth an individual is willing to pay to get rid of a proportional risk, $z \coloneqq Z/w$. It is defined implicitly by the following equation (Eeckhoudt et al., 2005, p. 18):

$$E[u(w(1+z)] = u(w(1-\hat{\pi})) \tag{4}$$

2.3.2 The Arrow-Pratt approximation

Arrow (1965) and Pratt (1964) developed a formula to approximate an individual's absolute risk-premium. Let Z be a zero-mean risk, such that $E[Z] = 0$. From equation (3), we then have:

$$E[u(w+Z)] = u[w - \pi(w,Z)]$$

Using a second-order Taylor approximation for the left-hand side and a first-order Taylor approximation on the right-hand side of this equation, respectively, one obtains

$$u[w - \pi(w,Z)] \simeq u(w) - \pi u'(w)$$

and

$$E[u(w+Z)] \simeq E\left[u(w) + Zu'(w) + \frac{1}{2}Z^2u''(w)\right]$$
$$= u(w) + u'(w)E[Z] + \frac{1}{2}u''(w)E[Z]^2$$
$$= u(w) + \frac{1}{2}\sigma^2u''(w)$$

where $\sigma^2 = E[Z]^2$ is the variance of Z. Replacing these two approximations in the previous equation yields

$$\pi \simeq \frac{1}{2}\sigma^2 A(w) \tag{5}$$

where

$$A(w) \coloneqq -\frac{u''(w)}{u'(w)} \tag{6}$$

Equation (5) is known as the Arrow-Pratt approximation. $A(w)$ is referred to as the degree of *absolute risk aversion* of the agent. Observe that the risk premium is approximately proportional to the variance of the risk. However, this approximation can be considered accurate only when the risk is small or in very special cases. In most cases however, the risk premium associated with any (large) risk will also depend on other moments of the distribution of the risk, not just its mean and variance (Eeckhoudt et al., 2005, p. 12).

Let $k > 0$ be a constant that represents the size of the risk, such that $k \cdot Z$ is a risk of size k. Then we can link the size of the risk premium with k. Since $var(kZ) = k^2\sigma^2$, we get

$$\pi(k) \simeq \frac{1}{2}k^2\sigma^2 A(w) \tag{7}$$

Thus, the risk premium is approximately proportional to the square of the size of the risk. This property is called *second-order risk aversion*. Observe that $\pi'(k = 0) = 0$. Hence, when considering very small risks, risk averse agents are predicted to act as if they were risk neutral. This is due to the property that π approaches zero faster than k. In an alternative model where π is proportional to k, there would be *first-order risk aversion* (Segal & Spivak, 1990).

The relative risk premium for a proportional risk z equals the absolute risk premium for absolute risk Z, divided by initial wealth. If $\tilde{\sigma}^2$ denotes the variance of z, then the variance of $w \cdot z$ equals $w^2\tilde{\sigma}^2$. Using the Arrow-Pratt approximation, and defining $R(w) \coloneqq wA(w)$, yields

$$\hat{\pi}(z) = \frac{\pi(w \cdot z)}{w} \simeq \frac{1}{2} \cdot \frac{w^2\tilde{\sigma}^2 A(w)}{w} = \frac{1}{2}\tilde{\sigma}^2\, R(w) \tag{8}$$

2.3.3 Absolute and relative risk aversion

Upon deriving the approximations of absolute and relative risk premium, two functions emerged: $A(w)$ and $R(w)$, respectively. It turns out that these functions are convenient measures of risk aversion.

The Arrow-Pratt measure of absolute risk aversion, $A(w)$, is a local measure of the degree of concavity of the utility function. From equation (6), we have

$$A(w) = -\frac{u''(w)}{u'(w)}$$

Absolute risk aversion (ARA) measures the rate at which marginal utility decreases when wealth is increased by one monetary unit (e.g. one dollar). An individual will be more risk averse, and have a more concave utility function, the higher ARA (Pratt, 1964). When comparing two individuals with different utility functions, you can say that person 1 is more risk averse than person 2 if $A(w_1) \geq A(w_2)\ \forall\ w$, with at least one strict inequality. This is equivalent to saying that person 1 has a higher risk-premium than person 2 for all lotteries and for all levels of wealth (Pratt, 1964).

ARA may be either an increasing, decreasing or constant function of wealth. It is most common to assume decreasing absolute risk aversion, which implies that the richer an individual is, the less worried he is about losing a fixed amount of money. This relationship seems intuitively appealing.

One problem with the measure of absolute risk aversion is that it is not unit free, as it is measured per monetary unit. By multiplying ARA with the initial wealth level, the unit-free coefficient of relative risk aversion (RRA) is obtained. This is a local measure of risk aversion as a proportion of wealth (Pratt, 1964). Thus, RRA is the rate at which marginal utility decreases when wealth is increased by one per cent (Eeckhoudt et al., 2005, p. 17).

$$R(w) = w \cdot \left[-\frac{u''(w)}{u'(w)}\right] = wA(w) \tag{9}$$

RRA may be either an increasing, decreasing or constant function of wealth. Constant RRA would imply that the individual is willing to pay a constant share of his wealth to get rid of a given proportional risk. If an agent faces a lottery that will either increase or reduce her wealth by a given per cent, then she has constant RRA if the share of her wealth that she is willing to pay to get rid of this risk is independent of her initial wealth. If the share she is willing to pay increases (decreases) as her wealth is increased, she exhibits increasing (decreasing) RRA. While ARA intuitively is easy to imagine being decreasing in wealth, RRA is not that simple. Empirical studies have offered conflicting results concerning the relationship between RRA and wealth level (Eeckhoudt et al., 2005, p. 18).

Whether an individual has increasing, constant or decreasing absolute risk aversion, or increasing, constant or decreasing relative risk aversion, depends on the functional form of his utility function.

2.4 Choice of utility function

The most used type of utility function in the literature is the set of power utility functions (Eeckhoudt et al., 2005, p. 21). These utility functions exhibit constant relative risk aversion (CRRA) and decreasing absolute risk aversion (DARA). Thus, such a utility function eliminates income effects when considering risks that are proportional to wealth level. The following utility function is often assumed in the literature, and will also be used in our analysis.

$$\begin{cases} u(x) = \dfrac{x^{1-\rho}}{1-\rho} \text{ if } \rho \neq 1 \\ u(x) = \ln(x) \text{ if } \rho = 1 \end{cases} \tag{10}$$

This utility function is convenient, because the constant ρ is equal to the individual's RRA. It also exhibits decreasing absolute risk aversion for all positive levels of wealth.

$$u'(x) = \frac{(1-\rho)x^{-\rho}}{1-\rho} = x^{-\rho}, u''(x) = -\rho x^{-1-\rho}$$

$$ARA = -\frac{u''(x)}{u'(x)} = -\frac{-\rho x^{-1-\rho}}{x^{-\rho}} = \frac{\rho}{x}$$

$$RRA = -x\frac{u''(x)}{u'(x)} = -x\frac{-\rho x^{-1-\rho}}{x^{-\rho}} = \rho$$

Assuming constant relative risk aversion is a relatively strong assumption, but there is substantial empirical evidence that supports the notion of CRRA. For example, Chiappori & Paiella (2011) use panel data to find out how the respondent's asset allocation changes in response to a change in total wealth. They find no significant response of portfolio structure to changes in wealth. Thus, their results support the CRRA assumption.

Moreover, Sahm (2012) finds no effect of wealth changes on their risk aversion measure, supporting the CRRA-assumption. Brunnermeier & Nagel (2008) find that the share of liquid assets that households invest in risky assets is not affected by wealth changes. They conclude that CRRA may be a good description of behaviour.[6]

[6] Of course, there are also studies that indicate that the CRRA-assumption is violated. See for example Holt & Laury (2002).

3 Extending expected utility theory

3.1 The Allais paradox

One of the major criticisms towards traditional EUT is that the independence axiom does not always hold.

In fact, the famous *Allais paradox* indicates that there are situations in which this relationship is systematically violated (Allais, 1979). Gul (1991) presents the paradox as follows:

Problem 1: Choose either L_1 or L_2 where L_1 grants 200 dollars for sure and L_2 yields 300 dollars with probability 0.8 and zero dollars with probability 0.2.

Problem 2: Choose either L_1' or L_2' where L_1' grants 200 dollars with probability 0.5 and 0 dollars with probability 0.5 and L_2' is a lottery that yields 300 dollars with probability 0.4 and 0 dollars with probability 0.6.

Allais' study involved approximately 100 students with good training in probability, so that they were expected to understand the problems well (Allais, 1979). The study indicated that most people tend to choose L_1 in the first problem and L_2' in the second one. Such preferences are not consistent with EUT, since

$$L_1 \succcurlyeq L_2 \Rightarrow u(200) > 0.8u(300) + 0.2u(0)$$
$$L_2' \succcurlyeq L_1' \Rightarrow 0.4u(300) + 0.6u(0) > 0.5u(200) + 0.5u(0)$$

By dividing the second inequality by 0.5, it follows that we must have

$$u(200) < 0.8u(300) + 0.2u(0)$$

However, if this inequality were true, then the subjects should have chosen L_2 in the first problem. Thus, we have a contradiction. This contradiction is caused by a violation of the independence axiom. Recall that the independence axiom states that if L_1, L_2 and L_3 are three lotteries where $L_1 \succcurlyeq L_2$ and $a \in [0,1]$, then $aL_1 + (1-a)L_3 \succcurlyeq aL_2 + (1-a)L_3$. Let r be a lottery that yields zero dollars for sure. Note that we can write $L_1' = aL_1 + (1-a)r$ and $L_2' = aL_2 + (1-a)r$ by choosing $a = 0.5$. The independence axiom then states that since $L_1 \succcurlyeq L_2$, we should have $aL_1 + (1-a)r \succcurlyeq \ aL_2 + (1-a)r$, i.e. $L_1' \succcurlyeq L_2'$, and hence there is a violation of the axiom (Gul, 1991).

In a test of the vNM-axioms by MacCrimmon (1968), subjects were given the possibility to reconsider choices they had made which violated certain axioms. In most cases, subjects who objected transitivity admitted that their choices had been faulty. However, subjects who had objected the independence axiom were unwilling to alter their choices (MacCrimmon, 1968). This indicates that violations of the independence axiom are not caused by response error, but is of a more systematic nature.[7]

There have been suggested several alternatives and extensions to traditional EUT that have attempted to solve this problem. In many of these specifications, the independence axiom is replaced by a weaker requirement, e.g. the betweenness axiom.

Axiom of betweenness

Let L_1 and L_2 be two lotteries, and let p be a probability such that $p \in [0,1]$. If $L_1 \succcurlyeq L_2$, then we must have $L_1 \succcurlyeq pL_1 + (1-p)L_2 \succcurlyeq L_2$.

Thus, the betweenness axiom states that if L_1 is preferred to L_2, the probability mixtures of the lotteries must lie between them in preference.[8] The independence axiom implies betweenness, but

[7] There also exist studies that have indicated systematic violations of the transitivity axiom (see e.g. Tversky, 1969). However, in a review of studies designed to elicit intransitive preferences, Regenwetter, Dana & Davis-Stober (2011) claim that the data from these studies are in fact consistent with the transitivity axiom.

[8] Observe that there are no indications that the betweenness axiom does not hold in the example above. The betweenness axiom indicates that since $L_1 \succcurlyeq L_2$, then $L_1 \succcurlyeq pL_1 + (1-p)L_2 \succcurlyeq L_2$. If we for example let $p = 0.5$, then, since the respondent preferred [200; 1] over [300, 0; 0.8, 0.2], he must also prefer [200; 1] to the lottery [200, 300, 0; 0.5, 0.4, 0.1], which must be preferred

not vice versa (Camerer & Ho, 1994). Combined with continuity, the betweenness axiom implies that if one is indifferent between L_1 and L_2, one should also be indifferent between a random mix of the two lotteries.

One of the utility theories that assume betweenness is Gul's (1991) theory of disappointment aversion.

3.2 Disappointment aversion theory

The theory of disappointment aversion was introduced by Gul (1991).[9] The theory is based on the observation that most agents get additional disutility when receiving less than expected from a lottery, due to a feeling of disappointment. While the independence axiom is replaced by the betweenness axiom, all other axioms of EUT are maintained (Ang, Bekaert & Liu, 2005).

DAT is an axiomatic extension of EUT where the goal is to account for the Allais paradox, while at the same time creating a parsimonious model (Gul, 1991). In fact, the model is only one parameter richer than traditional EUT, making it one of the most restrictive extensions of expected utility. Gul argues that the independence axiom fails in Allais' experiment because the lottery with a lower probability of disappointment suffers more when mixed with an inferior lottery.[10]

In Gul's theory, there is an asymmetric treatment of losses versus gains. In particular, *disappointment averse* subjects attach greater marginal disutility to a marginal income loss below a certain reference level, than marginal utility to a marginal income increase above this reference level. The certainty equivalent (c) of the lottery is used as the reference level. Likewise, subjects who are defined as *elation loving* attach greater marginal utility to a marginal income increase

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over [300, 0; 0.8, 0.2]. To find out whether this relationship holds, more questions would have been necessary.

[9] Note that Bell (1985) and Loomes & Sugden (1986) were the first to propose theories with utility functions exhibiting some sort of disappointment aversion. However, in this text we focus on the specification given by Gul (1991).

[10] See appendix A.1 for proof that Gul's utility function can explain the choices made in the Allais paradox.

above the certainty equivalent, than marginal disutility to a marginal income loss below the certainty equivalent. Accordingly, all elation prizes are evaluated with respect to one utility function, while all disappointment prizes are evaluated with respect to another utility function (Gul, 1991). Such a specification is not consistent with traditional EUT, where the marginal utility associated with a gain always equals the marginal utility of a loss (Aizenman, 1998).

In Gul's framework, the preferences of a disappointment averse agent are given by his constant coefficient of disappointment aversion (β) as well as a conventional utility function $u(x)$, where $u'(x) > 0$. Then we can define the expected total utility, denoted $V(\beta, x)$, as

$$V(\beta, x) = \int u(x) f(x) dx - \beta \int_{x<c} [u(c) - u(x)] f(x) dx$$

$$\Updownarrow$$

$$V(\beta, x) = E[u(x)] - \beta E[(u(c) - u(x)) | x < c] \Pr[x < c] \tag{11}$$

where $f(x)$ is the probability density function of the gamble and $E[u(c) - u(x) | \, x < c]$ is the average disappointment, measured as the difference between the utility at the certainty equivalent and the actual utility at the realized income x, given that $x < c$ (Aizenman, 1998).

If $\beta > 0$, the agent is defined as disappointment averse. Accordingly, if $-1 < \beta < 0$, the agent is defined as elation loving. Remark that if $\beta = 0$ then this formula reduces to the conventional EUT formula. Thus, EUT is a special case of DAT. This property is analytically convenient, as it makes it possible to estimate the parameters of disappointment aversion and then test if the predictions of EUT hold on average by investigating whether β is significantly different from zero.

Next, we restrict our attention to a lottery with only two possible outcomes, (x_1, x_2), with probability p and $1 - p$ respectively, where $x_1 > x_2$. Note that $u(c) = V(\beta, x)$ by definition.

Moreover, we assume that the agent is risk averse, i.e. that $u''(x) < 0$.[11] Under these assumptions, equation (11) becomes

$$V(\beta, x) = pu(x_1) + (1-p)u(x_2) - \beta(1-p)[V(\beta, x) - u(x_2)$$

$$= \frac{p}{1+(1-p)\beta}u(x_1) + \frac{(1-p)(1+\beta)}{1+(1-p)\beta}u(x_2) \tag{12}$$

In Figure 1, the contours of Gul's utility function, given by equation (12), are drawn for the case when $p = 0.5, \beta = 1$ and $\rho = 5$. We assume that $u(x)$ is the power utility function, so that ρ is the agent's coefficient of relative risk aversion. Notice the kinks in the indifference curves through the 45-degree line for this disappointment averse agent.

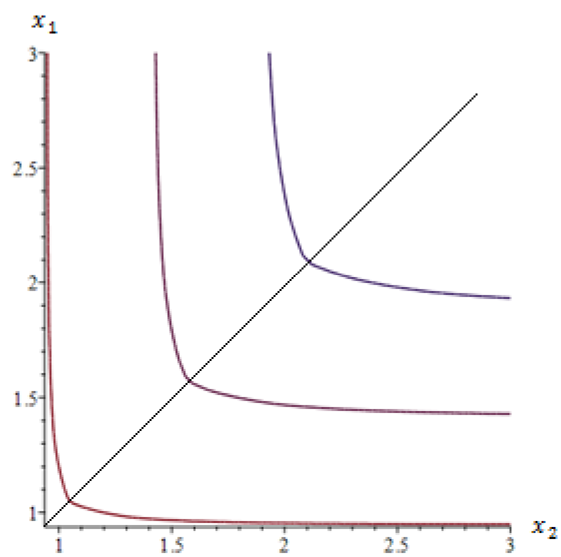

***Figure 1**: Contours of Gul's utility function when the agent is disappointment averse.*

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[11] Assuming $u''(x) < 0$ is necessary, as this guarantees that the certainty equivalent is lower than the expected value of the lottery. Then we have $x_2 < c < E(x) < x_1$. Thus, in equation (11), $\Pr(x < c)$ can be substituted with $\Pr(x = x_2) = (1-p)$.

In this framework, a person is defined as strictly risk averse if and only if $\beta > 0$ and $u(x)$ is concave (Gul, 1991). Thus, risk aversion implies disappointment aversion. However, it is also possible to have a concave utility function and $-1 < \beta < 0$.[12] Such preferences would make it possible to model behaviour where the respondent shows risk aversion in some cases, and risk-loving behaviour in other. Thus one can model the behaviour for someone who, for instance, both participates in the national lottery and has insurance.

If $u''(x) < 0$ and $-1 < \beta < 0$, the agent is risk seeking for small changes in income, but risk averse with respect to larger risks. In Figure 2, the contours of the utility function are drawn for $p = 0.5, \beta = -0.9$ and $\rho = 5$. Notice that the contours are locally convex in a region around the 45-degree line for this elation loving agent.

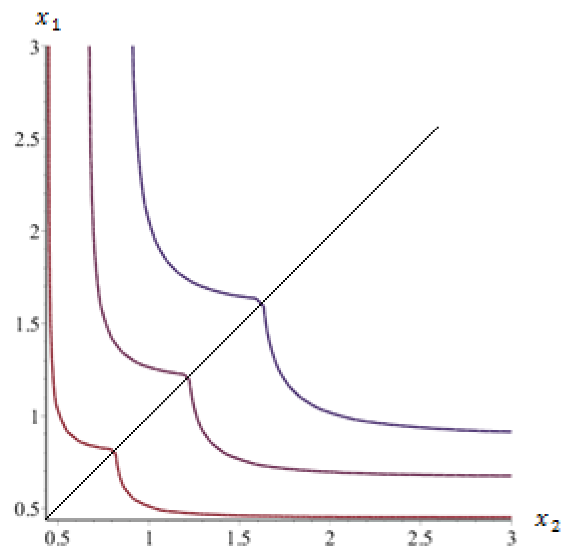

***Figure 2**: Contours of Gul's utility function when the agent is elation loving.*

While comparing two individuals' risk aversion is relatively simple in the EUT framework, it is not as simple in Gul's framework. Let one person have the utility function $V(u_1, \beta_1)$, and the other $V(u_2, \beta_2)$, where u_i is person i's local utility function and β_i is his or her coefficient of

[12] Gul (1991) also discusses the case where $\beta > 0$ and $u''(x) > 0$. However, in our subsequent analysis we have to assume that $u''(x) < 0$.

disappointment aversion ($i = 1,2$). Person 1 is more risk averse than person 2 if $\beta_1 \geq \beta_2$ and $A_1(x) \geq A_2(x)\ \forall\ x$ (Gul, 1991). If we assume a CRRA-utility function, [13] $A_1(x) \geq A_2(x)$ implies $\frac{\rho_1}{x} \geq \frac{\rho_2}{x}$. For this to hold for all $x > 0$, we need $\rho_1 \geq \rho_2$. However, when comparing individuals where e.g. $\rho_1 < \rho_2$ but $\beta_1 > \beta_2$, the comparison of risk aversion is ambiguous. However, one possibility is to compare risk premiums instead, which depends on both β and ρ.

Define the risk premium, π, associated with a symmetric gamble ($p_1 = p_2 = 0.5$) by

$$u(x-\pi) = \frac{0.5}{1+0.5\beta}u(x+\varepsilon) + \frac{0.5(1+\beta)}{1+0.5\beta}u(x-\varepsilon) \tag{13}$$

where $E(\varepsilon) = 0$. By applying a second order Taylor approximation, we get

$$\pi \approx \frac{0.5\beta}{1+0.5\beta}\varepsilon + 0.5A(w)\sigma^2 \tag{14}$$

where $\sigma^2 = var(\varepsilon) = \varepsilon^2$. Observe that if $u(x)$ is the CRRA-function, then β has a first order-effect on the risk premium, while ρ has a second order-effect.[14] The result is that β may dominate the determination of risk premium (Aizenman, 1998). Also note that the individual now exhibits risk aversion of order one, as the risk premium is proportional with the size of the risk. The fact that the utility function exhibits first order risk aversion gives it several interesting properties, some of which we will examine in the following section.

Finally, note that DAT not only accounts for the Allais paradox, but also accounts for other

[13] Note that for $V(u,\beta)$ to exhibit constant relative risk aversion, it is a necessary and sufficient condition that the local utility function's coefficient of relative risk aversion, $R(w)$, is constant (Gul, 1991).
[14] That is, ρ is proportional to the square of the coefficient of variation, while β is proportional with the coefficient of variation.

inconsistencies in EUT. For example, Kahneman & Tversky (1979) suggest that people have a tendency to overweight outcomes that are viewed as certain, relative to outcomes that are merely probable. They call this the “certainty effect”. In Gul’s utility function, if the agent is disappointment averse ($\beta > 0$), a small increase in the probability of obtaining a good outcome increases utility much more when the chance of obtaining the good price is already high (Gul, 1991). This seems to be in line with the observation of Kahneman & Tversky (1979). Likewise, DAT can reflect the ”possibility effect” if the agent is elation loving ($-1 < \beta < 0$). The possibility effect refers to the observation that people are particularly sensitive to small changes in probability from impossible to possible. However, note that DAT cannot reflect both the possibility effect and the certainty effect simultaneously for one agent (Abdellaoui & Bleichrodt, 2007).

3.3 Applications of DAT

Since DAT was proposed, the theory has been applied in various studies. The theory can be used to explain several observed phenomena that EUT cannot explain.

Choi, Fisman, Gale & Kariv (2007) conducted a series of experiments using a graphical representation of portfolio choice to examine whether the observed choices were well explained by a utility function exhibiting disappointment aversion. Their findings indicated that over half of the respondents had a significant degree of disappointment aversion, and they conclude that the theory provides a good interpretation of the data.

Artstein-Avidan & Dillenberger (2010) extended the theory of disappointment aversion to a dynamic setting. They showed that splitting a lottery into several stages reduces its value for disappointment averse agents. Moreover, they show that moderately disappointment averse agents are more likely to purchase dynamic insurance contracts, such as periodic insurance for cellular phones, at considerably more than actuarially fair prices. The reason is that they are prepared to pay a premium to avoid being exposed to a gradual resolution of uncertainty (Artstein-Avidan & Dillenberger, 2010).

Gill & Prowse (2012) found significant evidence of disappointment aversion in a study where the respondents were asked to participate in a game that involved moving sliders across the screen. They found that disappointment aversion with an endogenous reference point could cause a discouragement effect, where a competitor slacks off when his rival works hard.

The theory of disappointment aversion has also been used as an explanation to the equity premium puzzle, which refers to the phenomenon that the high observed equity premiums on stocks could only be explained by an unrealistically large ρ when assuming traditional EUT with a CRRA-utility function (Mehra & Prescott, 1985). Bonomo & Garcia (1993) and Ang et al. (2005) used a utility function exhibiting disappointment aversion to successfully explain the equity premium puzzle.

Moreover, using traditional EUT, it can be shown that investors should always hold a positive amount of equity if the risk premium is positive. By applying disappointment aversion, Ang et al. (2005) show that it may be optimal not to participate in the asset market, which is more in line with what is observed.[15]

Another problem with EUT is that it is predicted that if the price of insurance is not actuarially fair, no one will buy full insurance. Let $I(x)$ denote the indemnity schedule of the insurance contract, i.e. the money that is paid out for a loss of x. The insurance contract is defined as actuarially fair if the expected payout of the contract equals the premium, $\mathrm{E}[I(x)] = P$. However, the insurance premium is rarely actuarially fair, and yet many people purchase full insurance, which contradicts the predictions of EUT. However, using a utility function exhibiting disappointment aversion, it can be shown that individuals might purchase full insurance even if the price is not actuarially fair (Gul, 1991).

Assume the indemnity schedule is such that $I(x) = \gamma x$, where $\gamma \in [0,1]$. As shown by Mossin (1968), when the insurance premium is not fair, $\gamma < 1$ for individuals maximising conventional expected utility. Segal & Spivak (1990) show that this result applies to any model exhibiting

[15] Spivak & Segal (1990) show that this holds in general for utility functions that exhibit risk aversion of order one.

second order risk aversion. Let μ denote the loading. The individual pays the premium $(1+\mu)\cdot E[I(X)]$ for an insurance contract with expected payout equal to $E[I(x)]$. When $\mu > 0$, reducing γ increases risk, but also increases expected wealth. For very small risks, the first order effect of increasing expected wealth dominates the second order effect of reducing risk. Thus, $\gamma = 1$ is never optimal when $\mu > 0$ (Mossin, 1968). However, as shown by Segal and Spivak (1990), any model with first order risk aversion allows for the optimality of full insurance, even when $\mu > 0$.

To see this, assume that an agent wants to optimise her insurance coverage. Thus, she maximises expected utility with respect to γ, subject to her budget constraint. Assume that there are only two possible future states, s_1 and s_2 with probabilities p and $(1-p)$, where the agent's final wealth is either x_1 or x_2. The slope of the agent's budget line is then given by

$$-\frac{p(1+\mu)}{1-[p(1+\mu)]} \tag{15}$$

Figure 3a illustrates the agents maximisation problem under EUT when $\mu = 0$ and $p = 0.5$. If the agent chooses to have no insurance ($\gamma = 0$), she is at point A. At this point, she will have the highest possible attainable level of wealth in s_1, but she is rather poor if s_2 occurs. The agent can also choose to purchase full insurance ($\gamma = 1$), and place herself at point B. This point is at the 45-degree line (where $x_1 = x_2$), and the agent obtains the same level of wealth independent of the outcome. The agent's opportunity set consists of all points along the budget line, between the points A and B.

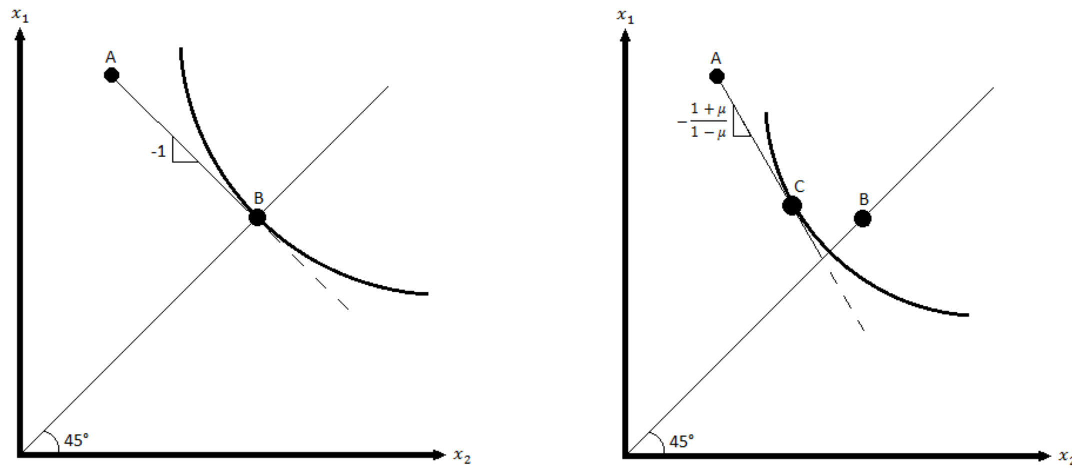

Figure 3a/b: *The left panel illustrates the optimal insurance problem under EUT with no loading. The right panel illustrates the problem under EUT when there is a positive loading (modified from Segal & Spivak, 1990).*

As shown in Figure 3a, the highest attainable indifference curve is at point B. With $\mu = 0$, this EU maximiser purchases full insurance. In Figure 3b, she faces the same problem, but there is a positive loading ($\mu > 0$), making the budget line steeper. Point B, which was optimal before, is no longer affordable. The agent can still choose to buy full insurance, but she is better off at point C, where $\gamma < 1$.

Figure 4 shows the maximisation problem for an agent with first order risk aversion. The kink in the indifference curve allows for the optimality of full insurance even when $\mu > 0$. As shown earlier, DAT exhibits first order risk aversion, and therefore can explain why some individuals purchase full insurance. Hence, individuals who are observed to purchase full insurance may have preferences that are better explained by DAT than conventional EUT.

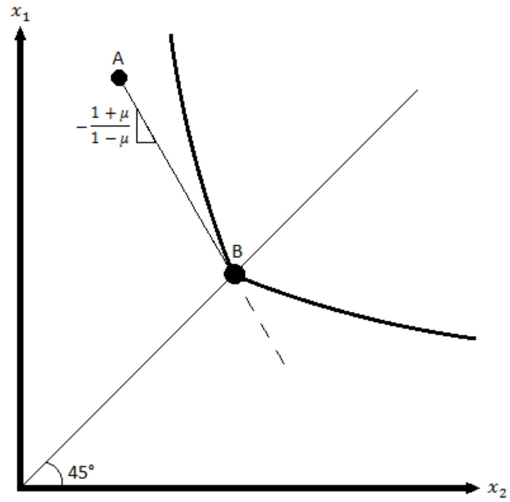

Figure 4: *Optimal insurance under DAT when there is a positive loading (modified from Segal & Spivak, 1990).*

In conclusion, it appears that DAT can explain several observed phenomena. As illustrated by the examples above, taking disappointment aversion into consideration could be important for e.g. insurance companies and finance institutions.

3.4 Alternative specifications

DAT is only one of many extensions of expected utility theory. Several other theories have attempted to account for the Allais paradox, as well as further inconsistencies concerning EUT. Kahneman & Tversky (1979) presented several examples where the predictions of traditional EUT did not hold. To account for such problems, numerous alternative specifications have been developed. In this section, we will briefly discuss a few alternatives to Gul's model. Note that this is by no means a complete review, as there exists more than 40 different generalisations of EUT (Eeckhoudt et al., 2005, p. 227).

<u>Prospect theory</u>

Kahneman & Tversky (1979) argue that losses and gains are treated in an asymmetric matter, with different marginal utilities above and below the status quo. Instead of utility depending on the final outcome, it depends on gains and losses with respect to a reference point. They suggest an S-shaped utility function with a kink at initial wealth.

As such, prospect theory has many similarities with DAT. However, they also present other effects present in decision making, such as the isolation effect (people often disregard components that alternatives share), the reflection effect (risk aversion in the positive domain is accompanied by risk-loving in the negative domain) as well as the rounding of probabilities up and down. Moreover, instead of using the probabilities of outcomes when calculating the total utility of a prospect, they apply decision weights, which depend on the actual probability.

One problem with this theory is that it violates stochastic dominance, and thus admits intransitivity for pairwise choices (Quiggin, 1982). Later, they extended their theory so that it transforms cumulative rather than individual probabilities (Tversky & Kahneman, 1992). This model is called cumulative prospect theory, and is based on the rank dependent probability transformation that was introduced by Quiggin (1982).

Rank-dependent utility theory

Rank-dependent utility theory, proposed by Quiggin (1982), is another generalisation of EUT that can solve the Allais paradox (Eeckhoudt et al., 2005, p. 217).[16] The theory models behaviour as the ranking of outcome in order of preference, and then distorting the decumulative probabilities through a probability weighting function. Instead of calculating expected utility using the probabilities of the outcomes, one calculates *anticipated utility* where decision weights substitute probabilities (Quiggin, 1982).

Thus, an individual's attitudes to different lotteries are determined by both their attitudes to the possible outcomes and their attitudes to the probabilities. The theory is based on a weaker set of axioms than those of vNM. In particular, the independence axiom is replaced by a weaker requirement.

Regret theory

Bell (1982) and Loomes & Sugden (1982) introduced the concept of regret theory

[16] In fact, it can be shown that Gul's utility function is a special case of rank dependent theory when considering binary lotteries (Gul, 1991).

simultaneously. The idea is that behaviour incorporates either regret or rejoice, and is dependent on whether the outcome under the chosen alternative is worse or better than the outcome from an alternative choice. Controversially, the theory does not assume transitivity in preferences. Loomes & Sugden (1982) argue that regret theory explains the same puzzles as prospect theory does, while also being a simpler and more intuitive model.

3.4.1 Comparing models

In this section, we will review a selection of studies where EUT has been compared with alternative extensions, such as DAT and rank-dependent utility theory.

Morone & Schmidt (2006) conducted an experiment where they investigated the respondents' willingness to pay for a lottery (maximum buying price) and willingness to accept a lottery (minimal buying price). They found that in a comparison between EUT, DAT and rank-dependent utility theory, DAT had the best fit for these measures. However, when comparing certainty equivalents, rank-dependent utility theory appeared to have the best fit.

Camerer & Ho (1994) tested the axiom of betweenness, which is assumed in DAT, and found several systematic violations. While the violations were not as widespread as the violations of the stronger independence axiom, it was still dramatic. Afterwards, they tested three generalisations of expected utility theories using a representative agent approach.[17] Those theories were DAT, cumulative prospect theory (Tversky & Kahneman, 1992) and traditional prospect theory (Kahneman & Tvesky, 1979).

Despite the violation of the betweenness axiom, they still found that DAT fit the data very well. In fact, it performed better than cumulative prospect theory, which does not depend on betweenness.[18] Their explanation is that since there is only a minority that do not obey

[17] That is, they assume a single pattern of preference for all agents. In order to explain the heterogeneity in individual choices, they introduce a stochastic element in the equation. This is normally referred to as a random utility model (Camerer & Ho, 1994).

[18] However, Blavatskyy (2006) argues that most of the studies indicating violations of the betweenness axiom could simply be caused by random errors in choice under risk. He concludes

betweenness, DAT fits very well on aggregate data. In general, DAT explained the observed choices much better than EUT. They conclude with a recommendation that researchers should focus on such a parsimonious model, which is only one parameter richer than EUT, but fits the data better than traditional theory.

In contrast, Abdellaoui & Bleichrodt (2007) criticise Gul's model, claiming that it is too parsimonious. They use two different experiments, one involving gambles with monetary gains and losses and the other concerning hypothetical gambles about life-years. They find that disappointment aversion increases with the probability of obtaining an elation outcome, which contradicts Gul's (1991) hypothesis that β is constant. They argue that this is an intuitive finding, as with a small probability of success, people will feel little degree of disappointment when the desired outcome is not obtained. However, when the probability of success is high, they will feel more disappointed if the desired outcome is not obtained.[19]

Hey & Orme (1994) tested several generalisations of utility theory using experimental data, where the subjects were asked to choose between different lotteries. They found that DAT had one of the poorest fits amongst the eight models tested. Quiggin's (1982) rank-dependent utility theory came out on top, while regret theory also performed very well. However, for 39 per cent of the subjects, EUT fit no worse than any of the alternative specifications. Yet, with a sample of only 80 respondents, they admit that their results are not representative.

In general, there appears to be conflicting evidence as to which model is most adequate. However, DAT is appealing for several reasons. First of all, it is intuitive. Secondly, it is far less complex than some of its alternatives, such as rank-dependent utility theory, as it is a parsimonious model with only one additional parameter compared to EUT. Lastly, it appears to perform well in most experimental comparisons, with a few notable exceptions.

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that this may explain the puzzle that DAT outperformed cumulative prospect theory in the test conducted by Camerer & Ho (1994).

[19] This is consistent with Loomes & Sugden's (1986) alternative theory of disappointment aversion (Abdellaoui & Bleichrodt, 2007).

4 Literature review on hypothetical income lotteries

4.1 The BJKS-approach

Barsky et al. (1997) developed a method to use survey responses in order to measure preference parameters relating to risk tolerance (the reciprocal of risk aversion). They asked a sample of senior US citizens participating in the Health and Retirement Study (HRS) to choose between hypothetical lotteries concerning lifetime income. The following question was asked first:

> Suppose that you are the only income earner in your family, and you have a good job guaranteed to give you your current (family) income every year for your life. You are given the opportunity to take a new and equally god job, with a 50-50 chance it will double your (family) income and a 50-50 chance it will cut your (family) income by a third. Would you take the new job*?* (Barsky et al., 1997, p. 540)

Dependent on the answer to the first question, the respondent was asked a new question. If the answer to the first question was “yes”, the respondent was presented with a similar question; with the only difference being that “a third” was now replaced by “cut in half”. If the answer to the first question was “no”, then the following question was similar, except that the potential downside now only contained a cut by 20 per cent.

The combined answers to these income lotteries were used to map the respondents risk preferences. Based on these answers, each respondent was grouped in one of four mutually exclusive risk aversion categories. More specifically, for each respondent, they obtained an interval for what fraction (λ) of their current income (x) the individual must maintain in the bad state in order to be indifferent between the risky and the safe alternative. Under the assumption of EUT, the comparison between lotteries is then

$$\frac{1}{2}u(2x) + \frac{1}{2}u(\lambda x) = u(x) \tag{16}$$

Based on the respondents' risk-group, they created a measure of relative risk aversion when assuming CRRA. They found that the measured risk tolerance is positively related to risky behaviours, like smoking, drinking and failing to have insurance, and that these relationships are both statistically and quantitatively significant.

4.2 Problems with the BJKS-approach

A weakness of using a questionnaire to reveal risk preferences of individuals is that answers to these questions may be sensitive to how questions are formulated. Kahneman & Tversky (1981) showed that the answer to a question concerning a hypothetical risky situation depended on how the question was framed. This is referred to as *framing*.

Kimball, Sahm & Shapiro (2008) argue that when comparing a new situation to a current one, as in BJKS, a bias towards preferring the current situation arises. This *status quo bias* is created because the current situation would be relatively free of uncertainty. When considering a current job to a new one, factors like working environment, the nature of the job tasks and more would be considered by the respondent to be relatively safe in the current job as opposed to in the new job. Consequently, the answers of the respondents could depend on factors that are not intended. A different framing of the question might have removed this problem.

BJKS address the possible problem of a status quo bias in their questions. Then the comparison between alternatives is given by

$$u(2x) + u(\lambda x) = u(\eta x) \tag{17}$$

η equal to one would mean no status quo bias. In the presence of a status quo bias, η is above one, expressing reluctance to switching job. In the presence of this bias, λ would tend to be overestimated, or equivalently, risk aversion would tend to be overestimated. Measures of risk tolerance were derived for different, hypothetical values of η. The paper recommends that future surveys reword the income questions, for instance by asking respondents to choose between two new jobs, to remove the status quo bias.[20]

Moreover, Hanna, Gutter & Fan (2001) identify three different problems with the hypothetical income question posed by BJKS. The first problem concerns the lack of information about taxes. The questions do not say anything about gross income versus after tax-income. If the respondents perceive that the higher income state will also result in a higher marginal tax rate, or that the lower income state will result in a lower marginal tax rate, the results may be biased in either direction.

The second problem is that the questions alone cannot identify a group with a risk aversion higher than 3.8. It might be convenient to be able to identify higher levels of risk aversion. This problem was addressed in editions of the HRS after 1998, where there now were six instead of four implicit risk-categories.

In addition, Hanna et al. (2001) point out that the respondents might not be able to understand that the changes in income are supposed to be permanent. They argue that some respondents, particularly younger ones, may not be able to imagine this. In order for the measure to explain relative risk aversion, it is very important that the respondents understand that the income changes are permanent and inflexible.

4.3 Other studies using the BJKS-approach

Since BJKS developed the method, various researchers have used similar questionnaires to estimate parameters of risk aversion.

Kapteyn & Teppa (2002) extended the questionnaire to include six rather than four risk-categories, and employed the method to estimate risk aversion amongst Dutch respondents. This estimate was then used to explain asset allocation amongst households. Arrondel & Calvo-Pardo (2002) applied the method in France, and used their estimate of risk aversion to explain

[20] Kimball et al. (2008) analyse the status quo bias by comparing individuals answering two versions of the lottery questions, where one of them was formulated as to remove status quo bias. They found that the status quo bias was significantly different from zero, but “modest”.

stockholding. Hanna & Lindamood (2004) compared different variations of the income-gambles, such as replacing the notion of lifetime income with pension. They also added a graphical presentation to the questions, which they claim increases the probability that the respondents understand the hypothetical situations.

Kimball et al. (2008) used the new six scale income lotteries of the HRS to construct a cardinal measure of relative risk tolerance. Subsequently, they examined the relationship between asset allocation and risk tolerance. The fact that some respondents had responded to the questionnaire in several waves allowed them to use panel data to reduce measurement error and improve the estimates. Sahm (2012) also used the HRS, focusing on how risk attitudes change over time. She found that risk tolerance changes with age and macroeconomic conditions. However, time constant factors (such as gender, race and education) turned out to be a more important source of systematic variation in risk preferences.

Aarbu & Schroyen (2014) used hypothetical income gambles to measure and explain the distribution of relative risk aversion for a representative sample of the Norwegian population. They estimated a cardinal measure of risk aversion, and compared the sample mean of risk aversion with that obtained by other studies, for four other OECD countries. They found that the average coefficient of relative risk aversion was lower for Norway than the other countries, and suggested that this observation might be caused by a lower background risk in Norway due to welfare mechanisms.

5 Survey design

In this section, we will discuss how the survey was designed in order to be able to elicit parameters of risk aversion. First, we will examine the advantages of using a survey compared to a laboratory experiment. Next, we will explain how our survey was worded and how we plan to use the first and second set of hypothetical income questions in order to establish intervals for each respondent’s level of risk aversion.

5.1 Survey versus experiment

One common alternative to using a questionnaire to identify individuals' risk preferences is to use a controlled experiment. In a controlled experiment, the individuals being tested would be allowed to actually face the risks that are being considered. For instance, they could be given the opportunity to choose between different gambles and be awarded with any price they might obtain. Thus, they have incentives to answer truthfully, which is not necessarily the case for surveys.

However, a controlled experiment has some weaknesses. The researcher would have to pay out these prizes, which could be expensive. In addition, the downside risk the respondents would face would be bounded at the income that could justifiably be confiscated from them (the participation fee). For these reasons, the individuals being tested would only be exposed to, and tested over, relatively small risks. As shown earlier, expected utility maximisers behave as if they were risk neutral with respect to small risks even if they are risk averse to larger risks. Thus, in a controlled experiment, one might get estimates of risk aversion that are not informative about attitudes towards large risks.

In a questionnaire, however, it is possible to expose the respondents to arbitrarily large (hypothetical) risks. In addition, it is easier and less costly to obtain a sample that is large enough for reliable statistical inference. Consequently, the method is relatively inexpensive, and may reveal attitudes toward large risks (Aarbu & Schroyen, 2014). However, this comes at the cost of a higher likelihood of survey response-error, meaning that people give responses that for some reason do not reflect their real preferences. This may for example be caused by miss clicking, lack of attention or difficulty in understanding the question. In a controlled experiment, one would have more incentives to be attentive, and it would be easier for the subjects to ask for help if they do not understand the questions.

Empirical tests gives conflicting conclusions when it comes to differences in how people react to real-life gambles, versus how they react to hypothetical ones. Holt & Laury (2002) found that the degree of risk aversion was unaffected by increasing the lottery payoffs for a hypothetical lottery. Conversely, when the cash was paid out in money, risk aversion increased sharply for high payoffs. The difference between behaviour in real-world and hypothetical circumstances may be problematic. Anderson & Mellor (2009) also find that risk preferences are not stable across elicitation methods. They find that factors such as comprehension and effort affect risk preference stability. In contrast, Noussair, Trautmann & van de Kuilen (2014) compare choices made for lotteries that are paid out versus hypothetical ones. They find no significant differences for the estimated attitudes toward risk.

In conclusion, both methods have their strengths and weaknesses. When deciding which method to choose, both the intention of the study and practical purposes may be considered. In our case, we are interested in estimating risk aversion with respect to large risks. As discussed, this may be problematic in a controlled experiment. Thus, hypothetical gambles might be preferable, even if it comes at the cost of possible survey response-error.

5.2 The first set of income lotteries

In the first part of the questionnaire, respondents were asked to choose among alternative hypothetical income lotteries, inspired by the BJKS-approach. The income lottery questions are similar to the three questions in Aarbu & Schroyen (2014).

While BJKS's hypothetical income questions ask the respondent to consider a new job relative to their current job, Aarbu & Schroyen (2014) ask the respondents to choose between two new jobs. The purpose of this formulation was to remove the status quo bias. This formulation is close to the formulation used in the HRS after 1998, with a slight difference. Rather than suggesting a cause for a job change (allergy), they use the phrase "factors beyond your control". This phrase is believed to be more neutral and less likely to cause potential framing or priming problems (Aarbu & Schroyen, 2014).[21]

Our first income lottery question was as follows:[22]

[21] «*Priming* refers to the incidental activation of knowledge structures, such as trait concepts and stereotypes, by the current situational context» (Bargh, Chen & Burrows, 1996, p. 230).
[22] Our translation. The questions were asked in Norwegian.

"*Suppose that you are the only income earner in your household and that you have a good job which guarantees your household an income which is equal to today's income for all years henceforth. Suppose also that reasons beyond your control force you to change occupation. You can choose between two alternative jobs. Except from the income, the jobs are identical (with respect to content, distance and so on). Job 1 guarantees you the same income as your current income. Job 2 gives you a 50 per cent chance of an income twice as high as your current income, but with a 50 per cent chance it results in a reduction of your current income by one third (i.e., new income is per cent of current income). What is your immediate reaction? Would you choose job 1 or job 2?*"

After answering this question, the respondent was asked to consider new income lotteries, depending on his answer to the first lottery. If he chose job 1 (the safe alternative), the next income lottery was identical, except that the possible reduction now was by one fifth instead of one third. If the respondent chose job 2 in the first question, the second question would involve a possible reduction of current income by one half.

Following BJKS, we define $\lambda \in [0,1]$ as the fraction of income maintained in the bad state that makes the individual indifferent between the gamble and the safe outcome. Under EUT, we then have

$$\frac{1}{2}u(2x) + \frac{1}{2}u(\lambda x) = u(x)$$

Thus, λ is a unit free measure of risk aversion. $\lambda = 1$ would imply infinite risk aversion, while $\lambda = 0$ would imply risk neutrality. We cannot observe λ precisely, but we can derive an interval of it for each respondent.

Each observation belongs in one of four risk categories. If the respondent chose job 1 in the first question, his λ must be above $\frac{2}{3}$. If he chose job 1 also in the second lottery, his λ must be above $\frac{4}{5}$, while it must be below $\frac{4}{5}$ if he chose job 2. If the respondent chose job 2 in the first question, his λ must be below $\frac{2}{3}$. If he then chose job 1 in the second question, his λ must be above $\frac{1}{2}$, while it must be below $\frac{1}{2}$ if he also chose job 2 in the second question. Thus, each respondent has a λ that belongs in one of the following observable intervals: (0, $\frac{1}{2}$], ($\frac{1}{2}$, $\frac{2}{3}$], ($\frac{2}{3}$, $\frac{4}{5}$] or ($\frac{4}{5}$, 1]. [23]

Unfortunately, the problems identified by Hanna et al. (2001) were not taken into account in the formulation of the questions. For future studies, we would recommend specifying that the income gambles concern after tax income. Moreover, the inclusion of more risk aversion categories could have been beneficial.

5.3 The new set of income lotteries

After answering the first set of income lottery questions, the respondents were asked to consider a new set of income lotteries, where there now was a potential upside of 150 per cent. These questions have not been used in previous studies, and were added in order to make the estimation of disappointment aversion possible. Moreover, they can also be used to estimate an alternative interval of ρ. The following question was asked first:[24]

"*… Job 1 guarantees you the same income as your current income. Job 2 gives you a 50 per cent chance of an income 50 per cent higher than your current income (i.e., new income is 150 per cent of current income), but with a 50 per cent chance it results in a reduction of your current income by one sixth (i.e., new income is 83 per cent of current income). What is your immediate reaction? Would you choose job 1 or job 2?*"

If job 1 (the safe alternative) were chosen, the respondent received a new question where the possible reduction in income was now one tenth. If the respondent chose job 2 (the risky alternative) in the first question, he or she was asked a new question where the possible reduction

[23] In this context, $\lambda = 0$ would imply that one would be willing to accept a gamble with a 50 per cent chance of losing all future income, and a 50 per cent chance of doubling one's income. However, since zero income for the rest of one's life would imply death or at least extreme poverty, it is reasonable to assume that no one would accept such a gamble (Hanna & Lindamood, 2004).
[24] The beginning of the question is omitted, as it is identical with the previous question.

in income was now one fourth. Hence, all respondents can once again be assigned to one out of four groups.

Now, define $\kappa \in [0, 1]$ as the fraction of income maintained in the bad state that makes the respondent indifferent between the safe option and the risky gamble with payoffs $(\frac{3}{2}x, \kappa x)$, such that

$$\frac{1}{2}u\left(\frac{3}{2}x\right) + \frac{1}{2}u(\kappa x) = u(x) \tag{18}$$

under EUT. Based on the answers to the new income questions, we observe which of the following intervals each respondent's κ belongs to: $(0, \frac{3}{4}]$, $(\frac{3}{4}, \frac{5}{6}]$, $(\frac{5}{6}, \frac{9}{10}]$ or $(\frac{9}{10}, 1]$.

Thus, we have established intervals for each respondent's κ and λ. Later, these observed intervals will be used to estimate parameters of EUT and DAT.

6 Data collection

The questionnaire was sent out to customers of a Nordic insurance company in the fall of 2011. In total, 5000 customers received the questionnaire on email. 937 answered, so the response rate was 18.74 per cent.

In addition to the hypothetical income gambles, the questionnaire also contained questions about the respondents' socioeconomic characteristics. In total, 72.4 per cent of the respondents indicated that they were male. Moreover, the average age was 60.2. 66.1 per cent had at least three years of university education. Furthermore, 62.6 per cent of the respondents were active in the labour force at the time of the study. For more summary statistics on relevant variables, see appendix A.2.

Unfortunately, we cannot say that our sample is representative for the Norwegian population or even for insurance customers in general. At best, we can say that our sample is representative for the customers of this particular insurance company. However, there may be differences in characteristics of those who chose to respond and those who did not. For example, it may be problematic that the survey was only distributed through email, as some customers may not have access to Internet. If those with no access were different from those with access, we could have selection bias.

Due to those problems, our results might not be externally valid. However, Aarbu & Schroyen (2014) argue that selection bias is unlikely when it comes to hypothetical income lotteries, as nothing could be gained or lost by participating.

7 Econometric analysis of risk aversion

In this section we will fit interval regression models based on the respondents' answers to the hypothetical income questions. Subsequently, we will look at which factors that appear to be correlated with our measure of risk aversion, compare the results with earlier studies and discuss the findings. We will first estimate separate models for each set of income gambles, and then present the results from a simultaneous estimation.

By using λ or κ as cardinal measures for risk aversion, we avoid having to make any assumptions about the shape of the respondents' utility functions or whether their preferences adhere to the vNM-axioms. Later, the estimates obtained from the following econometric analyses will be used to elicit the parameters of EUT and DAT.

7.1 Using the first set of income gambles

First, we will restrict our attention to the first set of income lotteries, where we obtained intervals for λ for each respondent. Recall that λ denotes the lowest fraction of current income retained in the bad state that makes the respondent accept the gamble with a potential upside of 200 per cent of current income.

Table 1 shows the distribution of responses to the first set of income lotteries, first for the entire sample and then for various subsamples.

Table 1: Distribution of responses to the first set of income lotteries (in per cent)

	$\lambda < \frac{1}{2}$	$\frac{1}{2} < \lambda < \frac{2}{3}$	$\frac{2}{3} < \lambda < \frac{4}{5}$	$\frac{4}{5} < \lambda < 1$
All	5.98	7.48	15.71	70.83
Men	7.23	7.52	16.08	69.17
Women	2.71	7.36	14.73	75.19
18-39 y.o.	4.55	0.00	36.36	59.09
40-55 y.o.	5.59	11.19	18.53	64.69
56-70 y.o.	5.94	5.52	15.50	73.04
71+ y.o.	7.01	7.64	8.28	77.07
Only primary school	5.71	4.29	12.86	77.14
Up to high school	4.86	6.48	13.77	74.90
Up to 3 years of university	8.66	6.69	12.60	72.05
4 years or more of university	4.93	9.32	19.73	66.03
income ∈ [0, 300]	2.86	2.14	15.00	80.00
income ∈ (300, 500]	5.15	6.37	12.25	76.23
income ∈ (500, 800]	5.38	9.23	18.46	66.92
income ∈ (800, ∞)	13.79	16.09	25.29	44.83
No children	3.57	5.95	13.69	76.79
1 or more children	6.51	7.81	16.15	69.53
Married	5.83	5.67	16.05	72.45
Unmarried	6.27	10.97	15.05	67.71

Note that as much as 70.83 per cent reject all income gambles. Thus, they are unwilling to take a bet where there is a 50 per cent probability of doubling one's income and a 50 per cent probability of losing one fifth. This bet has an expected value of 140 per cent of current income, so at first glance, it appears that our sample is very risk averse on average.

Moreover, it appears that men are slightly less risk averse than women, as the distribution of risk aversion for women first order stochastically dominates that of men. Additionally, it seems that risk aversion increases with age, since the proportion in the most risk averse group is larger for the older respondents. There does not seem to be a strong relationship between education and risk aversion. We also observe that the highest income groups appear to be considerably less risk averse than the lowest income groups, and that married people could potentially be more risk averse than those who are not married. It also seems like those with children are less risk averse than those with no children. However, based only on the distribution, one cannot conclude whether these characteristics have a significant, partial effect on risk aversion.

To investigate these relationships further, we will perform an interval regression. Following Aarbu & Schroyen (2014), λ is regarded as a latent variable depending on a vector of observable covariates, x_i, with coefficients β, and a random component ε. λ is assumed to follow a logit-normal distribution, so that

$$\lambda_i = \frac{\exp(x_i'\beta + \varepsilon_i)}{1 + \exp(x_i'\beta + \varepsilon_i)}, \varepsilon_i \sim N(0, \sigma^2) \tag{19}$$

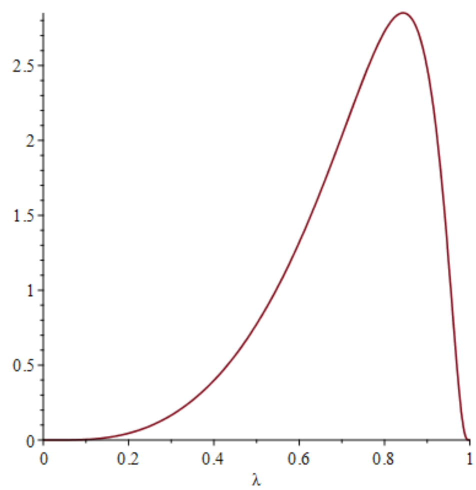

Figure 5: *The distribution of λ when $x_i'\beta + \varepsilon_i = 1.15$ and $\sigma = 0.844$.*

Figure 5 illustrates the distribution of λ for a given set of parameters. By rearranging expression (19) and taking logs, we can rewrite it as

$$\log\frac{\lambda_i}{1-\lambda_i} = x_i'\beta + \varepsilon_i,\ \varepsilon_i \sim N(0,\sigma^2) \tag{20}$$

Substituting for the known cut-offs for λ $(0, \frac{1}{2}, \frac{2}{3}, \frac{4}{5}$ and 1) in equation (20), we find that the relevant intervals for the LHS are: (– ∞, 0], (0, log 2], (log 2, log 4] and (log 4, ∞).

Since we observe to which interval λ_i belongs for each respondent, we have interval-coded data. Hence, we can use interval regression in order to estimate β and σ. In an interval regression, the likelihood for belonging to the given intervals is estimated. This is equivalent to an ordered probit model with fixed cut-off points. The parameters of the model can then be estimated by maximum likelihood techniques (Wooldridge, 2002, p. 508).

Let y_i denote the risk group of respondent *i*. The respondents are distributed into four different risk groups based on their answers to the first set of hypothetical income gambles, where group 1 is the least risk averse group.

$$y_i = 1 \text{ if } 0 < \lambda_i \leq \frac{1}{2}$$

$$y_i = 2 \text{ if } \frac{1}{2} < \lambda_i \leq \frac{2}{3}$$

$$y_i = 3 \text{ if } \frac{2}{3} < \lambda_i \leq \frac{4}{5}$$

$$y_i = 4 \text{ if } \frac{4}{5} < \lambda_i \leq 1$$

Using equation (20), the conditional likelihood of belonging to the least risk averse group is then

$$\Pr(y_i = 1|x_i) = \Pr\left(\log\frac{\lambda_i}{1-\lambda_i} < 0 \middle| x_i\right) = \Pr(\varepsilon_i < -x_i'\beta) = \phi(-\frac{x_i'\beta}{\sigma})$$

where $\phi(\cdot)$ denotes the cumulative distribution function of a standard normal variable. Likewise, the conditional probability of belonging to the remaining groups is then given by

$$\Pr(y_i = 2|x_i) = \Pr\left(0 \leq \log\frac{\lambda_i}{1-\lambda_i} < \log 2 \,\middle|\, x_i\right) = \phi\left(\frac{\log 2 - x_i'\beta}{\sigma}\right) - \phi\left(-\frac{x_i'\beta}{\sigma}\right)$$

$$\Pr(y_i = 3|x_i) = \Pr\left(\log 2 \leq \log\frac{\lambda_i}{1-\lambda_i} < \log 4 \,\middle|\, x_i\right) = \phi\left(\frac{\log 4 - x_i'\beta}{\sigma}\right) - \phi\left(\frac{\log 2 - x_i'\beta}{\sigma}\right)$$

$$\Pr(y_i = 4|x_i) = \Pr\left(\log 4 \leq \log\frac{\lambda_i}{1-\lambda_i} < \infty \,\middle|\, x_i\right) = 1 - \phi\left(\frac{\log 4 - x_i'\beta}{\sigma}\right)$$

By multiplying these probabilities over all respondents ($N = 936$), we get the likelihood function. Taking logs then yields the following log-likelihood function, which is to be maximised.

$$\begin{aligned}\ell = \sum_{i=1}^{N} 1_{[y_i=1]} \log\left[\phi\left(\frac{-x_i'\beta}{\sigma}\right)\right] + 1_{[y_i=2]} \log\left[\phi\left(\frac{\log 2 - x_i'\beta}{\sigma}\right) - \phi\left(\frac{-x_i'\beta}{\sigma}\right)\right] \\ + 1_{[y_i=3]} \log\left[\phi\left(\frac{\log 4 - x_i'\beta}{\sigma}\right) - \phi\left(\frac{\log 2 - x_i'\beta}{\sigma}\right)\right] \\ + 1_{[y_i=4]} \log\left[1 - \phi\left(\frac{\log 4 - x_i'\beta}{\sigma}\right)\right]\end{aligned} \tag{21}$$

where $1_{[y_i=n]}$ is the indicator variable, which is equal to 1 if $y_i = n$ and 0 otherwise.

As covariates (x_i), we used the socioeconomic characteristics age, gender, education, income, civil status and number of children, as well as an interaction term between age and gender. When it comes to education, we have dummies indicating the maximum educational attainment of each subject. Those who quit after primary school are then the base level. Likewise, we have income dummies indicating to which interval the respondents' yearly income belongs. In addition, we created a dummy for those who chose the alternative "do not want to answer" on the income question. The base level is the lowest income group, from 0 to NOK 300 000 per anno.

In addition to the interval regression, we performed an ordered probit regression on the four risk groups identified by the questions, to check the robustness of our results. The log-likelihood function for the ordered probit-model is similar, however, now the cut-off points (α_i) are estimated and σ is standardized to unity (Wooldridge, 2002, p. 509). The log-likelihood function is then

$$\begin{aligned}\ell = \sum_{i=1}^{N} 1_{[y_i=1]} \log[\phi(\alpha_1 - x_i'\beta)] + 1_{[y_i=2]} \log[\phi(\alpha_2 - x_i'\beta) - \phi(\alpha_1 - x_i'\beta)] \\ + 1_{[y_i=3]} \log[\phi(\alpha_3 - x_i'\beta) - \phi(\alpha_2 - x_i'\beta)] \\ + 1_{[y_i=4]} \log[1 - \phi(\alpha_3 - x_i'\beta)]\end{aligned} \tag{22}$$

We follow most related literature and apply a five per cent significance level throughout the text. This implies that a null hypothesis is rejected if the estimated probability of obtaining the observed outcome or a more extreme outcome is below five per cent, given that the null hypothesis is true.[25] In Table 2, column (1) and (2) gives the results of the interval regression and the ordered probit, respectively, for the first set of income lotteries.

[25] In general, we will refer to p-values below 0.10 as *weakly significant*, p-values below 0.05 as *significant* and p-values below 0.01 as *strongly significant*.

Table 2: Interval regression and ordered probit

	i) First set of lotteries		ii) Second set of lotteries	
	(1) Interval regression	(2) Ordered probit	(3) Interval regression	(4) Ordered probit
male	-0.459	-0.368	-0.278	-0.333
	(0.668)	(0.523)	(0.377)	(0.447)
age	0.00495	0.00389	0.00839	0.00963
	(0.00933)	(0.00730)	(0.00515)	(0.00611)
age*male	0.00375	0.00309	0.00333	0.00398
	(0.0112)	(0.00877)	(0.00628)	(0.00745)
up to high school	0.0778	0.0601	0.0338	0.0398
	(0.237)	(0.186)	(0.131)	(0.156)
≤ 3 years of university	-0.0665	-0.0516	-0.137	-0.166
	(0.239)	(0.187)	(0.133)	(0.158)
≥ 4 years of university	-0.0994	-0.0811	-0.129	-0.151
	(0.238)	(0.187)	(0.133)	(0.158)
income ∈ (300, 500]	-0.131	-0.101	-0.128	-0.149
	(0.183)	(0.144)	(0.100)	(0.119)
income ∈ (500, 800]	-0.348*	-0.272*	-0.289***	-0.335**
	(0.201)	(0.158)	(0.112)	(0.132)
income ∈ (800, ∞)	-0.972***	-0.761***	-0.676***	-0.806***
	(0.246)	(0.191)	(0.145)	(0.171)
income, no answer	-0.628**	-0.489**	-0.345**	-0.413**
	(0.288)	(0.225)	(0.167)	(0.199)
married	0.326***	0.255***	0.163**	0.192**
	(0.119)	(0.0925)	(0.0679)	(0.0804)
# of children	-0.0876**	-0.0687**	-0.0546**	-0.0631**
	(0.0423)	(0.0330)	(0.0242)	(0.0287)
constant	2.254***	/	1.686***	/
	(0.624)		(0.343)	
sigma	1.276***	1	0.844***	1
	(0.0757)		(0.0341)	

cut-off 1	0	-1.734*** (0.491)	log 3	-0.767* (0.408)
cut-off 2	log 2	-1.262*** (0.488)	log 5	0.00450 (0.407)
cut-off 3	log 4	-0.675 (0.487)	log 9	0.556 (0.407)
Log Likelihood	-812.775	-811.596	-1237.236	-1224.233
McKelvey & Zevoina's R^2	0.083	0.083	0.100	0.099
N	936	936	936	936

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

First of all, observe that the interval regression (column 1) and the ordered probit model (column 2) yield very similar results. The same variables are significant in the different models, and the coefficients are also qualitatively similar.

The male dummy is not significant in either model, neither is the interaction between gender and age. Interestingly, this is not in line with most previous studies, where men typically have appeared to be less risk averse than women. Significant gender effects with respect to risk aversion are found in Barsky et al. (1997), Aarbu & Schroyen (2014), Hanna & Lindamood (2004), Hartog, Ferrer-i-Carbonell & Jonker (2002), Kimball et al. (2008), Dohmen et al. (2005) and Sahm (2012). However, Kapteyn & Teppa (2001) and Guiso & Paiella (2008) also found no significant relationship between risk aversion and gender.

The fact that we do not find a significant gender effect could be due to the high average age (60) in the sample. Aarbu & Schroyen (2014) found that an interaction term between the male dummy and age had a significant, positive coefficient, while the male-dummy had a negative coefficient. This implies that men are more risk averse than women, but this difference diminishes with age. Thus, if this is true, then it could be harder for us to identify a difference between the genders given our relatively old sample.

The age variable is not significant either, which contradicts the findings of Barsky et al. (1997), Sahm (2012), Kapteyn & Teppa (2001) and Dohmen et al. (2005), all of whom found that risk aversion increases with age.[26] However, note that identified age effects could also be due to cohort effects, i.e. society wide changes in risk preference over time (Dohmen et al., 2005).

It is possible that the lack of a significant effect could be caused by the high average age in the sample. Due to the low number of respondents in low age groups, the hypothesized difference is not identified. However, the studies that used the HRS also had a high average age, as all respondents asked were 50 or older (Sahm, 2012), yet many of these studies found significant effects of both age and gender. Nonetheless, these studies had access to far more observations than we did, giving them more statistical power to reject a null hypothesis of no effect.

We also see that none of the education dummies are significant individually. A Wald-test shows that they are not jointly significant either, with a p-value of 0.6563 ($\chi^2(3) = 1.61$) for the interval regression and 0.6464 ($\chi^2(3) = 1.66$) for the ordered probit model. Thus, we cannot reject a null hypothesis that all of the coefficients are equal to zero. Sahm (2012), Hartog et al. (2002) and Guiso & Paiella (2008) found that individuals with a high level of education are less risk averse than those with no university education.

We observe that the highest income group seems to be significantly more inclined to take risks. This corresponds to the findings of Sahm (2012) and Hartog et al. (2002). We believe these results may reflect that risk-tolerant people self-select themselves into the higher income groups, as they are willing to take the risks required in such jobs. Compared to the lowest-income group, the highest earners have an estimated 28.67 per cent lower likelihood of belonging to the most risk averse group.[27] This effect is both statistically and economically significant.

Moreover, those who do not want to provide an answer to the income question also seem to be significantly less risk averse than those in the lowest income group. These respondents have an estimated 18.21 per cent lower likelihood of being in the most risk averse group compared to the

[26] Note that Sahm (2012) used panel-data in her paper, allowing her to more accurately measure the effects of age, as the respondents grew older over time.

[27] These calculations and similar numbers presented throughout the text are calculated using the prchange command in Stata, see Long & Freese (2014). The percentage change is calculated at the sample mean of the independent variables.

lowest income group. One explanation could be that the average salary of those who do not want to answer is higher than the average salary for the lowest income group, reflecting the possible negative correlation between income and risk aversion. The income dummies are also jointly significant, with a p-value of 0.0001 ($\chi^2(4) = 23.42$) in the interval regression and 0.0000 ($\chi^2(4) = 27.86$) for the ordered probit model.

As one might expect, it appears that married individuals tend to be significantly more risk averse than others. This is in line with the findings of Sahm (2012). The model predicts that those who are married have an 8.83 per cent higher likelihood of being in the most risk averse group, so the effect is not very large.

The positive correlation between marriage and risk aversion is to be expected due to the formulation of the question, where it says specifically that you should suppose that you are "the only income earner in the household". Accordingly, those who are married might have one more person to take care of with the given income, making the potential downside of the risky gamble larger.[28] Furthermore, it is also possible that those who are strongly risk averse are self-selected into the safe comfort of a stable marriage.

Likewise, one might expect that having more children increases the risk and potential downside of accepting the income gamble, thus inducing people with more children to reject the gamble. Unexpectedly, the opposite effect is observed in this study, as can be seen by the significant negative coefficient on the children variable.

The explanation for this might be that the average age is so high that the majority of the respondents' children have moved out, making the point about a larger downside close to irrelevant. Instead, the identified effect may reflect the possibility that people with a higher risk tolerance could have a tendency to have a larger quantity of children. Having children can be viewed as risky behaviour, as it makes you more vulnerable to earnings risk due to increased domestic expenditures. Thus, it is possible that people with high risk-tolerance could be self-

[28] Of course, if you compare those who are married with those who live together, but are not married, the argument does not hold. On average, however, it is reasonable to assume that those who are married will have more people to take care of in their household.

selected into having more children.

Finally, note that σ is estimated at 1.276, with a standard error of only 0.076.

7.2 Using the new set of income gambles

Next, we go through the same procedure using the risk groups identified by the new income gambles. This will allow us to compare the results obtained from the traditional income lotteries with the results from the new set of income lotteries. Recall that κ denotes the lowest fraction of current income retained in the bad state that makes the respondent accept the gamble with a possible upside of 150 per cent of current income. Table 3 shows the distribution of responses.

Table 3: Distribution of responses to the second set of income lotteries (in per cent)

	$\kappa < \frac{3}{4}$	$\frac{3}{4} < \kappa < \frac{5}{6}$	$\frac{5}{6} < \kappa < \frac{9}{10}$	$\frac{9}{10} < \kappa < 1$
All	18.59	25.11	20.41	35.90
Men	19.91	24.93	19.91	35.25
Women	15.12	25.58	21.71	37.60
18-39 y.o.	9.09	50.00	18.18	22.73
40-55 y.o.	22.73	29.37	19.93	27.97
56-70 y.o.	16.99	24.63	20.38	38.00
71+ y.o.	17.20	15.29	21.66	48.86
Only primary school	12.86	20.00	20.00	47.14
Up to high school	14.17	25.10	19.03	41.70
Up to 3 years of university	23.23	20.87	20.87	35.04
4 years or more of university	19.45	29.04	21.10	30.41
income $\in$ [0, 300]	12.14	15.00	21.43	51.43
income $\in$ (300, 500]	15.69	23.53	20.83	39.95
income $\in$ (500, 800]	18.46	31.92	22.31	27.31
income $\in$ (800, ∞)	40.23	28.74	14.94	16.09
No children	16.67	19.05	20.83	43.45
1 or more children	19.01	26.43	20.31	34.24
Married	17.83	24.31	19.61	38.25
Unmarried	20.06	26.65	21.94	31.35

First, note that the respondents are more evenly dispersed across the different groups, compared to the first set. As much as 18.59 per cent belong to the least risk averse group, which indicates that they would accept a lottery with a 50 per cent probability of getting 150 per cent of current income and 50 per cent probability of getting an income reduction by one fourth.

For this set of income gambles, income still appears to be negatively correlated with risk aversion. Moreover, at first glance, it appears that more educated individuals have a lower level of risk aversion. [29] There also appears to be a positive correlation between risk aversion and age. To investigate these relationships thoroughly, we will use econometric techniques.

Assume that κ follows a logit-normal distribution, so that

$$\log \frac{\kappa}{1-\kappa} = x_i'\beta_\kappa + \varepsilon_i \,, \varepsilon_i \sim N(0, \sigma_\kappa^2) \tag{23}$$

where β_κ is a new vector of coefficients and σ_κ^2 is the variance of ε_i. We then observe whether the LHS belongs to the intervals (– ∞, log3], (log3, log 5], (log 5, log 9] or (log 9, ∞).

The log-likelihood function for the interval-regression is then

$$\begin{aligned} \ell_\kappa = \sum_{i=1}^{N} 1_{[y_i=1]} \log\left[\phi\left(\frac{\log 3 - x_i'\beta_\kappa}{\sigma_\kappa}\right)\right] \\ + 1_{[y_i=2]} \log\left[\phi\left(\frac{\log 5 - x_i'\beta_\kappa}{\sigma_\kappa}\right) - \phi\left(\frac{\log 3 - x_i'\beta_\kappa}{\sigma_\kappa}\right)\right] \\ + 1_{[y_i=3]} \log\left[\phi\left(\frac{\log 9 - x_i'\beta_\kappa}{\sigma_\kappa}\right) - \phi\left(\frac{\log 5 - x_i'\beta_\kappa}{\sigma_\kappa}\right)\right] \\ + 1_{[y_i=4]} \log\left[1 - \phi\left(\frac{\log 9 - x_i'\beta_\kappa}{\sigma_\kappa}\right)\right] \end{aligned} \tag{24}$$

[29] However, this could potentially reflect the fact that higher educated individuals have a higher wage (see e.g. Aakvik, Salvanes, & Vaage, 2003). Thus, what appears like a strong relationship between education and risk aversion could disappear when controlling for income.

By maximising (24), we were able to estimate β_κ and σ_κ. The results are shown in column (3) of Table 2 for the interval regression and column (4) for an ordered probit model.

In general, the results are qualitatively similar when we use the new set of questions instead of the previous one. In fact, all of the coefficients have the same sign as before. For the most part, the same covariates turn out to be significant in the new model. One interesting difference is that the age variable is much closer to being significant, with a p-value of 0.103. Moreover, the dummy for the highest income group is still strongly significant, but now the second-highest income group (with income between NOK 500 000 and 800 000) also has a significant, negative coefficient.

The fact that the results are fairly similar across the sets of income gambles is a signal that the respondents are at least moderately consistent when it comes to answering the hypothetical income question. If the two variations of the income lotteries resulted in completely different predictions as to how risk aversion is related to different characteristics, we would be worried that the respondents' answers did not truly reflect real risk preferences, and were vastly influenced by random errors.

Finally, note that σ_κ is estimated at 0.844, with a standard error of only 0.034.

7.3 Simultaneous estimation

Instead of estimating the regressions for the first set and the second set of income gambles independently; it is possible to estimate the equations simultaneously using a variation of seemingly unrelated regression (SUR). In general, parameters in SUR-systems can be estimated consistently by performing the regressions independently, but simultaneous estimation is more efficient (Roodman, 2011).

We assume the error terms are bivariate normally distributed, with correlation coefficient ς. It is reasonable to believe that the errors are correlated, as unobserved factors that affect λ will also affect κ, as both are measures of risk aversion. Thus, we estimate the following system of equations

$$\begin{aligned} \theta_i &= x_i'\beta_1 + \varepsilon_{i1} \\ \Psi_i &= x_i'\beta_2 + \varepsilon_{i2} \end{aligned}$$

$$\begin{bmatrix} \varepsilon_{i1} \\ \varepsilon_{i2} \end{bmatrix} \sim N \begin{pmatrix} 0 & & \sigma_1 & \varsigma \\ 0 & , & \varsigma & \sigma_2 \end{pmatrix} \tag{25}$$

where $\theta_i := \ log \frac{\lambda}{1-\lambda}$, $\psi_i := \ log \frac{\kappa}{1-\kappa}$, σ_1 is the standard deviation of ε_{i1} and σ_2 is the standard deviation of ε_{i2}. This is like a bivariate ordered probit with fixed cut-off points, which we will refer to as a bivariate interval regression. The system is estimated by maximum-likelihood methods using the cmp add-on in Stata (see Roodman, 2011). The tedious log-likelihood function, which involves 16 possible combinations, can be found in appendix A.3.

Table 4: Bivariate interval regression

	(1) First set	(2) Second set
male	-0.599	-0.279
	(0.635)	(0.342)
age	0.00398	0.00843*
	(0.00879)	(0.00466)
age*male	0.00673	0.00327
	(0.0106)	(0.00571)
up to high school	0.108	0.0411
	(0.229)	(0.121)
≤ 3 years of university	0.0119	-0.137
	(0.233)	(0.123)
≥ 4 years of university	-0.0509	-0.109
	(0.231)	(0.123)
income (300, 500]	-0.143	-0.131
	(0.177)	(0.0914)
income (500, 800]	-0.397**	-0.289***
	(0.195)	(0.102)
income (800, ∞)	-0.988***	-0.685***
	(0.241)	(0.132)
income, no answer	-0.599**	-0.351**
	(0.281)	(0.154)
married	0.364***	0.166***
	(0.114)	(0.0619)
# of children	-0.102**	-0.0536**
	(0.0406)	(0.0221)
cons	2.306***	1.670***
	(0.594)	(0.312)
sigma	1.324***	0.852***
	(0.0983)	(0.0295)
ς	0.804***	0.804***
	(0.0186)	(0.0186)
N	936	936

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

First, observe that the standard errors of the estimated coefficients are, in general, lower in Table 4 compared to the corresponding standard errors in the univariate interval regressions (Table 2). As a result, the age variable is now weakly significant for the second set of income gambles. Moreover, now the second-highest income group is also significant for the first set of income gambles. Except from these small changes, the estimates are very similar.

At last, observe that the correlation coefficient, ς, is estimated at 0.804. The estimates obtained from Table 4 will be used in order to elicit the parameters of disappointment aversion later.

7.4 Potential specification issues

First of all, there could be some potential endogeneity issues in the models given by Table 2 and 4. For instance, it could be that cognitive ability (Ω) is related to risk aversion. Frederick (2005) finds that those who perform better in a cognitive test are systematically more willing to take risks, so that $cov(\lambda, \Omega) < 0$. Cognitive ability is also positively related to income (see e.g. Irwing & Lynn, 2006), but Ω is unobserved in our model. Thus, we might have an explanatory variable that is correlated with the error term, $cov(Income, \varepsilon) \neq 0$. If that is the case, the estimates of the model will be inconsistent (Greene, 2012, p. 753), and thus the observed relationship between income and risk aversion may be spurious. A similar argument can be made concerning the relationship between cognitive ability and education. Unfortunately, since we cannot observe Ω, it is not possible to test these hypotheses.

Moreover, there could also be reverse causality. For example, the significant relationship between income and risk does not necessarily mean that obtaining a higher income will make you less risk averse. Instead, the significant relationship might be caused by the possibility that those with higher risk tolerance are self-selected into high income groups. Similar arguments were made for other covariates. Thus, we stress that we cannot give any of the relationships from Table 2 and 4 a causal interpretation. We simply observe a correlation, but cannot identify the direction of causation based on this model.[30]

In an ordered probit or logit model, it is implicitly assumed that the vector of coefficients, β, affects each response category in an identical matter.[31] This has been labelled the parallel regression assumption (Greene, 2012, p. 831), or the proportional odds assumption. Brant (1990) suggested a test for this in the case for logit-models, which involves splitting the model into n binary models, and estimate each β_j $(j = 1,2 \dots n)$ separately. The null hypothesis is then $\beta_1 = \beta_2 = \cdots = \beta_n$. Brant (1990) suggests that a potential failure could for example be caused by 1) misspecification of the latent regression, 2) heteroskedasticity of ε or 3) misspecification of the distributional form of the latent variable. Violation of the assumption can lead to misleading and invalid results (Liu & Koirala, 2012).

We cannot perform a Brant-test since this is an ordered probit model, but we perform a corresponding LR-test instead (see Long & Freese, 2001, p. 151). The null hypothesis is that the parallel regression assumption holds. For the ordered probit model on the second set of income gambles, we cannot reject that the assumption holds (p-value = 0.132). However, this hypothesis is strongly rejected for our ordered probit model on the first set of income gambles (p-value = 0.006). Thus, one could consider other specifications.

Alternatively, one could for instance use a *generalised ordered probit model*, originally developed by Fu (1998) and further developed by Williams (2006), to allow for the estimation of partial proportional odds models. This allows β to vary across risk groups for those variables for which the proportional odds assumption was violated. In appendix A.4, we estimate such a model and discuss the results. In general, this did not alter our conclusions considerably. However, we were now able to identify that the older the respondents are, the less likely they are to be in the least risk averse group. This effect was (close to) statistically significant. Furthermore, those with the lowest level of education (i.e., those who have not finished high school) turned out to be

[30] In order to see if any covariates included affect the results considerably, we have done a robustness-analysis where we add the covariates to the interval regression models one by one. See appendix A.6.
[31] The same is true for interval regressions. However, since the tests we applied only are available for the ordered probit-specification, we restrict our attention to these models.

significantly more likely to be in the least risk averse group, compared to those who at least have finished high school. Hence, by allowing β to vary across groups, we were able to identify some new significant effects.

Nonetheless, fitting generalised ordered probit or logit-models is rarely done in practice, despite the fact that the proportional odds assumption is often violated (Liu & Koirala, 2012). Applying such a model could cause more problems than it would fix. First of all, a substantial amount of additional parameters must be estimated. Secondly, the model produces negative fitted probabilities. In our case, 66 respondents had a fitted probability below zero. At last, it would make the subsequent analysis inconveniently complex, as we would have different values of β for each risk group. For these reasons, we will stick with the estimates from Table 2 and 4 in the subsequent analyses, even if there exists some uncertainty as to whether the results are valid.

8 Measures of risk aversion under EUT

8.1 The conditional expectation of λ

Recall that for each respondent, we have observed an interval for their values of λ and κ. In this section, we will attempt to find a point estimate of λ for each respondent.

We would ideally want to find the conditional expectation of λ, $E(\lambda_i|x_i, \Lambda_i)$, where Λ_i is respondent i's revealed interval of λ, $\Lambda_i \in \{[0,\frac{1}{2}], (\frac{1}{2}, \frac{2}{3}],(\frac{2}{3}, \frac{4}{5}], (\frac{4}{5},1]\}$. Thus, to estimate λ_i we use the information concerning the respondents' answers to the hypothetical income gambles, as well as individual characteristics that are believed to affect risk aversion. We can find a consistent estimate of this expectation by following Aarbu & Schroyen (2014).

To find the density function of λ, conditional on the vector of covariates, x, we use the change of variable technique (see Greene, 2012, p. 1068), so that

$$f_\lambda(\lambda) = f_\varepsilon\big(g^{-1}(\lambda)\big) \cdot \left|g^{-1\prime}(\lambda)\right| \tag{26}$$

where f_λ is the probability density function of λ, f_ε is the probability density function of the error term and $g(\cdot)$ is the distribution of λ, given by equation (19). We have

$$g^{-1}(\lambda) = \log\frac{\lambda_i}{1-\lambda_i} - x_i'\,\beta \Rightarrow g^{-1'}(\lambda) = \frac{1}{(1-\lambda)\lambda} \tag{27}$$

Substituting this expression in equation (26) gives

$$f_\lambda\left(\lambda \middle| x_i'\hat{\beta}, \hat{\sigma}\right) = \frac{1}{\lambda(1-\lambda)}\frac{1}{\hat{\sigma}}\,\phi\left(\frac{\log\frac{\lambda}{1-\lambda} - x_i'\hat{\beta}}{\hat{\sigma}}\right) \tag{28}$$

where $\phi(\cdot)$ is the probability density function of the standard normal distribution. $\hat{\beta}$ and $\hat{\sigma}$ were estimated in the interval regression model of Table 2.

We can now compute the expected value of λ given the respondent's characteristics and his revealed interval.

$$E\left(\lambda_i \middle| x_i'\hat{\beta}, \hat{\sigma}, \Lambda_i\right) = \int\limits_{\lambda\in\Lambda_i} \tilde{\lambda}\,\frac{f_\lambda(\tilde{\lambda}|x_i'\widehat{\beta}, \hat{\sigma})}{\Pr(\lambda \in \Lambda_i|x_i'\widehat{\beta}, \widehat{\sigma}\,)}\,d\tilde{\lambda} \tag{29}$$

The calculation of the probabilities in the denominator was given in the derivation of equation (21). The expression in the numerator has no analytical solution, so we compute the integral numerically. We do this for each respondent in the sample, and denote the result as $\hat{\lambda}_i$.

8.1.1 An estimate of relative risk aversion

Under the assumption of EUT and CRRA, we can convert each person's $\hat{\lambda}$ into an estimate of the coefficient of relative risk aversion, denoted $\hat{\rho}_\lambda$.

As shown by Barsky et al. (1997), there is a relationship between λ and the coefficient of risk aversion, ρ. Suppose that an individual is indifferent between the safe lottery (x, x) and the risky lottery $(2x, \lambda x)$.[32] Then we have [33]

$$V(x, x) = V(2x, \lambda x)$$
$$2u(x) = u(2x) + u(\lambda x)$$
$$2\frac{x^{1-\rho}}{1-\rho} = \frac{(2x)^{1-\rho}}{1-\rho} + \frac{(\lambda x)^{1-\rho}}{1-\rho}$$

$$\Rightarrow \lambda = [2 - 2^{1-\rho}]^{\frac{1}{1-\rho}} \tag{30}$$

However, since equation (30) does not have a closed form inverse, we follow Aarbu & Schroyen (2014) and approximate the expression using non-linear least squares (NLLS), generating 100 data points from ρ = 0.1, 0.2…10. This yields the very accurate approximation [34]

$$f(\lambda) = \frac{0.2309\lambda + 2.6146\lambda^2 - 2.1585\lambda^3}{1-\lambda} \tag{31}$$

where $f(\lambda)$ is the approximated value of ρ given a value of λ. Thus, from this set of questions, one can induce whether a respondent has $\rho \leq 1, 1 < \rho \leq 2, 2 < \rho \leq 3.76$ or $\rho > 3.76$. The relationship between λ and ρ is illustrated in Figure 6.

[32] For notational simplicity, the probabilities ($p_1 = p_2 = 0.5$) are omitted in the representation of the lotteries henceforth.
[33] This equation holds for $\rho \neq 1$. If $\rho = 1$, then $\lambda = 0.5$.
[34] R^2 =100 per cent, all p-values = 0.000.

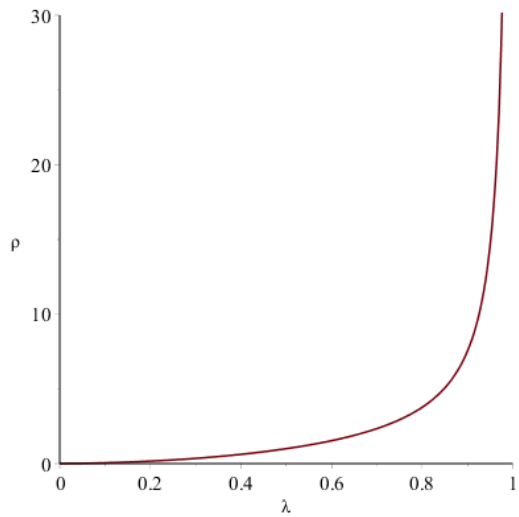

***Figure 6**: The mapping from λ to ρ.*

However, since this is not a linear function, it would not be appropriate to simply substitute $\hat{\lambda}$ for λ in equation (30). Thus, in order to convert our measure of $E(\lambda_i|x_i, \Lambda_i)$ to $E(\rho|x_i, \Lambda_i)$, we use a third order Taylor approximation

$$\rho \approx f(E\lambda) + f'(E\lambda)(\lambda - E\lambda) + \frac{1}{2}f''(E\lambda)(\lambda - E\lambda)^2 + \frac{1}{6}f'''(E\lambda)(\lambda - E\lambda)^3$$

By taking the conditional expectation on both sides, we then obtain

$$E(\rho|x_i\hat{\beta}, L_i) \approx f(\hat{\lambda}) + \frac{1}{2}f''(\hat{\lambda}) \cdot Var(\lambda) + \frac{1}{6}f'''(\hat{\lambda}) \cdot Skewness(\lambda) \qquad (32)$$

where $E[\lambda - E\lambda]^2 = Var(\lambda)$ and $E[\lambda - E\lambda]^3 = Skewness(\lambda)$.

Table 5 provides summary statistics for the distribution of $\hat{\lambda}$ and the estimated value of ρ (denoted $\hat{\rho}_\lambda$) for the total sample, as well as subsamples defined by the risk-category groups (where group 1 is the least risk averse group, for whom $\lambda < \frac{1}{2}$).

Table 5: Summary statistics of $\hat{\lambda}$ and $\hat{\rho}_\lambda$

	N	Mean	Std. Dev.	Min	Max
$\hat{\lambda}$	936	0.836	0.155	0.338	0.945
Group 1	56	0.372	0.013	0.338	0.389
Group 2	70	0.594	0.002	0.588	0.599
Group 3	147	0.742	0.002	0.736	0.745
Group 4	663	0.921	0.009	0.889	0.945
$\hat{\rho}_\lambda$	936	9.024	4.592	0.499	13.702
Group 1	56	0.582	0.033	0.499	0.625
Group 2	70	1.523	0.015	1.489	1.552
Group 3	147	2.879	0.026	2.810	2.929
Group 4	663	11.891	1.091	8.171	13.702

The average $\hat{\lambda}$ is 0.836 for the entire sample, with a standard deviation of 0.155. Thus, the average respondent belongs to the most risk averse group. This corresponds to an average estimated coefficient of relative risk aversion of 9.024, with a standard deviation of 4.592. Hence, there appears to be considerable heterogeneity in risk preferences.

This estimate of relative risk aversion is substantially higher than what was found by Aarbu & Schroyen (2014), ρ = 3.7, but more in line with other similar studies in different countries, such as Kimball et al. (2008) who found ρ = 8.2, BJKS, who found $\rho \approx$ 8.0 and Sahm (2012) who found ρ = 9.6.

Aarbu & Schroyen (2014) argued that the low figure they found amongst Norwegian respondents might be caused by the extensive welfare state, which provides insurance against risk, thus reducing background risk. Yet, it is not surprising that we found a significantly higher estimate. With a sample of insurance customers, it is to be expected that our respondents are on average more risk averse than a representative sample of the population. In addition, our sample is significantly older on average. In fact, our sample had an average age of 60, while Aarbu & Schroyen's (2014) sample had an average age of 44. This, and other differences in sample selection, may affect the distribution of risk aversion.

Moreover, it is also possible that the major financial crisis that has occurred since they submitted their questionnaire in 2006 has resulted in the general population becoming more risk averse. In fact, Sahm (2012) found that worsening macro-economic conditions results in increased risk aversion.

8.2 The conditional expectation of κ

We use the same procedure to find $E(\kappa_i|x_i, \omega_i)$ for each respondent, where ω_i is respondent i's revealed interval of κ. The probability density function of κ is given by

$$f_\kappa\left(\kappa \middle| x_i'\hat{\beta}_\kappa, \hat{\sigma}_\kappa\right) = \frac{1}{\kappa(1-\kappa)}\frac{1}{\hat{\sigma}_\kappa}\,\phi\left(\frac{\log\frac{\kappa}{1-\kappa} - x_i'\hat{\beta}_\kappa}{\hat{\sigma}_\kappa}\right) \tag{33}$$

Then we calculate the conditional expectation of κ by

$$E(\kappa_i|x_i'\beta_\kappa, \hat{\sigma}_\kappa, \omega_i) = \int_{\kappa\in\omega_i} \tilde{\kappa}\,\frac{f_\kappa\left(\tilde{\kappa}\middle|x_i'\hat{\beta}_\kappa, \hat{\sigma}_\kappa\right)}{\Pr\left(\kappa \in \omega_i\middle|x_i'\hat{\beta}_\kappa, \hat{\sigma}_\kappa\right)}\,d\tilde{\kappa} \tag{34}$$

and denote the result as $\hat{\kappa}$.

8.1.1 A new estimate of relative risk aversion

We can convert $\hat{\kappa}$ into an alternative measure of relative risk aversion, denoted ρ_κ. This can be used to test the robustness of our results. If the respondents have answered consistently, and EUT under the CRRA-assumption is reasonable, then we would expect the difference between the two estimations of relative risk aversion to be statistically insignificant.

The relationship between κ and ρ is

$$\kappa = \left[2 - \left(\frac{3}{2}\right)^{1-\rho}\right]^{\frac{1}{1-\rho}} \tag{35}$$

Just like equation (30), this equation has no closed-form inverse. Using NLLS, this expression can be approximated by: [35]

$$f(\kappa) = \frac{-3.7533\kappa + 10.1889\kappa^2 - 5.7053\kappa^3}{1-\kappa} \tag{36}$$

From the new set of gambles, one can obtain the implicit intervals for the coefficient of relative risk aversion: $\rho_\kappa \leq 2.04$, $2.04 < \rho_\kappa \leq 3.88$, $3.88 < \rho_\kappa \leq 7.16$ or $\rho_\kappa > 7.16$.

The results are shown in Table 6, where the groups now indicate the intervals for κ (with group 1 being the least risk averse group, for whom $\kappa < \frac{3}{4}$).

Table 6: Summary statistics of $\hat{\kappa}$ and $\hat{\rho}_\kappa$

	Obs	Mean	Std. Dev.	Min	Max
$\hat{\kappa}$	936	0.833	0.107	0.589	0.946
Group 1	174	0.642	0.019	0.589	0.677
Group 2	235	0.796	0.001	0.792	0.799
Group 3	191	0.869	0.001	0.866	0.871
Group 4	336	0.937	0.003	0.927	0.946
$\hat{\rho}_\kappa$	936	6.837	5.175	0.592	16.274
Group 1	174	0.935	0.130	0.592	1.202
Group 2	235	2.942	0.030	2.860	3.006
Group 3	191	5.368	0.059	5.205	5.496
Group 4	336	13.451	0.940	10.887	16.274

[35] R^2 =100 per cent, all p-values=0.000.

The average $\hat{\kappa}$ is 0.833. Interestingly, this implies that the average respondent would be indifferent between accepting and rejecting the first gamble (where the downside was 0.833 times current income). Moreover, the average $\hat{\rho}_\kappa$ is estimated at 6.837 with a standard deviation of 5.175.

8.3 Comparing the estimates

Surprisingly, our average estimate of $\hat{\kappa}$ turns out to be slightly lower than $\hat{\lambda}$**.** This difference is not significant, but note that one should expect that $\lambda < \kappa$ for all respondents, since the upside is larger for the first set of income gambles.

It appears that a large reduction in the potential upside of the gambles (from 200 per cent to 150 per cent) did not significantly change the estimate of the respondents' lowest fraction of current income that makes them indifferent between the gamble and the safe outcome. One explanation for this could be that they put far more weight on bad outcomes than on good outcomes. In that case, it is possible that their preferences would be better explained by a utility function with kinks, e.g. Gul's utility function.

Moreover, we obtained two different estimates of ρ. Using a Wilcoxon signed rank-test, the distribution of ρ_κ appears to be significantly different from ρ_λ (p-value = 0.000).[36] The difference between ρ_κ and ρ_λ may be caused by survey response-error, or perhaps EUT is inadequate for explaining the heterogeneity in the respondents' answers.

For later applications, we will use an average of the two estimates obtained under EUT, such that $\bar{\rho}_i = 0.5(\rho_{\lambda i} + \rho_{\kappa i})$. The mean value of $\bar{\rho}_i$ is 7.930.

[36] The estimated distributions of ρ are very non-normal, so we chose to apply a non-parametric test. The null hypothesis is that the difference between the pairs follow a symmetric distribution around zero, while the alternative is that they do not.

8.4 Risk and choices

In this section, we wish to investigate whether our risk-measures ($\hat{\lambda}$ and $\hat{\kappa}$) are correlated with the likelihood of engaging in risky activities. If not, it could be that the estimates are mostly noise, which would make them poor measures of risk aversion. We will first look at the effects of $\hat{\lambda}$, and subsequently look at the effects of $\hat{\kappa}$.

For instance, it may seem reasonable that people who work in the public sector are more risk averse than those who work in the private sector. Bonin, Domen, Falk, Huffman & Sunde (2007) found that individuals with low risk tolerance are more likely to enter jobs with low earnings risk, such as public-sector jobs. We can investigate whether our risk aversion measure is partially correlated with the likelihood of working in the private sector by performing a probit-regression, where a dummy-variable for private sector is the dependent variable and $\hat{\lambda}$ is used as a regressor together with a set of control variables, x. The modelled likelihood for working in the private sector is then

$$\Pr\{PrivateSector = 1|x_i\} = \phi(x_i'\beta + \tau\hat{\lambda}) \tag{37}$$

where ϕ is the cumulative distribution function of the normal distribution. τ is then the coefficient of interest. Using a Wald-test, we can test the null hypothesis that $\tau = 0$ where the alternative is $\tau \neq 0$. If we can reject the null hypothesis, we can conclude that our risk aversion proxy has a significant partial correlation with the likelihood of working in the private sector. The results can be seen in column (1) of Table 7.[37]

[37] Note that those whose answers indicated they are not active in the labour force are not included in the sample for column (1), (2) and (3).

Table 7: Correlation between λ and risky behaviour

	(1) Private	(2) Top manager	(3) Self-employed	(4) Borrow for stocks[38]
$\hat{\lambda}$	-1.815***	-1.100**	-0.543	-0.652*
	(0.431)	(0.462)	(0.440)	(0.359)
male	0.827***	0.512**	0.600***	0.546***
	(0.132)	(0.241)	(0.200)	(0.172)
age	-0.0112*	0.0293***	-0.269***	-0.0144**
	(0.00680)	(0.0102)	(0.0779)	(0.00600)
age^2	/	/	0.0027***	/
			(0.0007)	
# of children	-0.102**	-0.00880	0.00349	0.0332
	(0.0507)	(0.0711)	(0.0622)	(0.0472)
married	0.215*	0.313	0.266*	0.0604
	(0.123)	(0.191)	(0.161)	(0.133)
education	Yes	Yes	Yes	Yes
income	No	No	No	Yes
cons	2.645***	-3.101***	5.326**	/
	(0.637)	(0.883)	(2.176)	
Log-Likelihood	-313.3228	-139.2249	-188.3671	-362.5929
R^2	0.368	0.183	0.190	0.120
N	581	586	570	932

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

$\hat{\lambda}$ turns out to be statistically significant with a negative coefficient, which implies that those with a higher $\hat{\lambda}$ have a lower likelihood of working in the private sector. This is precisely what one would expect, and it is consistent with the findings of Aarbu & Schroyen (2014). The model

[38] Ordered probit model. The estimated cut-off points are omitted from the table.

predicts that going from the lowest estimated $\hat{\lambda}$ (0.338) to the highest $\hat{\lambda}$ (0.945) reduces the likelihood of working in the private sector by as much as 34.60 per cent.

It also seems intuitive that the likelihood of being a top manager could be correlated to risk aversion. Since most top manager positions constitute high earnings risk (e.g. due to bonus-schemes), it is to be expected that top managers are more risk tolerant. This hypothesis is supported by our results, as $\hat{\lambda}$ has a significant, negative coefficient. Going from the lowest observed $\hat{\lambda}$ to the highest is predicted to reduce the likelihood of being a top manager by 9.76 per cent.[39]

It can also be argued that higher risk aversion could decrease the likelihood of being self-employed, as such a job is often affiliated with high earnings risk and low stability (see e.g. Ahn, 2010). However, for our sample, we find no significant effect of $\hat{\lambda}$. This is in contrast to Arrondel & Calvo-Pardo (2002), Hartog et al. (2002), Guiso & Paiella (2008) and Dohmen et al. (2005) who found a significant effect of their measure of risk aversion on the likelihood of being self-employed.

Lastly, our survey also involved the question "how likely is it that you would borrow money to invest in stocks?". The respondents had five alternatives, ranging from "not likely at all" to "very likely". One would expect that people who are more risk-tolerant would be more likely to express interest in borrowing money to invest.

In the ordered probit regression in column (4), $\hat{\lambda}$ is only weakly significant with a negative coefficient. If $\hat{\lambda}$ were to increase from the lowest to the highest, the likelihood of belonging to the first group is estimated to increase by 6.65 per cent, while the likelihood of belonging to the remaining groups would decrease by 3.46, 1.12, 0.60 and 1.37 per cent respectively. Thus, the effect seems to be quite small.

[39] Like Aarbu & Schroyen (2014), we also find that the male-dummy is strongly significant despite controlling for risk aversion. Thus, the popular hypothesis that women are less likely to be leaders due to having low risk tolerance is not supported by our results

Afterwards, we ran the same regressions again, except that we replaced $\hat{\lambda}$ with $\hat{\kappa}$. That is, we now wish to investigate whether the same relationships hold for our measure of risk aversion based on the second set of income gambles.

Table 8: Correlation between κ and risky behaviour

	(1) Private	(2) Top Manager	(3) Self-employed	(4) Borrow for stocks[40]
κ	-2.436***	-1.172	-1.489**	-0.755
	(0.573)	(0.745)	(0.677)	(0.556)
male	0.851***	0.555**	0.601***	0.558***
	(0.132)	(0.240)	(0.200)	(0.172)
age	-0.0106	0.0295***	-0.272***	-0.0139**
	(0.00680)	(0.0102)	(0.0789)	(0.00608)
age^2	/	/	-0.0027***	/
			(0.0007)	
# of children	-0.102**	-0.00544	-0.00262	0.0353
	(0.0505)	(0.0708)	(0.0626)	(0.0472)
married	0.200	0.300	0.269*	0.0510
	(0.123)	(0.190)	(0.162)	(0.133)
education	Yes	Yes	Yes	Yes
income	No	No	No	Yes
cons	3.184***	-3.045***	6.197***	/
	(0.714)	(1.005)	(2.260)	
Log-Likelihood	-313.6722	-140.7284	-186.7015	-363.2823
R^2	0.361	0.179	0.208	0.117
N	581	586	570	932

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Compared to Table 7, we see that all of the coefficients have the same sign as when $\hat{\lambda}$ was used. We still find that the measure of risk aversion is negatively correlated with the likelihood of working in the private sector. However, no significant relationship between $\hat{\kappa}$ and the likelihood

[40] Ordered probit model. The estimated cut-off points are omitted from the table.

of being top manager is found. Nonetheless, we now find a significant, negative relationship between $\hat{\kappa}$ and the likelihood of being self-employed, which is consistent with the aforementioned findings of earlier studies. However, the risk aversion measure turns out to be insignificant in the model for borrowing to invest.

In conclusion, it seems like all the risky choices are affected by our risk aversion measures in the expected direction, even if not all of the investigated relationships are statistically significant. In general, it appears that the answers to the hypothetical income gambles reflect real preferences fairly well.

8.4.1 Noise in regressor

Since we use a generated regressor ($\hat{\lambda}$ or $\hat{\kappa}$) as an independent variable, the coefficients given in Table 7 and 8 may be biased and subject to errors-in-variables problems (Kimball et al., 2008). Ideally, one could improve the estimates by having access to panel data, i.e., observing the same individual answering the questionnaire several times (see e.g. Kimball et al., 2008, or Sahm, 2012). This would allow for the quantification of survey response-error. However, we only have cross-sectional data. As an alternative method, Aarbu & Schroyen (2014) used bootstrapping to obtain a consistent estimate of the standard errors. Unfortunately, we were unable to replicate these methods.

Instead, we performed the regressions once more, replacing the generated regressors with dummy-variables, thus largely avoiding the problem with error-in-variables. That is, we created dummy variables for three of the four risk-groups and tested if these dummies were jointly significant using a Wald test. The results can be seen in appendix A.5. In general, we found that the risk aversion groups were jointly significant in the same models as in Table 7 and 8. Moreover, the coefficients on the other covariates were practically unchanged. This suggests that our conclusions are mostly unaffected by the potential problem of error-in-variables, even if there may be a small bias in the coefficients or standard errors.

9 Estimating disappointment aversion

In this section, we will attempt to estimate the parameters of disappointment aversion by using the answers to the two sets of hypothetical income questions. First, we will explain how λ and κ can be related to the parameters of disappointment aversion. Next, we will estimate the parameters through simulation techniques. Finally, we will look at how the parameters are correlated with socioeconomic characteristics.

As far as we know, this is the first study where hypothetical income gambles of the BJKS-type are used to estimate the parameters of disappointment aversion.

9.1 Framework to estimate parameters

There are two possible outcomes in each of the income lotteries. One includes an increase in income (x_1), and the other involves a loss (x_2). Recall that in the case with only two possible outcomes, where $x_1 > x_2$ and $u''(x) < 0$, Gul's total utility function can be written as

$$V(\beta, x) = \frac{p}{1 + (1-p)\beta} u(x_1) + \frac{(1-p)(1+\beta)}{1 + (1-p)\beta} u(x_2)$$

where p and $(1-p)$ are the probabilities of x_1 and x_2, respectively. Since $p = 0.5$ for all the income gambles in our survey, this reduces to

$$V(\beta, x) = \frac{0.5}{1 + 0.5\beta} u(x_1) + \frac{0.5(1+\beta)}{1 + 0.5\beta} u(x_2)$$
$$= \frac{1}{2+\beta} u(x_1) + \frac{1+\beta}{2+\beta} u(x_2)$$

We then multiply by $2+\beta$ (this is a positive affine transformation, so it does not alter the preferences), and define $\alpha \coloneqq \beta + 1$, to obtain the simplified expression: [41]

$$V(\alpha, x) = u(x_1) + \alpha u(x_2) \tag{38}$$

Using equation (38), there is disappointment aversion if $\alpha > 1$ and elation loving if $0 < \alpha < 1$. If $\alpha = 1$, the expected utility function is simply $V(\alpha, x) = u(x_1) + u(x_2)$, which corresponds to EUT. As before, we still assume that the utility function is the CRRA-function.

By applying the total utility function given by equation (38), we now have the following relationship between λ, α and ρ:

$$V(x, x) = V(2x, \lambda x)$$
$$\alpha u(x) + u(x) = u(2x) + \alpha u(\lambda x)$$
$$(1+\alpha)\frac{x^{1-\rho}}{1-\rho} = 2^{1-\rho}\frac{x^{1-\rho}}{1-\rho} + \alpha\lambda^{1-\rho}\frac{x^{1-\rho}}{1-\rho}$$
$$(1+\alpha) = 2^{1-\rho} + \alpha\lambda^{1-\rho}$$

$$\Rightarrow \lambda = \left[\frac{1+\alpha}{\alpha} - \frac{2^{1-\rho}}{\alpha}\right]^{\frac{1}{1-\rho}} \tag{39}$$

Recall that in the first set of income gambles, the respondents were asked to compare a safe alternative with lotteries $(2x, \frac{1}{2}x)$, $(2x, \frac{2}{3}x)$ and $(2x, \frac{4}{5}x)$, where x is current income. The level-curves for $\lambda = \left[\frac{4}{5}, \frac{2}{3}, \frac{1}{2}\right]$ in the (ρ, α)-space are shown in Figure 7. For instance, an individual who rejected all income gambles must have a (ρ, α)- combination above the green line. The solid, black line through $\alpha = 1$ represents the case for traditional EUT.

[41] In the more general case, without knowing that $x_1 > x_2$, this can be written as

$$V(x_1, x_2) = \min\{\alpha u(x_1) + u(x_2), u(x_1) + \alpha u(x_2)\}\ if\ \alpha \geq 1$$
$$= \max\{\alpha u(x_1) + u(x_2), u(x_1) + \alpha u(x_2)\}\ if\ 0 \leq \alpha < 1$$

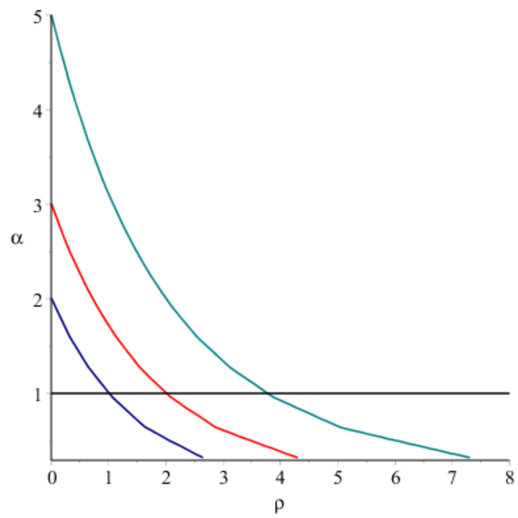

***Figure 7**: The level curves for the cut-off points of λ.*

Afterwards, in the new set of income gambles, the respondents were asked to compare the safe alternative with the lotteries $\left(\frac{3}{2}x, \frac{3}{4}x\right)$, $\left(\frac{3}{2}x, \frac{5}{6}x\right)$ and $\left(\frac{3}{2}x, \frac{9}{10}x\right)$.

Correspondingly, the relationship between κ, α and ρ is then

$$V(x, x) = V\left(\frac{3}{2}x, \kappa x\right)$$

$$\alpha u(x) + u(x) = u\left(\frac{3}{2}x\right) + \alpha u(\kappa x)$$

$$\Downarrow$$

$$\kappa = \left[\frac{1+\alpha}{\alpha} - \frac{\left(\frac{3}{2}\right)^{1-\rho}}{\alpha}\right]^{\frac{1}{1-\rho}} \tag{40}$$

We now have two equations in two unknowns. In theory, it should then be possible to elicit both α and ρ if we know λ and κ. In Figure 8, the dotted lines represent the level-curves in the (ρ, α)-space for $\kappa = \left[\frac{9}{10}, \frac{5}{6}, \frac{3}{4}\right]$.

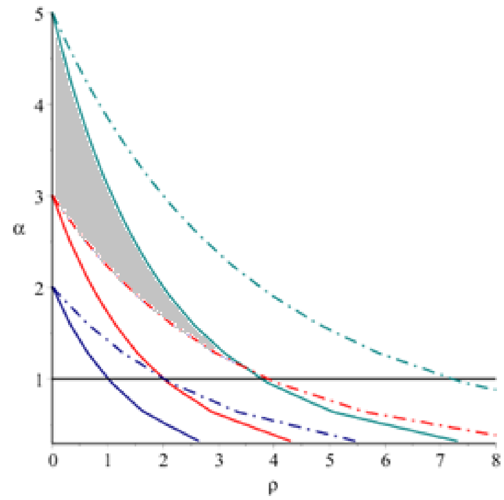

***Figure 8**: The level curves for the cut-off points of λ and κ.*

A respondent's pair of α and ρ belongs to a certain interval in Figure 8, depending on her answers to both sets of lotteries. For example, respondents who have $\frac{2}{3} < \lambda < \frac{4}{5}$ and $\frac{5}{6} < \kappa < \frac{9}{10}$, must have a combination in the shaded area of the curve. Hence, the respondent's revealed (λ, κ)-interval can be converted into a (ρ, α)-interval.

However, some respondents have given answers that are not consistent with this framework. In total, 21 respondents have answers which indicate $\lambda > \frac{4}{5}$, while also indicating $\kappa < \frac{3}{4}$. This implies that their combination of α and ρ should be above the green, solid line in Figure 8, but below the blue, dashed line. This is impossible in this framework, as it is inconsistent with the monotonicity axiom.[42]

If they have answered truthfully, their answers imply that they are willing to take a gamble with a 50 per cent chance of a 25 per cent reduction in income and a 50 per cent chance of a 150 per

[42] To see this, note that rejecting the $(2x, \frac{4}{5}x)$ gamble from the first set of income lotteries implies that $V(2x, \frac{4}{5}x) < V(x, x)$, where the latter is the safe alternative. However, by accepting both the first gambles in the second set, they must have $V(\frac{3}{2}x, \frac{3}{4}x) > V(x, x)$. Thus, they have revealed that $V(2x, \frac{4}{5}x) < V(x, x) < V(\frac{3}{2}x, \frac{3}{4}x)$. However, the monotonicity axiom implies that we must have $V(2x, \frac{4}{5}x) > V(\frac{3}{2}x, \frac{3}{4}x)$, since the outcomes on the LHS are strictly larger. Thus, we have a contradiction.

cent gain, but not willing to take a gamble with a 50 per cent chance of a 20 per cent reduction and a 50 per cent probability of a 200 per cent gain. Unless they have a negative marginal utility of income, such preferences are not feasible. It seems reasonable to assume that such responses are caused by survey response-error, e.g. caused by miss clicking, lack of attention or misunderstanding of the questions.

Moreover, a total of 21 respondents have answers that imply that they must have $\rho < 0$.[43] Since we have assumed $u''(x) < 0$ in the derivation of equation (38), we choose to exclude these respondents from the following analysis. In total, 42 respondents are dropped from the analysis.

Table 9: Frequency table and inconsistent responses

	$\frac{9}{10} < \kappa < 1$	$\frac{5}{6} < \kappa < \frac{9}{10}$	$\frac{3}{4} < \kappa < \frac{5}{6}$	$\kappa < \frac{3}{4}$	Total
$\frac{4}{5} < \lambda < 1$	325	177	140	21**	663
$\frac{2}{3} < \lambda < \frac{4}{5}$	4*	7	81	55	147
$\frac{1}{2} < \lambda < \frac{2}{3}$	2*	7*	11	50	70
$\lambda < \frac{1}{2}$	5*	0*	3*	48	56
Total	336	191	235	174	936

Table 9 shows the number of respondents in the different risk-groups. The respondents who are inconsistent with the monotonicity axiom are marked with a double asterisk (**), while those respondents whose combinations imply $\rho < 0$ are marked with a single asterisk (*).

To check whether the inconsistencies appear to be random, we performed a probit-regression on the likelihood of being inconsistent given certain characteristics, namely gender, age, number of children, income, education and civil status. The results can be found in appendix A.7. The regression indicated two significant relationships. First of all, it appears that age is positively

[43] That is, the entirety of their (α, ρ)-interval lies to the left of the α-axis in Figure 8.

correlated with the likelihood of answering inconsistently. This is not very surprising, as some senior citizens might have a harder time comprehending the question, and/or a higher probability of miss-clicking (e.g. due to trembling of the hand). Moreover, those who have the highest level of education (4 years or more) appear to have a lower likelihood of being inconsistent, compared to those who have not finished high school. This result seems intuitive as well, as higher educated individuals may tend to have a more sophisticated understanding of the hypothetical income lotteries.

9.2 Estimating parameters of DAT using simulation

To estimate the parameters of disappointment aversion, we model the distribution of λ and κ as a system of equations. We assume a bivariate-normal distribution for the error-terms, and denote the correlation coefficient as ς. Recall that

$$\theta_i = x_i'\beta_1 + \varepsilon_{i1}$$
$$\Psi_i = x_i'\beta_2 + \varepsilon_{i2}$$

$$\begin{bmatrix}\varepsilon_{i1}\\ \varepsilon_{i2}\end{bmatrix} \sim N\begin{pmatrix}0 & & \sigma_1 & \varsigma\\ 0 & , & \varsigma & \sigma_2\end{pmatrix}$$

where $\theta_i \coloneqq \log\frac{\lambda_i}{1-\lambda_i}, \Psi_i \coloneqq \log\frac{\kappa_i}{1-\kappa_i}$. The parameters of this system ($\beta_1, \beta_2, \sigma_1, \sigma_2$ and ς) were estimated in section 7.3 using a bivariate interval regression.

The goal is to find an estimate of λ and κ for each respondent when we assume that the errors are correlated. Then we would have the following system of equations in two unknowns, making it possible to estimate α and ρ.

$$
\begin{cases}
\lambda = \left[\dfrac{1+\alpha}{\alpha} - \dfrac{2^{1-\rho}}{\alpha}\right]^{\frac{1}{1-\rho}} \\
\kappa = \left[\dfrac{1+\alpha}{\alpha} - \dfrac{\left(\frac{3}{2}\right)^{1-\rho}}{\alpha}\right]^{\frac{1}{1-\rho}}
\end{cases}
\tag{41}
$$

In order to find λ and κ for each individual, we use simulation. For each respondent i, we take random draws of $x_i'\beta_1 + \varepsilon_{i1}$ and $x_i'\beta_2 + \varepsilon_{i2}$ from the bivariate normal distribution. Recall that we modelled the distribution of λ and κ as follows

$$
\lambda = \frac{\exp(x_i'\beta_1 + \varepsilon_{i1})}{1 + \exp(x_i'\beta_1 + \varepsilon_{i1})}
$$

$$
\kappa = \frac{\exp(x_i'\beta_2 + \varepsilon_{i2})}{1 + \exp(x_i'\beta_2 + \varepsilon_{i2})}
$$

Thus, each draw of $x_i'\beta_1 + \varepsilon_{i1}$ and $x_i'\beta_2 + \varepsilon_{i2}$ corresponds to a draw of λ and κ. We restrict the draws so that the corresponding values of λ_i and κ_i are within the boundaries of the interval that matches with respondent i's answers to the hypothetical income questions.

In addition, we require that the draw satisfies the monotonicity axiom, so that $\lambda_i < \kappa_i$. If this does not hold, the system of equations (41) becomes unsolvable.[44] In order to avoid unrealistically high values of α, we also had to add the restriction that $\kappa \leq 0.96$, which implies that $\lambda < 0.96$. The cut-off value of 0.96 might seem somewhat arbitrary, but it is based on a trial-and-error approach where a higher cut-off would result in some very unrealistic values of α. Without this restriction, we occasionally got simulated values of α close to 200, which would distort the average. For example, $\lambda = 0.92$ and $\kappa = 0.99$ gives $\alpha = 196.306$.

We continue taking draws until we have 1000 eligible draws of $x_i'\beta_1 + \varepsilon_{i1}$ inside the given

[44] In fact, we had to add the restriction that $\kappa - \lambda > 0{,}001$, as the solver was not able to find a solution if the difference between the simulated values of κ and λ were too small.

interval.[45] This corresponds to 1000 draws of λ_i and κ_i. For each pair of λ and κ, we then solve the set of equations given by (41) numerically and obtain a draw of α and ρ. Next, we take the average of these 1000 simulated values of α and ρ and obtain the pair (α', ρ'). This cumbersome procedure was performed in Maple (see appendix A.8 for a complete transcript of the code).

Table 10 shows the estimated parameters for the first ten respondents, along with their corresponding revealed intervals of λ and κ.

Table 10: Parameters for respondent 1-10

Respondent id	ρ'	α'	λ interval	κ interval
1	4.871	0.371	$\lambda \in (\frac{2}{3}, \frac{4}{5}]$	$\kappa \in (0, \frac{3}{4}]$
2	3.106	1.089	$\lambda \in (\frac{2}{3}, \frac{4}{5}]$	$\kappa \in (\frac{3}{4}, \frac{5}{6}]$
3	2.653	5.489	$\lambda \in (\frac{4}{5}, 1]$	$\kappa \in (\frac{9}{10}, 1]$
4	6.216	0.463	$\lambda \in (\frac{4}{5}, 1]$	$\kappa \in (\frac{3}{4}, \frac{5}{6}]$
5	2.518	5.484	$\lambda \in (\frac{4}{5}, 1]$	$\kappa \in (\frac{9}{10}, 1]$
6	2.940	1.177	$\lambda \in (\frac{2}{3}, \frac{4}{5}]$	$\kappa \in (\frac{3}{4}, \frac{5}{6}]$
7	2.636	6.460	$\lambda \in (\frac{4}{5}, 1]$	$\kappa \in (\frac{9}{10}, 1]$
8	2.897	5.385	$\lambda \in (\frac{4}{5}, 1]$	$\kappa \in (\frac{9}{10}, 1]$
9	2.999	5.221	$\lambda \in (\frac{4}{5}, 1]$	$\kappa \in (\frac{9}{10}, 1]$
10	3.047	1.124	$\lambda \in (\frac{2}{3}, \frac{4}{5}]$	$\kappa \in (\frac{3}{4}, \frac{5}{6}]$

The percentile distributions of α' and ρ' for all respondents are shown in Table 11. In total, we obtain an average ρ' of 3.617 and α' of 2.405. Empirical estimates of loss aversion are typically in the neighbourhood of 2 (Aizenman, 1998), so this estimate seems plausible. The fact that we get a slightly higher average α and ρ than earlier studies (see e.g. Choi et al. (2007), who found an average α of 1.315 and ρ of 1.662) is not very surprising, considering that previous estimations imply that our sample is extraordinarily risk averse.

[45] This may require as much as 220000 draws from the bivariate normal distribution for certain respondents.

Table 11: Percentile distribution of α and ρ

Percentiles	α	ρ
5 %	0,3865	1,0364
25 %	0,7186	2,7118
50 %	1,7130	3,0196
75 %	4,6159	4,0441
95 %	4,9931	6,5725
Mean	2,4052	3,6167
Std.Dev	1,8228	1,5647

Note that the estimated ρ is substantially lower than when EUT was applied. This is because the observed answers can only be explained by a very high value of ρ under EUT, whereas in DAT, α absorbs some of the curvature in ρ.

Since EUT is a special case of DAT, it is possible to test whether the customers' preferences adhere to EUT on average by testing the null hypothesis that the true population mean of α is equal to 1. Using a t-test, we can reject that $\alpha = 1$ with a p-value of approximately zero. Thus, we can reject that EUT holds, so it appears that the customers have a significant degree of disappointment aversion on average. In fact, 605 respondents have an estimated $\alpha > 1$, implying that they are disappointment averse. 289 respondents have an estimated $\alpha < 1$, which would imply that they are elation loving.[46] The latter figure seems a bit high, and might be caused by the high variance in the estimates.

Finally, note that these results could have been improved. For instance, increasing the number of draws of λ and κ would improve the accuracy of the estimates, but at the cost of increasing the duration of the iteration.[47] Moreover, it might have been preferable if there were asked more questions in each set of income gambles (for instance, if both sets had six implicit risk categories instead of four). This would have made some of the (ρ, α)-intervals given by Figure 8 smaller, and could have reduced the variance of the estimates. Moreover, note that we initially wanted to estimate α and ρ using maximum-likelihood methods, instead of simulation. This would have

[46] Of course, those with an estimated α sufficiently close to 1 might as well be EU-maximisers.
[47] With our computer hardware, the execution of the code to find α' and ρ' took no less than 15 hours.

made it simpler to conclude whether EUT and DAT had the best fit for the respondents' choices under risk, and could potentially have resulted in more precise estimates.

9.3 The determinants of disappointment aversion

We have earlier looked at how risk aversion is affected by socioeconomic characteristics, but it might also be interesting to see how these characteristics are correlated with α and ρ separately.

Since it is reasonable to assume that the error terms of α' and ρ' are correlated (the same, unobserved variables might affect both parameters), we model this in a linear SUR-system, where

$$\alpha = x_i'\beta_1 + \varepsilon_{1i}$$

$$\rho = x_i'\beta_2 + \varepsilon_{2i} \tag{42}$$

The estimated coefficients are equal to what would be obtained by estimating each model separately using OLS, but since the errors are in fact correlated, the magnitude of the standard errors is reduced. The results are shown in Table 12.

Table 12: A SUR-model for α and ρ

	(1) ρ	(2) α
male	-0.235	-0.156
	(0.647)	(0.720)
age	-0.0168*	0.0299***
	(0.0089)	(0.0099)
age*male	0.00197	0.000660
	(0.0108)	(0.0120)
up to high school	0.322	-0.167
	(0.225)	(0.250)
≤ 3 years of university	0.429*	-0.525**
	(0.228)	(0.254)
≥ 4 years of university	0.439*	-0.532**
	(0.228)	(0.253)
income (300, 500]	0.0420	-0.228
	(0.167)	(0.186)
income (500, 800]	0.181	-0.602***
	(0.187)	(0.208)
income (800, ∞)	-0.0296	-1.162***
	(0.241)	(0.268)
income, no answer	0.0496	-0.528*
	(0.287)	(0.319)
married	0.0874	0.294**
	(0.116)	(0.129)
# of children	-0.00756	-0.103**
	(0.0416)	(0.0462)
cons	4.221***	1.506**
	(0.590)	(0.656)
R^2	0.025	0.111
Corr ($\varepsilon_{1i}, \varepsilon_{2i}$)	-0.508***	-0.508***
N	894	894

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

First, observe that there appears to be few significant coefficients and a very low R^2 in the model for ρ. In contrast, there appears to be several significant variables in the model for α. Moreover, α and ρ appears to be negatively correlated. One explanation for this is that a moderate level of risk aversion could either be explained by a high α and a low ρ, or the other way around. Thus, there might be a tendency that a low ρ could be accompanied by a high α and vice versa.

Interestingly, age appears to have a significant, positive effect on α. This implies that the older respondents are significantly more disappointment averse. All else equal, the model implies that increasing age by one year increases the coefficient of disappointment aversion by 0.03. Previously, we were unable to establish a significant effect of age on risk aversion, but now we see the expected effect of age on disappointment aversion. In contrast, age has a weakly significant, negative effect on ρ. The fact that these effects seem to work in opposite directions could explain why we were not able to identify an effect of age on total risk aversion previously.

In addition, those with some university education appear to have a significantly lower coefficient of disappointment aversion compared to those who have not finished high school. However, the effect works in the opposite direction for ρ, as there appears to be a weakly significant, positive partial correlation between education and ρ. Once again, the observation that these effects appear to work in opposite directions could explain the lack of a significant effect of education on total risk aversion.

Moreover, those with income of more than NOK 500 000 have a significantly lower degree of disappointment aversion than those with income lower than NOK 300 000. This negative *ceteris paribus* relationship between income and α is almost twice as large for the highest income group, as for the second highest income group.[48]

Furthermore, those who are married appear to have a significantly higher degree of disappointment aversion, while those with more children appear to have a significantly lower α.

[48] However, note that there could be endogeneity bias in this model as well. In section 7.4 we discussed the possible omitted variable bias that would arise if cognitive ability is correlated with risk aversion and income or education are correlated with cognitive ability.

This is consistent with our earlier conclusions, except that the notion of risk aversion is replaced by disappointment aversion.

Finally, note that it might be problematic that we first used the observed covariates to estimate α' and ρ', and then investigate if these same covariates have an effect on α' and ρ'. Thus, the results above should be viewed with caution.

10 Applying the estimates

10.1 Relative risk premium

As discussed previously, disappointment aversion affects the calculation of an agent's absolute and relative risk premium. Recall that the relative risk premium denotes the share of initial wealth an agent would be willing to pay to avoid a proportional zero-mean risk. Earlier, we have shown that α has a first order effect on the risk premium, whereas ρ has a second order effect. Thus, it would be interesting to estimate the respondents' relative risk premium under EUT and DAT respectively, and compare the results.

Under DAT, the relative risk premium $(\tilde{\pi})$ for a symmetric lottery is given by

$$(1+\alpha)u\big(x(1-\tilde{\pi})\big) = \alpha u\big(x(1-\varepsilon)\big) + u(x(1+\varepsilon)) \tag{43}$$

where ε is the fraction of wealth lost or gained in the two possible states (Choi et al., 2007). Substituting the CRRA-function leads to

$$(1+\alpha)(1-\tilde{\pi})^{1-\rho} = \alpha(1-\varepsilon)^{1-\rho} + (1+\varepsilon)^{1-\rho}$$

$$\Rightarrow \tilde{\pi}(\varepsilon) = 1 - \left[\frac{\alpha(1-\varepsilon)^{1-\rho} + (1+\varepsilon)^{1-\rho}}{1+\alpha}\right]^{\frac{1}{1-\rho}} \tag{44}$$

Next, we calculate this value for each respondent for $\varepsilon = 0.5$, i.e. for a gamble that yields either a 150 per cent gain or a loss of 50 per cent with equal probability.

On average, we find that the relative risk premium is 0.3843. This indicates that the average respondent is willing to pay as much as 38.43 per cent of his income to avoid the zero-mean gamble described above. This seems like a very high number, and illustrates the substantial level of risk aversion among the respondents.

In comparison, under EUT, the risk premium is given by

$$\tilde{\pi}(\varepsilon) = 1 - \left[\frac{(1-\varepsilon)^{1-\rho} + (1+\varepsilon)^{1-\rho}}{2}\right]^{\frac{1}{1-\rho}} \tag{45}$$

If we apply the first estimate of ρ_λ for each respondent, this results in an average relative risk premium of 0.404. The estimate of ρ_κ gives a relative risk premium of 0.362. We can also use the average of the two estimates of ρ, such that $\bar{\rho}_i = 0.5(\rho_{\lambda i} + \rho_{\kappa i})$. By substituting for $\bar{\rho}_i$, we get an average relative risk premium of 0.394 under EUT. The distribution of risk premiums under both theories is shown in Table 13.

Table 13: Distribution of risk-premium

Percentiles	DAT	EUT
5 %	0.1215	0.1144
25 %	0.3486	0.3247
50 %	0.4201	0.4501
75 %	0.4518	0.4685
95 %	0.4539	0.4721
Mean	0.3843	0.3940
Std. Dev.	0.0909	0.1133

Thus, for this sample, it seems that applying disappointment aversion did not significantly change the calculation of risk premium.

10.2 Optimal insurance

As discussed previously, DAT allows for the optimality of full insurance ($\gamma = 1$) even when there is a positive loading ($\mu > 0$). This is in contrast to EUT, where it is predicted that full insurance is never optimal when $\mu > 0$. In this section, we want to investigate how the predictions by EUT and DAT differ when facing an insurance problem.

Assume that an agent with initial wealth $w > 0$ faces a binary risk, where he either loses nothing or loses half of his initial wealth ($\frac{w}{2}$), with probabilities $p_1 = p_2 = 0.5$. However, he can choose to insure a fraction (γ) of this loss for the price of γP.

His total utility under DAT is then given by:

$$V(\alpha, w, \gamma) = u(w - \gamma P) + \alpha u(w - \gamma P - (1 - \gamma)\frac{w}{2})$$

By substituting for $P = (1 + \mu) \cdot \mathrm{E}[x] = (1 + \mu)\frac{w}{4}$ and letting $u(\cdot)$ be the CRRA-utility function, we get

$$V(\alpha, w, \gamma) = \frac{\left(w - \frac{\gamma w}{4} - \frac{\gamma \mu w}{4}\right)^{1-\rho}}{1 - \rho} + \alpha \frac{\left(\frac{w}{2} + \frac{\gamma w}{4} - \frac{\gamma \mu w}{4}\right)^{1-\rho}}{1 - \rho} \tag{46}$$

The agent wants to maximise (46) with respect to γ, subject to the constraint that $0 \leq \gamma \leq 1$. Note that since $w^{1-\rho}$ is strictly positive, this is equivalent to maximising

$$V(\alpha, \gamma) = \frac{\left(1 - \frac{\gamma}{4} - \frac{\gamma \mu}{4}\right)^{1-\rho}}{1 - \rho} + \alpha \frac{\left(\frac{1}{2} + \frac{\gamma}{4} - \frac{\gamma \mu}{4}\right)^{1-\rho}}{1 - \rho} \tag{47}$$

Thus, the optimisation-problem does not depend on initial wealth, which is an implication of the

CRRA-assumption. If we let λ denote the shadow price of the $\gamma \leq 1$ restriction, the Lagrangian is

$$L = V(\alpha, y) - \lambda(\gamma - 1) \tag{48}$$

The Kuhn-Tucker conditions are satisfied if we have

$$\frac{\delta L}{\delta \gamma} \leq 0 \qquad \gamma \geq 0$$
$$\frac{\delta L}{\delta \lambda} \geq 0 \qquad \lambda \geq 0$$

with at least one equality in each line, where

$$\frac{\delta L}{\delta \gamma} = \frac{\left(1 - \frac{\gamma}{4} - \frac{\gamma\mu}{4}\right)^{1-\rho} \cdot \left(-\frac{1}{4} - \frac{1}{4}\mu\right)}{1 - \frac{\gamma}{4} - \frac{\gamma\mu}{4}} + \frac{\alpha\left(\frac{1}{2} + \frac{\gamma}{4} - \frac{\gamma\mu}{4}\right)^{1-\rho} \cdot \left(\frac{1}{4} - \frac{1}{4}\mu\right)}{\frac{1}{2} + \frac{\gamma}{4} - \frac{\gamma\mu}{4}} - \lambda$$
$$\frac{\delta L}{\delta \lambda} = \gamma - 1$$

Based on data from Finance Norway (2015), we find that the average loading in the insurance industry has been close to 0.40 over the past few years. Thus, we assume that $\mu = 0.40$. We then solve the optimisation problem for the respondents ($N = 894$) by substituting for their respective values of α and ρ.

In total, we find that 333 respondents (37.25 per cent) are predicted to buy full insurance under DAT. 48 respondents (5.37 per cent) are predicted to not buy any insurance. The average optimal fraction of insurance coverage, γ^*, is 0.779.

Next, we want to compare our results with that of EUT. That is, we now maximise:

$$V(\alpha,\gamma) = \frac{\left(1-\frac{\gamma}{4}-\frac{\gamma\mu}{4}\right)^{1-\rho}}{1-\rho} + \frac{\left(\frac{1}{2}+\frac{\gamma}{4}-\frac{\gamma\mu}{4}\right)^{1-\rho}}{1-\rho} \tag{49}$$

Since $\alpha = 1$ under EUT. For ρ, we substitute for the average values we found based on the first and second income gambles respectively, $\bar{\rho}_i$.

Table 14 shows the distribution of γ^* under DAT and EUT.

Table 14: Distribution of γ

Percentiles	DAT	EUT
5 %	0	0
10 %	0.359	0.047
25 %	0.684	0.604
50 %	0.896	0.864
75 %	1	0.910
95 %	1	0.919
Mean	0.779	0.725
Std. Dev.	0.267	0.292

Under EUT, $\gamma = 1$ is never optimal, so no one is predicted to buy full insurance. The highest predicted γ^* was 0.925. 75 respondents (8.39 per cent) were predicted to not buy insurance. The average γ^* is 0.725, which is slightly lower than what we found under DAT.

In conclusion, it appears that DAT and EUT result in slightly different results for the optimal insurance problem. Whereas 37.25 per cent of the respondents were predicted to buy full insurance under DAT, EUT does not allow for the optimality of full insurance when there is a positive loading. In reality, it is common to observe customers who choose to buy full insurance. Thus, it seems that applying DAT may give more realistic predictions for this particular problem, even if the predicted average fractions of insurance coverage were not vastly different.

11 Summary and conclusion

In this thesis, we have analysed the risk preferences of a sample of Norwegian insurance customers using two different theories of decision making under risk, EUT and DAT, and investigated which of these theories that seem to be best suited to explain risky choices among the respondents. Our analysis was based on hypothetical income lotteries, inspired by Barsky et al. (1997). Such lotteries have been used in several studies to study risk aversion under EUT, but as far as we know, this is the first study where such questions were used to estimate the parameters of DAT.

In order to estimate the parameters of both theories, two cardinal measures of risk aversion, λ and κ, were defined. These variables can be interpreted as the lowest fraction of income retained in the bad state that makes the individual indifferent between the gamble and the safe alternative. Based on the respondents' answers to the hypothetical income questions, we first established intervals for their values of λ and κ. Then we used interval regression to determine the effect of socioeconomic characteristics on these cardinal measures of risk aversion.

Following Aarbu & Schroyen (2014), the estimates obtained from the interval regressions were used to estimate the expectation of λ and κ conditional on the respondents' characteristics and their answers to the hypothetical income questions. Interestingly, the estimated conditional expectations of λ and κ turned out to be nearly identical. This may be a sign that the respondents put more weight on bad outcomes than good outcomes, supporting the idea of a total utility function with kinks. The estimates of λ and κ were then converted to the coefficient of relative risk aversion, resulting in an average ρ of 7.930 under EUT. We also investigated the relationship between the measures of risk aversion and the likelihood risky behaviour, and found that the measures predict risky behaviour reasonably well. This indicates that we are measuring what we intended to measure.

Next, we estimated the parameters of disappointment aversion through simulation, and found that, on average, $\alpha = 2.41$ and $\rho = 3.62$. Subsequently, we tested a hypothesis that the customers' preferences adhere to EUT on average, by testing if $\alpha = 1$. We were able to reject this hypothesis, and conclude that the customers of this insurance company appear to be significantly disappointment averse on average. Thus, it appears like their choices are better explained by Gul's utility function.

While it appears that DAT is more suited to explain the respondents' choices, this does not necessarily mean that DAT is more adequate than EUT when it comes to modelling decision making under risk. Adding more parameters to a model will increase its explanatory power, but there is an inevitable trade-off between complexity and precision. Whether it may be beneficial to apply DAT over EUT could depend on the intention of the study and the particular problem at hand. For example, we showed that when calculating the optimal fraction of insurance for each respondent, DAT and EUT might result in quite different predictions. However, in our case, applying DAT had little effect on the calculation of the risk premium.

Furthermore, while the results indicate that DAT might fit better than EUT, there could exist other theories that fit even better, such as Quiggin's (1982) rank-dependent utility theory or Tversky & Kahneman's (1992) cumulative prospect theory. It would have been interesting to estimate these models as well, but that would have been beyond the scope of this text. Moreover, throughout the analysis, we restricted our attention to CRRA-utility functions, which is a reasonably strong assumption. It would be interesting to see how the choice of different utility functions would affect the results.

Likewise, it could be interesting to perform a similar analysis with access to a representative sample of the Norwegian population. Remember, our sample was not representative, so the results are not generalisable beyond the customers of this particular company. By analysing a representative sample, one might for example find out whether Norwegians are disappointment averse on average. Our study illustrates how one might estimate both parameters of disappointment aversion based on hypothetical income gambles of the BJKS-type, and the methods used could be replicated in a larger study. However, for potential future studies, we would recommend including more risk aversion categories in both sets of hypothetical income gambles. This could substantially improve the accuracy of the estimated risk preference parameters.

Appendices

A.1 Proof that DAT can solve the Allais paradox

Remember, the problem was formulated as follows:

<u>Problem 1:</u> Choose either L_1 or L_2 where L_1 grants 200 dollars for sure and L_2 yields 300 dollars with probability 0.8 and zero dollars with probability 0.2.

<u>Problem 2:</u> Choose either L_1' or L_2' where L_1' grants 200 dollars with probability 0.5 and 0 dollars with probability 0.5 and L_2' is a lottery where you get 300 dollars with probability 0.4 and 0 dollars with probability 0.6.

The study indicated that most people tend to choose L_1 in the first problem and L_2' in the second one, which is inconsistent with the EUT-framework.

To prove that DAT can explain their choices, we need to show that it is possible for an individual to have $V(L_1) > V(L_2)$ and $V(L_2') > V(L_1')$, where V is Gul's utility function. Thus, it is sufficient to show that these inequalities can hold for one set of parameters.

We assume that the individual has a CRRA-utility function with $\rho = 3$ and $\beta = 2$. If $x_1 > x_2$, recall that the total utility of a gamble is given by

$$V(x) = \frac{p}{1 + (1-p)\beta} u(x_1) + \frac{(1-p)(1+\beta)}{1 + (1-p)\beta} u(x_2)$$

For the first problem, we then get

$$V(L_1) = u(200) = \frac{200^{1-3}}{1-3} = -1.25 \cdot 10^{-5}$$

$$V(L_2) = \frac{0.8}{1 + (0.2 \cdot 2)} u(300) = -3.1746 \cdot 10^{-6}$$
$$\Rightarrow V(L_1) > V(L_2)$$

Similarly, for the second problem, we get

$$V(L_1') = \frac{0.5}{1 + (0.5 \cdot 2)} u(200) = -3.125 \cdot 10^{-6}$$
$$V(L_2') = \frac{0.4}{1 + (0.6 \cdot 2)} u(300) = -1.0101 \cdot 10^{-6}$$
$$\Rightarrow V(L_2') > V(L_1')$$

Thus, we have shown that the observed choices are possible to explain by a utility function exhibiting disappointment aversion.

A.2 Summary statistics

Table 15: Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
male	936	0.724	0.447	0	1
age	936	60.190	10.806	29	101
number of children	936	1.953	1.288	0	13
married	936	0.659	0.474	0	1
no more than primary school	936	0.075	0.263	0	1
up to high school	936	0.264	0.441	0	1
≤ 3 years of university	936	0.271	0.445	0	1
≥ 4 years of university	936	0.390	0.488	0	1
income [0, 300]	936	0.150	0.357	0	1
income (300, 500]	936	0.436	0.496	0	1
income (500, 800]	936	0.278	0.448	0	1
income (800, ∞)	936	0.093	0.291	0	1
income, no answer	936	0.044	0.205	0	1
currently employed	935	0.626	0.484	0	1
self-employed	570	0.123	0.329	0	1
top manager	586	0.073	0.261	0	1
public sector	581	0.413	0.493	0	1
private sector	581	0.582	0.494	0	1
volunteering	581	0.005	0.072	0	1

A.3 Log-likelihood for the bivariate interval regression

Let y_{1i} and y_{2i} indicate the risk-groups respondent *i* belongs to based on the first and second set of income gambles, respectively. In this framework, the probabilities of belonging to each of the 16 different combinations of risk groups is given by

$$\Pr(y_{1i} = 1, y_{2i} = 1) = \Pr(\theta_i \leq 0, \Psi_i \leq log3) = \phi_2\left(\frac{-x_{i1}'\beta_1}{\sigma_1}, \frac{log3 - x_{i2}'\beta_2}{\sigma_2}, \varsigma\right)$$

$$\Pr(y_{1i} = 1, y_{2i} = 2) = \phi_2\left(\frac{-x_{i1}'\beta_1}{\sigma_1}, \frac{log5 - x_{i2}'\beta_2}{\sigma_2}, \varsigma\right) - \phi_2\left(\frac{-x_{i1}'\beta_1}{\sigma_1}, \frac{log3 - x_{i2}'\beta_2}{\sigma_2}, \varsigma\right)$$

$$\Pr(y_{1i} = 1, y_{2i} = 3) = \phi_2\left(\frac{-x_{i1}'\beta_1}{\sigma_1}, \frac{log9 - x_{i2}'\beta_2}{\sigma_2}, \varsigma\right) - \phi_2\left(\frac{-x_{i1}'\beta_1}{\sigma_1}, \frac{log5 - x_{i2}'\beta_2}{\sigma_2}, \varsigma\right)$$

$$\Pr(y_{1i} = 1, y_{2i} = 4) = \phi_2\left(\frac{-x_{i1}'\beta_1}{\sigma_1}, \frac{\infty - x_{i2}'\beta_2}{\sigma_2}, \varsigma\right) - \phi_2\left(\frac{-x_{i1}'\beta_1}{\sigma_1}, \frac{log9 - x_{i2}'\beta_2}{\sigma_2}, \varsigma\right)$$

$$\Pr(y_{1i} = 2, y_{2i} = 1) = \phi_2\left(\frac{log2 - x_{i1}'\beta_1}{\sigma_1}, \frac{log3 - x_{i2}'\beta_2}{\sigma_2}, \varsigma\right) - \phi_2\left(\frac{-x_{i1}'\beta_1}{\sigma_1}, \frac{log3 - x_{i2}'\beta_2}{\sigma_2}, \varsigma\right)$$

$$\begin{aligned}\Pr(y_{1i} = 2, y_{2i} = 2) \\ &= \phi_2\left(\frac{log2 - x_{i1}'\beta_1}{\sigma_1}, \frac{log5 - x_{i2}'\beta_2}{\sigma_2}, \varsigma\right) - \phi_2\left(\frac{-x_{i1}'\beta_1}{\sigma_1}, \frac{log5 - x_{i2}'\beta_2}{\sigma_2}, \varsigma\right) \\ &- \phi_2\left(\frac{log2 - x_{i1}'\beta_1}{\sigma_1}, \frac{log3 - x_{i2}'\beta_2}{\sigma_2}, \varsigma\right) + \phi_2\left(\frac{-x_{i1}'\beta_1}{\sigma_1}, \frac{log3 - x_{i2}'\beta_2}{\sigma_2}, \varsigma\right)\end{aligned}$$

$$\begin{aligned}\Pr(y_{1i} = 2, y_{2i} = 3) \\ &= \phi_2\left(\frac{log2 - x_{i1}'\beta_1}{\sigma_1}, \frac{log9 - x_{i2}'\beta_2}{\sigma_2}, \varsigma\right) - \phi_2\left(\frac{-x_{i1}'\beta_1}{\sigma_1}, \frac{log9 - x_{i2}'\beta_2}{\sigma_2}, \varsigma\right) \\ &- \phi_2\left(\frac{log2 - x_{i1}'\beta_1}{\sigma_1}, \frac{log5 - x_{i2}'\beta_2}{\sigma_2}, \varsigma\right) + \phi_2\left(\frac{-x_{i1}'\beta_1}{\sigma_1}, \frac{log5 - x_{i2}'\beta_2}{\sigma_2}, \varsigma\right)\end{aligned}$$

$$\begin{aligned}\Pr(y_{1i} = 2, y_{2i} = 4) \\ &= \phi_2\left(\frac{log2 - x_{i1}'\beta_1}{\sigma_1}, \frac{\infty - x_{i2}'\beta_2}{\sigma_2}, \varsigma\right) - \phi_2\left(\frac{-x_{i1}'\beta_1}{\sigma_1}, \frac{\infty - x_{i2}'\beta_2}{\sigma_2}, \varsigma\right) \\ &- \phi_2\left(\frac{log2 - x_{i1}'\beta_1}{\sigma_1}, \frac{log9 - x_{i2}'\beta_2}{\sigma_2}, \varsigma\right) + \phi_2\left(\frac{-x_{i1}'\beta_1}{\sigma_1}, \frac{log9 - x_{i2}'\beta_2}{\sigma_2}, \varsigma\right)\end{aligned}$$

$$\begin{aligned}\Pr(y_{1i} = 3, y_{2i} = 1) \\ &= \phi_2\left(\frac{log4 - x_{i1}'\beta_1}{\sigma_1}, \frac{log3 - x_{i2}'\beta_2}{\sigma_2}, \varsigma\right) - \phi_2\left(\frac{log2 - x_{i1}'\beta_1}{\sigma_1}, \frac{log3 - x_{i2}'\beta_2}{\sigma_2}, \varsigma\right)\end{aligned}$$

$$\Pr(y_{1i}=3,y_{2i}=2) \\ = \phi_2\left(\frac{log4-x'_{i1}\beta_1}{\sigma_1},\frac{log5-x'_{i2}\beta_2}{\sigma_2},\varsigma\right)-\phi_2\left(\frac{log2-x'_{i1}\beta_1}{\sigma_1},\frac{log5-x'_{i2}\beta_2}{\sigma_2},\varsigma\right) \\ -\phi_2\left(\frac{log4-x'_{i1}\beta_1}{\sigma_1},\frac{log3-x'_{i2}\beta_2}{\sigma_2},\varsigma\right)+\phi_2\left(\frac{log2-x'_{i1}\beta_1}{\sigma_1},\frac{log3-x'_{i2}\beta_2}{\sigma_2},\varsigma\right)$$

$$\Pr(y_{1i}=3,y_{2i}=3) \\ = \phi_2\left(\frac{log4-x'_{i1}\beta_1}{\sigma_1},\frac{log9-x'_{i2}\beta_2}{\sigma_2},\varsigma\right)-\phi_2\left(\frac{log2-x'_{i1}\beta_1}{\sigma_1},\frac{log9-x'_{i2}\beta_2}{\sigma_2},\varsigma\right) \\ -\phi_2\left(\frac{log4-x'_{i1}\beta_1}{\sigma_1},\frac{log5-x'_{i2}\beta_2}{\sigma_2},\varsigma\right)+\phi_2\left(\frac{log2-x'_{i1}\beta_1}{\sigma_1},\frac{log5-x'_{i2}\beta_2}{\sigma_2},\varsigma\right)$$

$$\Pr(y_{1i}=3,y_{2i}=4) \\ = \phi_2\left(\frac{log4-x'_{i1}\beta_1}{\sigma_1},\frac{\infty-x'_{i2}\beta_2}{\sigma_2},\varsigma\right)-\phi_2\left(\frac{log2-x'_{i1}\beta_1}{\sigma_1},\frac{\infty-x'_{i2}\beta_2}{\sigma_2},\varsigma\right) \\ -\phi_2\left(\frac{log4-x'_{i1}\beta_1}{\sigma_1},\frac{log9-x'_{i2}\beta_2}{\sigma_2},\varsigma\right)+\phi_2\left(\frac{log2-x'_{i1}\beta_1}{\sigma_1},\frac{log9-x'_{i2}\beta_2}{\sigma_2},\varsigma\right)$$

$$\Pr(y_{1i}=4,y_{2i}=1) = \phi_2\left(\frac{\infty-x'_{i1}\beta_1}{\sigma_1},\frac{log3-x'_{i2}\beta_2}{\sigma_2},\varsigma\right)-\phi_2\left(\frac{log4-x'_{i1}\beta_1}{\sigma_1},\frac{log3-x'_{i2}\beta_2}{\sigma_2},\varsigma\right)$$

$$\Pr(y_{1i}=4,y_{2i}=2) \\ = \phi_2\left(\frac{\infty-x'_{i1}\beta_1}{\sigma_1},\frac{log5-x'_{i2}\beta_2}{\sigma_2},\varsigma\right)-\phi_2\left(\frac{log4-x'_{i1}\beta_1}{\sigma_1},\frac{log5-x'_{i2}\beta_2}{\sigma_2},\varsigma\right) \\ -\phi_2\left(\frac{\infty-x'_{i1}\beta_1}{\sigma_1},\frac{log3-x'_{i2}\beta_2}{\sigma_2},\varsigma\right)+\phi_2\left(\frac{log4-x'_{i1}\beta_1}{\sigma_1},\frac{log3-x'_{i2}\beta_2}{\sigma_2},\varsigma\right)$$

$$\Pr(y_{1i}=4,y_{2i}=3) \\ = \phi_2\left(\frac{\infty-x'_{i1}\beta_1}{\sigma_1},\frac{log9-x'_{i2}\beta_2}{\sigma_2},\varsigma\right)-\phi_2\left(\frac{log4-x'_{i1}\beta_1}{\sigma_1},\frac{log9-x'_{i2}\beta_2}{\sigma_2},\varsigma\right) \\ -\phi_2\left(\frac{\infty-x'_{i1}\beta_1}{\sigma_1},\frac{log5-x'_{i2}\beta_2}{\sigma_2},\varsigma\right)+\phi_2\left(\frac{log4-x'_{i1}\beta_1}{\sigma_1},\frac{log5-x'_{i2}\beta_2}{\sigma_2},\varsigma\right)$$

$$\Pr(y_{1i}=4,y_{2i}=4) \\ = \phi_2\left(\frac{\infty-x'_{i1}\beta_1}{\sigma_1},\frac{\infty-x'_{i2}\beta_2}{\sigma_2},\varsigma\right)-\phi_2\left(\frac{log4-x'_{i1}\beta_1}{\sigma_1},\frac{\infty-x'_{i2}\beta_2}{\sigma_2},\varsigma\right) \\ -\phi_2\left(\frac{\infty-x'_{i1}\beta_1}{\sigma_1},\frac{log9-x'_{i2}\beta_2}{\sigma_2},\varsigma\right)+\phi_2\left(\frac{log4-x'_{i1}\beta_1}{\sigma_1},\frac{log9-x'_{i2}\beta_2}{\sigma_2},\varsigma\right)$$

where $\phi_2(\cdot)$ is the cumulative distribution function of the bivariate normal distribution and ς is the correlation coefficient. The log-likelihood function is then:

$$\ell = \sum_{i=1}^{N} \log\{\Pr(y_{1i}=1,y_{2i}=1)\}+\log\{\Pr(y_{1i}=1,y_{2i}=2)\}+\cdots+\log\{\Pr(y_{1i}=4,y_{2i}=4)\}$$

A.4 Econometric analysis using generalised ordered probit

In this section we fit a partial proportional odds model, based on Williams (2006), for the first set of income gambles. Recall that we had to reject a null hypothesis that the vector of coefficients is equal across risk groups. First, each variable is tested for violation of the parallel lines assumption. The parallel lines restriction is imposed only on the regressors for which the assumption holds, while it is relaxed for the remaining covariates. Finally, the model that bests fits the data is chosen.[49]

It turns out that the assumption is violated for *male*, *age*, the interaction between *male* and *age* as well as all the education dummies. The assumption holds for *number of children*, all income dummies and *married*. For these variables, we do not need to allow β to vary across groups. Thus, these variables will have the same coefficients across all groups.

[49] This is done using the gologit2-command in Stata. For more information about the procedure, see Williams (2006).

Table 16: Generalised ordered probit

	(1)	(2)	(3)
male	2.648	-1.990	-0.881
	(1.987)	(1.388)	(0.954)
age	0.0650*	-0.0226	0.0101
	(0.0341)	(0.0202)	(0.0135)
age*male	-0.0749**	0.0285	0.0104
	(0.0366)	(0.0228)	(0.0161)
up to high school	2.763***	-0.374	-0.0365
	(0.926)	(0.509)	(0.346)
≤ 3 years of university	2.277**	-0.659	-0.189
	(0.908)	(0.500)	(0.349)
≥ 4 years of university	2.753***	-0.554	-0.394
	(0.907)	(0.503)	(0.347)
income (300, 500]	-0.0710	-0.0710	-0.0710
	(0.256)	(0.256)	(0.256)
income (500, 800]	-0.400	-0.400	-0.400
	(0.277)	(0.277)	(0.277)
income (800, ∞)	-1.227***	-1.227***	-1.227***
	(0.328)	(0.328)	(0.328)
income, no answer	-0.688*	-0.688*	-0.688*
	(0.394)	(0.394)	(0.394)
married	0.408**	0.408**	0.408**
	(0.161)	(0.161)	(0.161)
number of children	-0.118**	-0.118**	-0.118**
	(0.0579)	(0.0579)	(0.0579)
cons	-1.706	4.260***	0.977
	(2.348)	(1.381)	(0.890)
N	936	936	936

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The interpretation for the variables for which the assumption holds is equivalent to the interpretation for an ordinary ordered probit, and all the conclusions for these variables turn out to be unchanged. We see that the dummy for the highest income group is significant, with a negative coefficient. This implies that those with the highest income have a lower likelihood of belonging to the more risk averse groups than those in the lowest income group. Thus, we still observe a negative correlation between income and risk aversion. There also appears to be a significant negative correlation between number of children and risk aversion. Hence, those with more children are more likely to be in the lower risk categories. Moreover, it appears that those who are married are more likely to be more risk averse.

However, the interpretation for those variables for which the assumption was violated, is changed. In column (1), a binary model is fitted. It is a comparison between group 1 compared to a combined group of 2, 3 and 4. Recall that group 1 is the least risk averse group ($0 < \lambda \leq 0.5$) whilst group 4 is the most risk averse group ($\lambda > \frac{4}{5}$).

Remark that the age variable is close to significant in column (1) (p-value = 0.057) and has a positive coefficient. This implies that increasing age increases the probability of being in groups 2 to 4, i.e. the more risk averse groups. Before, we were unable to establish an effect of age, so this is a noteworthy observation. Now, we also see that all the education dummies are significant with a positive coefficient. This implies that, compared to someone with only primary school, those with higher education are more likely to be in groups 2 to 4.

Furthermore, in column (2) another binary model is fitted. Here, group 1 and 2 are compared against group 3 and 4. However, none of the variables of interest (i.e. those variables for which the assumption is violated) have a significant coefficient. Likewise, in column (3), group 1, 2 and 3 are compared against group 4. Once again, none of the variables of interest have significant coefficients.

Ultimately, estimating a generalised ordered probit-model did not alter our conclusions significantly. Mostly, the same variables as before turned out to be significant, but the coefficients have changed. Moreover, two observations were particularly interesting. Firstly, we learned that older respondents are (close to) significantly less likely to be in the least risk averse group. Secondly, we learned that those with higher education are less likely to be in the least risk averse group, compared with those who only have finished primary school.

Finally, note that the model produced negative fitted probabilities for 66 respondents. The possibility of negative probabilities is one of the weaknesses with such a method.

A.5 Effects of risk groups

The inclusion of generated regressors in the models given by Table 7 and 8 might cause error-in-variables problems. To check the robustness of our results, we replace the generated regressors with dummy variables indicating each respondent's risk group. Table 17 gives the results based on the first set of income gambles. The base level is group 1, i.e. the least risk averse group.

Table 17: Effect of risk groups based on the first set of income gambles

	(1) Private	(2) Top Manager	(3) Self-Employed	(4) Borrow for stocks
group 2	-0.427	0.0828	-0.0299	0.455
	(0.358)	(0.347)	(0.349)	(0.281)
group 3	-0.438	-0.726^{**}	-0.291	-0.0362
	(0.329)	(0.355)	(0.314)	(0.264)
group 4	-0.911^{***}	-0.509^{*}	-0.274	-0.116
	(0.308)	(0.285)	(0.278)	(0.237)
male	0.848^{***}	0.498^{**}	0.607^{***}	0.562^{***}
	(0.132)	(0.241)	(0.200)	(0.173)
age	-0.0110	0.0298^{***}	-0.272^{***}	-0.0139^{**}
	(0.00682)	(0.0104)	(0.0783)	(0.00604)
age^2	/	/	0.0027	/
			(0.0007)	
# of children	-0.0960^{*}	-0.0107	0.00368	0.0356
	(0.0506)	(0.0720)	(0.0623)	(0.0467)
married	0.199	0.319^{*}	0.265	0.0614
	(0.123)	(0.193)	(0.161)	(0.133)
education	Yes	Yes	Yes	Yes
income	No	No	No	Yes
cons	1.845^{***}	-3.562^{***}	5.216^{**}	
	(0.598)	(0.854)	(2.171)	
Log-Likelihood	-313.00132	-137.20414	-188.18948	-359.94164
R^2	0.368	0.203	0.191	0.129
N	581	586	570	932

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Wald tests for the joint significance of the group dummies (2-4) yielded the following results:

(1) Private: Strongly significant. $\Pr\{\chi^2(3) > 18.79\} = 0.0003$.
(2) Top Manager: Significant. $\Pr\{\chi^2(3) > 9.74\} = 0.0209$.
(3) Self-Employed: Not significant. $\Pr\{\chi^2(3) > 1.90\} = 0.5934$.
(4) Borrow for stocks: Significant. $\Pr\{\chi^2(3) > 9.03\} = 0.0289$.

The conclusions are the same as with the cardinal approach, given by Table 7. One difference is that the group-dummies are jointly significant in column (4), whilst λ was only weakly significant in Table 7, column (4).

Table 18 gives the results for the second set of income gambles, where the respondents were divided into four new risk groups. As before, group 1 is the base level, i.e. the least risk averse group.

Table 18: Effect of risk groups based on the second set of income gambles

	(1) Private	(2) Top Manager	(3) Self-Employed	(4) Borrow for stocks
group 2 new	-0.391**	-0.363	-0.484**	-0.332*
	(0.169)	(0.224)	(0.200)	(0.172)
group 3 new	-0.403**	-0.457*	-0.307	-0.137
	(0.184)	(0.257)	(0.213)	(0.176)
group 4 new	-0.734***	-0.260	-0.468**	-0.241
	(0.176)	(0.225)	(0.210)	(0.167)
male	0.859***	0.570**	0.604***	0.573***
	(0.132)	(0.240)	(0.200)	(0.174)
age	-0.0109	0.0280***	-0.279***	-0.0147**
	(0.00682)	(0.0102)	(0.0794)	(0.00610)
age^2	/	/	0.0027***	/
			(0.0007)	
# of children	-0.0983*	0.00285	0.00511	0.0409
	(0.0505)	(0.0708)	(0.0627)	(0.0473)
married	0.206*	0.271	0.265	0.0433
	(0.123)	(0.191)	(0.163)	(0.133)
education	Yes	Yes	Yes	Yes
Income	No	No	No	Yes
cons	1.597***	-3.735***	5.490**	/
	(0.529)	(0.820)	(2.196)	
Log-Likelihood	-314.03071	-139.94008	-185.51923	-362.12246
R^2	0.358	0.186	0.212	0.124
N	581	586	570	932

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We find that the coefficients on the significant variables are practically unchanged compared to the coefficients estimated in Table 8. Wald-tests for the joint significance of the group dummies yielded the following results:

(1) Private: Strongly significant. $\Pr\{\chi^2(3) > 17.47\} = 0.0006$

(2) Top Manager: Not significant. $\Pr\{\chi^2(3) > 4.08\} = 0.2528$

(3) Self-employed: Weakly significant. $\Pr\{\chi^2(3) > 7.30\} = 0.0630$

(4) Borrow for stocks: Not significant. $\Pr\{\chi^2(3) > 4.16\} = 0.2442$

The conclusions are the same as in Table 8, except that the risk categories for the likelihood of being self-employed are now only weakly significant.

A.6 Robustness analyses

In Table 19 and 20, we revisit the interval regression from Table 3. Now, we add the covariates to the models one by one. This allows for the visualisation of the effect of adding a given variable.

Table 19: Robustness analysis, first set of income lotteries

	(1)	(2)	(3)	(4)	(5)
male	-1.251*	-1.451**	-0.734	-0.592	-0.459
	(0.659)	(0.663)	(0.669)	(0.667)	(0.668)
age	0.00288	0.000828	0.00231	0.00361	0.00495
	(0.00929)	(0.00934)	(0.00935)	(0.00932)	(0.00933)
age*male	0.0157	0.0187*	0.00936	0.00571	0.00375
	(0.0111)	(0.0111)	(0.0112)	(0.0112)	(0.0112)
education	No	Yes	Yes	Yes	Yes
income	No	No	Yes	Yes	Yes
married				0.290**	0.326***
				(0.118)	(0.119)
# of children					-0.0876**
					(0.0423)
cons	2.164***	2.483***	2.414***	2.199***	2.254***
	(0.546)	(0.610)	(0.624)	(0.624)	(0.624)
sigma	1.327***	1.320***	1.290***	1.281***	1.276***
	(0.0790)	(0.0786)	(0.0766)	(0.0761)	(0.0757)
R^2	0.024	0.034	0.067	0.077	0.083
Log-Likelihood	-833.56652	-830.1350	-818.032	-814.973	-812.804
N	936	936	936	936	936

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 20: Robustness analysis, second set of income lotteries

	(1)	(2)	(3)	(4)	(5)
male	-0.673*	-0.836**	-0.413	-0.349	-0.278
	(0.372)	(0.372)	(0.376)	(0.377)	(0.377)
age	0.00880*	0.00733	0.00730	0.00779	0.00839
	(0.00516)	(0.00515)	(0.00516)	(0.00516)	(0.00515)
age*male	0.00897	0.0113*	0.00597	0.00431	0.00333
	(0.00625)	(0.00624)	(0.00625)	(0.00629)	(0.00628)
education	No	Yes	Yes	Yes	Yes
income	No	No	Yes	Yes	Yes
married				0.139**	0.163**
				(0.0672)	(0.0679)
# of children					-0.0546**
					(0.0242)
cons	1.407***	1.701***	1.729***	1.637***	1.686***
	(0.301)	(0.333)	(0.341)	(0.343)	(0.343)
sigma	0.874***	0.866***	0.850***	0.848***	0.844***
	(0.0353)	(0.0350)	(0.0343)	(0.0342)	(0.0341)
R^2	0.037	0.055	0.089	0.094	0.100
Log-Likelihood	-1263.9154	-1256.0092	-1241.9156	-1239.7832	-1237.236
N	936	936	936	936	936

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In both of the robustness-analyses, we see that introducing the income-variable causes the male coefficient to become insignificant. This may be caused by omitted variable-bias. In fact, men are heavily overrepresented in the highest income groups. For those with income over 800 000, 83 of them are men, while only 4 are women. Thus, for this sample, there seems to be a correlation between gender and income. Since risk aversion also seems to be correlated with income, there could be omitted variable bias when the income-dummies are not included.

A.7 Likelihood of being inconsistent

Table 21: Probit model on the likelihood of being inconsistent[50]

	Inconsistent
male	0.267
	(0.973)
age	0.0248**
	(0.0118)
age*male	-0.00884
	(0.0152)
up to high school	-0.228
	(0.263)
≤ 3 years of university	-0.371
	(0.273)
≥ 4 years of university	-0.511*
	(0.282)
income (300, 500]	0.0963
	(0.219)
income (500, 800]	0.00121
	(0.265)
income (800, ∞)	-0.315
	(0.452)
income, no answer	0.132
	(0.347)
married	-0.0194
	(0.166)
# of children	-0.0238
	(0.0539)
Log-Likelihood	-161.7805
R^2	0.093
N	936

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[50] With "Inconsistent" we mean those who either have answers that violate the monotonicity axiom, or an implicit $\rho < 0$.

A.8 Maple-code for simulation of α and ρ

We used Maple 2016 to estimate α and ρ. The following code shows the procedure to estimate the parameters of all respondents through simulation. The estimates from the bivariate interval regression ($\beta_1, \beta_2, \sigma_1, \sigma_2$ and ς) were used as inputs, in addition to the implied (λ, κ)-intervals of each respondent.

```
restart :

with(Statistics) :

# Defining the standard deviations and correlation coefficient for the bivariate normal distr of
    log(lambda:1-lambda)
# and log(kappa:1-kappa). These figures were calculted in the bivariate interval regression.



sigma1 := 1.322682 : sigma2 := .8515685 : rho := .8036916 :

# Defining the density function of the standard normal bivariate distribution

fBSN := (x1, x2, r) → (1/(2*Pi*sqrt(1 − r^2)))*exp((−1/(2*(1 − r^2)))*(x1^2 + x2
    ^2 − 2*r*x1*x2));

#defining the pdf of the bivariate normal

fBN := (x1, x2, s1, s2, r) → fBSN(x1/s1, x2/s2, r)/(s1*s2);

#computing the probability that a given pair (x1,x2) lies inside the acceptable region

int(int(fBN(x1, x2, sigma1, sigma2, rho), x2 = a2 ..b2), x1 = a1 ..b1)


#This probability can be used to find how many draws are necesarry
    to generate 1000 draws that lie inside the implicit region.
#now defining the standard random variables


Z1 := RandomVariable(Normal(0, 1))

Z2 := RandomVariable(Normal(0, 1))

X1 := Sample(Z1, 220000)

X2 := Sample(Z2, 220000)

#checking that the correlation is zero.

Correlation(X1, X2) ;
```

The following procedure replaces a placeholder value (100) by the random variables if both of these variables fall inside the acceptable region
We must also add the monotonicity requirement: κ>λ

We also restrict the draws so that κ<0.96, and κ-λ>0.001, in order to ensure realistic values.
V1 and V2 is equal to xβ1+ε1 and xβ2+ε2, respectively.
The count variable keeps track how many times the pair (V1,V2) falls inside the region

```
Pr1 := proc(V1, YY1, V2, YY2, a1, b1, a2, b2)
 local i, count;
count := 0 :
 for i from 1 to 100000 do
  if count < 1001 then
    if V1[i] > a1 and V1[i] < b1 and V2[i] > a2 and V2[i] < b2 and V1[i] < V2[i] and V2[i]
      < 3.17805
                  and (exp(V2[i])/(1 + exp(V2[i])) - exp(V1[i])/(1 + exp(V1[i]))) > 0.001 then
    YY1[i] := V1[i];
    YY2[i] := V2[i];
    count := count + 1;
    end if
  end if;
 end do;
count;
end proc;
```

===

The following proc generates 1000 draws of Lambda and Kappa for one respondent, then solves the resulting system of equations
to obtain 1000 draws of Alpha and Rho.

Finally, it takes the average value of these draws of alpha and rho and puts the averages in the "result" matrix.

===

```
myproc := proc (mu1, mu2, a1, b1, a2, b2)
 local sigma1, sigma2, rho, Y1, Y2, YY1, YY2, lambda, kappa, KL, i, Lambda, Kappa, AP;
 global Result;

 sigma1 := 1.322682 ; sigma2 := .8515685 ; rho := .8036916 ;

 #defining the bivariate normal distrubuted variables
 Y1 := sigma1·X1+~mu1; Y2 := sigma2·(rho·X1 + sqrt(1 − ρ^2)·X2)+~mu2 ;

 #filling two vectors with 100
 YY1 := Vector(220000,'fill'= 100) ; YY2 := Vector(220000,'fill'= 100) ;

 #using the relevant inputs in the proc described above
 Pr1(Y1, YY1, Y2, YY2, a1, b1, a2, b2);

 #Defining Lambda and Kappa
 λ := (Z1) → (exp(Z1) / (1 + exp(Z1))); κ := (Z2) → (exp(Z2) / (1 + exp(Z2)));

 KL := Matrix(1 ..220000, 1 ..2);


      #Calculate Lambda and Kappa (matrix KL) for all draws in the acceptable interval. The
      rest are set to zero.

 for i from 1 to 220000 do
 if YY1(i) ≥ 100 and YY2(i) ≥ 100 then
 KL[i, 1] := 0; KL[i, 2] := 0
 else KL[i, 1] := eval(λ(YY1(i))); KL[i, 2] := eval(κ(YY2(i)));
 end if
 end do ;

 #Defining new equations for Lambda and Kappa in the (α, ρ)-space.

 Λ := ((1 + alpha)/alpha − 2^(1 − P)/alpha)^(1/(1 − P)) ; K := ((1 + alpha)/alpha − (3/2)^(1 − P)/alpha)^(1/(1 − P)) ;

AP := Array(1 ..220000, 1 ..2);


      # Solve the resulting set of equations for each draw. When Kappa and Lambda are zero,
      Alpha and Rho are undefined.
 # In total, 1000 values of Alpha and Rho are calculated.

 for i from 1 to 220000 do
  if KL(i, 1) = 0 and KL(i, 2) = 0 then
AP[i, 1] := undefined; AP[i, 2] := undefined;
 elif KL(i, 2) − KL(i, 1) > 0.001 then
  AP[i, 1] := eval(P, fsolve( {Λ = KL[i, 1], K = KL[i, 2]}, {alpha = 0 ..200, P = −5 ..30}));
  AP[i, 2] := eval(alpha, fsolve( {Λ = KL[i, 1], K = KL[i, 2]}, {alpha = 0 ..200, P = −5 ..30}))
  end if;
 end do;

# Take average of the 1000 values of alpha and rho, and put the result in a vector.
Result := Mean(AP, ignore = true);

 end proc
```

===

#Define the final matrix which is to involve values for alpha and rho for each respondent

```
FINAL := Array(1 ..894, 1 ..2)
```

#then import the 894x6 matrix which contains mu1, mu2 and the limits for each observation (Tools--Assistant--Import data). Name= ZZ.

#This iteration goes through the proc above for all respondents, and puts the results in the "FINAL" matrix
#Note: this may take up to 15 hours.

```
for i from 1 to 894 do:

   mu1 := ZZ(i, 5) : mu2 := ZZ(i, 6) : a1 := ZZ(i, 1) : b1 := ZZ(i, 2) : a2 := ZZ(i, 3) : b2
      := ZZ(i, 4) :
   myproc(mu1,mu2,a1,b1,a2,b2) :
   FINAL(i, 1) := Result(1) :
  FINAL(i, 2) := Result(2) :
end do;
```

```
with(ExcelTools) :

Export(FINAL,"TEST2v15.xlsx", 1,"A1")
```

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