The Risk Attitudes of Professional Athletes: Optimism and Success are Related

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Abstract

This paper studies whether measured risk attitudes and athletic success are related. We measured the risk preferences of the players of the Dutch men's field hockey team, the reigning European champions, and runners-up in the 2012 Olympics and in the 2014 World Championships, and compared those with a matched sample of recreational hockey players. We had the rare opportunity to interview each professional individually. Our measurements were based on prospect theory. We disentangled the various components of risk attitudes using a parameter-free method that makes it possible to completely observe prospect theory without imposing simplifying assumptions and that captures individual heterogeneity. The professionals were more optimistic for gains than the non-professionals: they overweighted the probability of winning compared with the non-professional group. Utility curvature (diminishing sensitivity) and loss aversion were very close in the two groups. As probabilities were given, the difference in optimism was not due to inaccurate beliefs. It was also unrelated to differences in overconfidence or in venturesomeness and impulsivity, two psychological traits associated with risk taking. Our findings indicate that success in sports may be related to differences in optimism. They are consistent with previous findings that optimistic people are more successful and that optimism may be associated with better outcomes.

Keywords: Risk, prospect theory, optimism, sport psychology.

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1. Introduction

Are experimentally measured risk attitudes related to real-world behavior? Psychologists would probably reply "no" to this question. They commonly assume that risk attitudes are context-specific and that risk taking in one decision context is nearly independent of risk taking in other contexts (Slovic, 1972a; Slovic, 1972b; Weber, Blais, & Betz, 2002). For economists, on the other hand, the question is more meaningful as they generally believe in a common component that underlies risk attitudes in different contexts. Recent evidence, using large representative samples (Dohmen et al., 2011) and involving many countries (Vieider et al., 2015), indicates that there is indeed a common component of risk taking. While correlations between risk attitudes measured in different contexts are rather low (in line with what psychologists assume), they are highly significant. There seems to be a general component of risk taking that does leave room for variation by decision context.

Whether this common component of risk taking can explain real-world behavior is unclear. Measured risk attitudes were found to be related to sorting into occupations with higher earnings risk (Bonin, Dohmen, Falk, Huffman, & Sunde, 2007; Caliendo, Fossen, & Kritikos, 2009; Dohmen et al., 2011; Grund & Sliwka, 2010), geographical mobility (Jaeger et al., 2010), having insurance (Barsky, Kimball, Juster, & Shapiro, 1997), and various health behaviors (Anderson & Mellor, 2008). However, other studies found no or even the wrong relation between risk taking and behavior (Charles & Hurst, 2003; Guiso & Paiella, 2006; Sutter, Kocher, Rützler, & Trautmann, 2013). For a critical review of the predictive power of measured risk attitudes see Friedman, Isaac, James, & Sunder (2014). The relation between risk attitudes and real-world behavior appears unsettled and weaker than, for example, the relation between time preference and real-world behavior.

The abovementioned studies generally used rather crude, often survey-based, measures of risk taking. While the finding that such measures correlate with real-world behavior is valuable, this approach has its limitations. In particular, it does not permit to conclude anything about the finer characteristics of risk taking. For example, under prospect theory (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992), the main descriptive theory of decision under risk (Wakker, 2010), risk taking is determined simultaneously by utility curvature (reflecting diminishing sensitivity to gains and losses), probability weighting (the nonlinear transformation of probabilities), and loss aversion (the higher sensitivity to losses than to absolutely commensurate gains). Survey measures or elementary choices cannot identify which of these three components is responsible for any correlations between risk taking and real-world behavior that we might observe. To answer this question requires finer measurements of risk taking.

The aim of this study is to explore whether there is a connection between risk taking and athletic success and, if so, which of the components of risk taking are responsible for this connection. We study the risk preferences of professional athletes and explore whether they differ from those of non-professional athletes. The professional athletes are the players of the Dutch men's field hockey team, which is one of the best in the world. They are the reigning European champions[1] and won the silver medal both in the 2012 Olympics and in the 2014 World Championships. We had the rare opportunity to interview each of these players individually to measure their risk preferences in detail. We compare their preferences with those of a selected group of male recreational hockey players who are similar in age, background, education, and (obviously) gender (factors that have been shown to affect risk taking) to the professionals, but who do not play hockey at the top level.

The question whether professional athletes differ from non-athletes has been widely studied in psychology. Most of this literature has concentrated on personality characteristics and has observed that (former) professionals differ from non-professionals in, amongst others, leadership ability (Dobosz & Beaty, 1999), life satisfaction (Bäckmand, Kaprio, Kujala, & Sarna, 2001), and aggressiveness (Filho, Ribeiro, & García, 2005). By contrast, there is scant evidence on the differences in behavioral decision making between professional athletes and non-professional athletes.[2] Yet, such differences are plausible. This is particularly true for risk taking, the topic of this paper. Pursuing a professional career is a risky activity in terms of the opportunity costs of missed or delayed career opportunities. Professional hockey players usually have to suspend their education or career. Whether the pursuit of a professional career is successful depends on such uncertain factors as selection decisions by coaches and injuries. Hockey is a dangerous and injury-prone game and the risk of injuries increases with the level due to the higher intensity of play. On the other hand, the rewards of becoming a professional are substantial. Even though the income of top hockey players is not as extreme as the income of, for example, professional soccer players, the game has a high status in the Netherlands and the players are public figures. Consequently, businesses are keen to hire the players either during (for promotional activities) or after their career. Moreover, playing for the national team is considered a big honor.

If the risk preferences of the professional players do not differ from those of the recreational players then the probability to have a successful professional sports career may only be due to

[1] They beat Germany 6-1 in the final.

[2] An exception is Krumer, Shavit, & Rosenboim (2011) who studied time preferences and found more impatience in a sample of Israeli professional athletes than in a sample of non-athletes.

talent or chance. However, if they do differ then there may also be an association between behavioral aspects and the probability to succeed as a professional.

We analyzed risk taking using prospect theory. Measuring prospect theory is complex. Most previous measurements have made simplifying assumptions and have ignored individual heterogeneity. We measure prospect theory using the recently introduced method of Abdellaoui, Bleichrodt, L'Haridon, & Van Dolder (2016), which for the first time makes it possible to completely measure prospect theory without making simplifying assumptions.

The results indicate that the main difference between professional and recreational hockey players was in terms of probability weighting: professional hockey players overweighted the probabilities of gains and (to a smaller extent) underweighted the probabilities of losses more than recreational players did. In terms of prospect theory (Tversky & Kahneman 1992, Wakker 2010), this behavior entails that the professionals were more optimistic than the recreational players. Utility curvature and loss aversion were similar for the professional and the recreational players. At the aggregate level, both had concave utility for gains and convex utility for losses, in keeping with the predictions of prospect theory and they were loss averse with loss aversion coefficients slightly less than 2. At the individual level, the distributions of the individual parameters were close. Around 60% of the hockey players had prospect theory's S-shaped utility, concave for gains and convex for losses. Less than 20% of the hockey players had everywhere concave utility, which has traditionally been assumed in decision theory. Over 80% of the hockey players were loss averse.

To shed light on where the differences in optimism stem from, we performed a follow-up survey in which we measured professionals' and recreational players' overconfidence and their impulsiveness and venturesomeness, two personality traits that are related to risk taking (Eysenck, Pearson, Easting, & Allsopp, 1985; Lijffijt, Caci, & Kenemans, 2005). Confidence about own abilities has been shown to affect economic behavior (Daniel & Hirshleifer, 2015; Grubb, 2015; Herz, Schunk, & Zehnder, 2014) . In particular, previous studies found an association between overconfidence and more daring behaviors. Malmendier & Tate (2005, 2008) observed that overconfident CEOs made more risky merger decisions and Barber & Odean (2001) found that men, who are typically more overconfident than women (Lundeberg, Fox, & Punćcohaŕ, 1994, made worse investments in stocks. A recent study by Murad, Sefton, & Starmer (2016) found that self-reported confidence was significantly correlated with probability weighting. However, differences in overconfidence, impulsiveness, and venturesomeness could not explain our main finding that the professionals were more optimistic for gains suggesting that it did not stem from any of these traits.

People are excessively optimistic about, for example, marriage (Baker & Emery, 1993), work (Hoch, 1985), sports (Radzevick & Moore, 2008), health (Weinstein, 1980), and life expectancy (Puri & Robinson, 2007). In these studies optimism is measured either by inaccurate beliefs or as a personality trait characterized by the belief that good things tend to happen more often than bad. A popular measure of this dispositional optimism is the Life Orientation Test (Scheier, Carver, & Bridges, 1994). By contrast, in our study optimism was revealed through our participants' choices (i.e. we remain within the revealed preference paradigm) and it reflects how people transform probabilities. Optimism corresponds to overweighting gain probabilities and underweighting loss probabilities. Because probabilities were objectively given, what we call optimism does not reflect inaccurate beliefs and our study complements previous findings by showing that there is more to optimism than just inaccurate beliefs. A similar conclusion was obtained by Massey, Simmons, & Armor (2011) who observed that football fans remained optimistic about their team's performance throughout the NFL season, even though their beliefs became better calibrated.

Judgment biases are usually perceived as undesirable because they lead to suboptimal decisions. Our findings indicate that this need not be true for optimism. We observed that successful people (professional hockey players in our study) were more optimistic in the evaluation of risky bets. The finding that optimism may be associated with improved outcomes is consistent with Kaniel, Massey, & Robinson (2010) who found that (dispositional) optimists experienced significantly better job search outcomes than pessimists with similar skills and to Graham, Harvey, & Puri (2013) who found that CEOs were more optimistic than the lay population.[3] Puri & Robinson (2007) observed that optimists work harder and retire later. Perhaps optimism helps people to better face setbacks, adapt to changing circumstances, and accept negative feedback, which, in turn, makes them more likely to succeed. Interestingly, Armor, Massey, & Sackett (2008) found that many of their participants considered optimism bias to be rational.

The rest of the paper is organized as follows. In Section 2 we describe the method we used to measure prospect theory. Section 3 describes our experiment and Section 4 its results. Section 5 describes the follow-up study. Section 6 discusses our findings and Section 7 concludes.

[3] Graham, Harvey, & Puri (2013) also found that CEOs were more risk tolerant suggesting that their dispositional measure of optimism was closely related to risk tolerance. In our measurements, more optimism implies more risk tolerance.

2. Background

2.1. Prospect theory

Consider a decision maker who has to make a choice in the face of risk. Let $x_p y$ denote the binary prospect that pays €x with probability p and €y with probability $1-p$. Outcomes are expressed as gains and losses relative to a reference point x_0, which we assume equal to 0. The assumption that subjects take 0 as their reference point in lab experiments is commonly made. A recent study by Baillon, Bleichrodt, & Spinu (2016) provides support for this assumption.

The decision maker has a weak preference $\succcurlyeq$ over prospects and $\succ$ and $\backsim$ denote strict preference and indifference, respectively. *Gains* are positive money amounts (strictly preferred to 0) and *losses* are negative money amounts. A *gain prospect* involves no losses (i.e. both x and y are nonnegative), a *loss prospect* involves no gains, and a *mixed prospect* involves both a gain and a loss. For gain and loss prospects the notation $x_p y$ signifies that the absolute value of x is at least as large as the absolute value of y: if x and y are gains then $x \geq y$ and if x and y are losses then $x \leq y$. For mixed prospects, the notation $x_p y$ signifies that x is a gain and y a loss: $x > 0 > y$.

Under *prospect theory (PT)* the decision maker's preferences over gains and loss prospects $x_p y$ are evaluated by:

$$w^i(p)U(x) + \left(1 - w^i(p)\right)U(y), \tag{1a}$$

where $i = +$ for gains and $i = -$ for losses. Expected utility is the special case of prospect theory where $w^i(p) = p$.

Preferences over mixed prospects $x_p y$ are evaluated by:

$$w^+(p)U(x) + w^-(1-p)U(y). \tag{1b}$$

The function U is an overall utility function that includes loss aversion. It is strictly increasing (reflecting that higher payoffs are preferred) and satisfies $U(0) = 0$. The utility function is a ratio scale and we are free to choose the utility of one outcome other than the reference point. The probability weighting functions w^i, $i = +, -$, are strictly increasing and satisfy $w^i(0) = 0$ and $w^i(1) = 1$. The probability weighting functions may differ for gains and losses.

Kahneman & Tversky (1979) posited that the utility function U is (i) S-shaped, reflecting diminishing sensitivity and contributing to risk aversion for gains and risk seeking for losses, and (ii) steeper for losses than for gains, reflecting loss aversion. Diminishing sensitivity and loss aversion both affect a decision maker's risk attitude. More concave utility leads to more risk aversion in general and higher loss aversion leads to more risk aversion for mixed prospects.

The third component of a decision maker's risk attitude under prospect theory is probability weighting. Kahneman & Tversky (1979) hypothesized, based on empirical evidence, that the probability weighting function is inverse S-shaped reflecting diminishing sensitivity when moving away from probabilities 0 and 1. It implies overweighting of small probabilities, which contributes to risk seeking [aversion] for gains [losses], and underweighting of larger probabilities, which contributes to risk aversion [seeking] for gains [losses].

[FIGURE 1 HERE]

Gonzalez & Wu (1999) pointed out that the probability weighting function is characterized by two largely independent features, curvature and elevation (see also Abdellaoui, l'Haridon, & Zank, 2010). The curvature of the probability weighting function reflects the decision maker's ability to discriminate between probabilities. Its elevation reflects how attracted the decision maker is to (probabilistic) risk. A more elevated probability weighting function implies more risk seeking for gains and more risk aversion for losses. Probabilistic risk seeking is known as optimism and probabilistic risk aversion as pessimism (Wakker, 2001). Figure 1 shows the probability weighting functions of two decision makers, denoted DM1 and DM2. The weighting function of decision maker 1 lies everywhere above the weighting function of decision maker 2, which implies for gains that decision maker 1 is more optimistic than decision maker 2 and for losses that he is more pessimistic.

2.2. Measuring prospect theory

Table 1 summarizes how we measured prospect theory in four stages. The first three stages used a method that was recently proposed by Abdellaoui, Bleichrodt, L'Haridon, & Van Dolder (2016) to measure utility and loss aversion. The fourth stage measures probability weighting. Our measurements imposed no parametric assumptions on utility, loss aversion, and probability weighting and, consequently, they were entirely parameter-free. We completely measured prospect theory without making any simplifying assumptions.

[TABLE 1 HERE]

The first stage elicits a gain x_1^+ and a loss x_1^- with the same absolute utility. These two money amounts are used to connect the utility for gains and the utility for losses and serve as starting points in the second and third stage where we elicit utility on the gain and on the loss domain, respectively.

We first selected a probability p that was kept constant throughout stages 1 to 3 and a gain G. Then we elicited the loss L for which $G_pL{\sim}0$ and the certainty equivalents x_1^+ and x_1^- such that $x_1^+{\sim}G_p0$ and $x_1^-{\sim}L_{1-p}0$. Abdellaoui et al. (2016) show that these three indifferences imply that x_1^+ and x_1^- have the same absolute utility:

$$U(x_1^+) = -U(x_1^-). \tag{2}$$

In the second stage, x_1^+ served as an input in the elicitation of a standard sequence of gains $\{x_0, x_1^+, x_2^+, \dots, x_5^+\}$ using the trade-off method of Wakker & Deneffe (1996). Let ℓ be a preselected loss. In our experiment we used $\ell = -€750$. We first elicited the loss $\mathcal{L}$ such that the decision maker was indifferent between the prospects ${x_1^+}_p\mathcal{L}$ and $-750_{1-p}0$. Then we elicited a series of indifferences ${x_j^+}_p\mathcal{L}{\sim}{x_{j-1}^+}_p-750$, $j = 2, \dots, 5$, to obtain the sequence $\{x_0, x_1^+, x_2^+, \dots, x_5^+\}$ for which the utility difference between any two successive elements was constant:

$$U(x_j^+) - U(x_{j-1}^+) = U(x_1^+) - U(0). \tag{3}$$

The standard sequence of losses was constructed similarly. We selected a gain $\mathcal{g} = €750$ and used the loss x_1^- that we had elicited in the first stage to elicit the gain $\mathcal{G}$ such that $\mathcal{G}_px_1^-{\sim}750_p0$. We then constructed a standard sequence $\{x_0, x_1^-, x_2^-, \dots, x_5^-\}$ for which the utility difference between any two successive elements was constant by eliciting a series of indifferences $\mathcal{G}_px_j^-{\sim}750_px_{j-1}^-$, $j = 2, \dots, 5$.

From Eq. (2), it follows that $U(x_1^+) - U(0) = U(0) - U(x_1^-)$ and, consequently, by combining the second and the third stages we obtained a sequence $\{x_5^-, \dots, x_1^-, x_0, x_1^+, \dots, x_5^+\}$ that ran from the domain of losses through the reference point to the domain of gains and for which the utility difference between successive elements was constant. We scaled utility by setting $U(x_5^+) = 1$ from which it follows that $U(x_j^+) = j/5$ for $j = 1, \dots, 5$, and $U(x_j^-) = -j/5$, for $j = 1, \dots, 5$.

In the fourth stage, we used the elicited sequence $\{x_5^-, \dots, x_1^-, x_0, x_1^+, \dots, x_5^+\}$ to measure the probability weighting functions for gains and losses. For any probability p, we can measure its probability weight $w^+(p)$ by eliciting the certainty equivalent x_p^+ of the prospect $x_5^+{}_p0$. The indifference $x_p^+ \sim x_5^+{}_p0$ implies by Eq. $(1a)$ and the scaling of utility that:

$$U(x_p^+) = w^+(p). \tag{4}$$

The value of $U(x_p^+)$ was usually unknown (unless x_p^+ was an element of the standard sequence $\{x_5^-, \dots, x_1^-, x_0, x_1^+, \dots, x_5^+\}$), but it could be approximated using the elements of the standard sequence. Similarly, we could measure the probability weighting function for losses by eliciting the certainty equivalent x_p^- of the prospect $x_5^-{}_p x_0$. It follows that:

$$U(x_p^-) = w^-(p). \tag{5}$$

By eliciting certainty equivalents x_p^+ and x_p^- for different values of p, we could measure the probability weighting functions for gains and losses to any desired degree of precision.

3. Method

3.1 Participants

There were two groups of participants. The first group, the treatment group, consisted of 31 male professional field hockey players. They all played at the highest level in the Netherlands and were on a list of 40 players (called the *Dutch 40*) who are closely followed by the coaching staff of the Dutch men's national team. Nine players on the Dutch40 were unavailable for interviews, because they had not been selected for the Dutch national team. Twenty-eight of the interviewed players had played in the Dutch national team and at major international tournaments including the 2012 London Olympics (silver medal), the 2012 Champions Trophy (silver medal), the 2013 European Championships (bronze medal), the 2014 Hockey World League (gold medal), the 2014 World Championships (silver medal), and the 2015 European Championships (gold medal).[4]

The second group of participants, the control group, consisted of 31 recreational male hockey players. They were selected to match the professional players. For each professional hockey player we selected a recreational player of the same age, coming from the same neighborhood, and with the same educational level. Previous evidence has shown that risk preferences depend on age,

[4] The Dutch team is currently ranked second in the FIH (international hockey federation) world ranking behind Australia.

social background, gender, and education (e.g. Dohmen et al., 2011, Benjamin, Brown, & Shapiro, 2013) and we wanted to control for these variables. Recreational players played hockey on a weekly basis, but at a (much) lower level.

3.2. Procedures

The experiment was run on computers in individual sessions. Participants could choose where to be interviewed. Most professionals preferred to be interviewed between training sessions as they have several training sessions per day. There was sufficient time between training sessions and the professionals faced no time pressure in responding. The interviews lasted 30 minutes on average and they were all performed by the same interviewer (David van Ass).

Each session started with instructions and five training questions. We told the participants that there were no right or wrong answers and that they should go through the experiment at their own pace. They were encouraged to ask questions at any time they wished.

For both gains and losses, we elicited five points of the utility function and five points of the probability weighting function. We randomized the order of the gain and loss tasks. We also randomized the order in which the five points of the probability weighting functions were elicited. Because our method used chained measurements, the first stage, the elicitation of x_1^+ and x_1^-, always had to come first. For the same reason, we could not randomize the order of the questions within the first three stages either.

We did not immediately ask participants for their indifference values. Instead, we first used three binary choice questions to zoom in at them and only then asked participants for their indifference values. A choice-based procedure tends to give more reliable results than directly asking participants for their indifference values (Bostic, Herrnstein, & Luce, 1990). Figures A1-A3 in the appendix show examples of the screens participants faced. Figure A1 displays the typical choice that participants had to make. They had to choose between two prospects, denoted A and B, and could not state indifference. Choosing between the two prospects narrowed down the interval in which the participant's indifference value should lie. After three choices a scrollbar appeared (Figure A2), which allowed participants to exactly specify their indifference value. Participants were then asked to confirm their choice (Figure A3). If they confirmed their choice, the next elicitation started. Otherwise, the process started anew.

Table 1 shows the stimuli. We used relatively large outcomes to be able to detect utility curvature, as utility is usually close to linear for small outcomes (Wakker 2010). To measure probability weighting, we used both probabilities that are usually overweighted ($p = 0.05$) and probabilities that are usually underweighted ($p = 0.67, p = 0.95$) according to the empirical literature. The outcome of a prospect was determined by drawing a ball from an urn containing red and black balls in known proportions. Participants could state which color they preferred to bet on. In the first three stages, the elicitation of utility and loss aversion, the chance of winning was always equal to 50 percent. Bleichrodt, Cillo, & Diecidue (2010) found that measurements of utility by the trade-off method do not depend on the probability that is used in the elicitations.

3.3. Analysis

Utility

We used two methods to investigate utility curvature, one nonparametric and the other parametric. They led to the same results and we will, therefore, only present the results of the nonparametric analysis. The results of the parametric analysis are in Section D of the online appendix.

In the nonparametric method, we calculated the area under the normalized utility function. We normalized the domain of U to [0,1], by dividing every gain x_j^+ by x_5^+ and every loss x_j^- by x_5^- and used linear interpolation between the points.[5] If utility is linear, the area under this normalized curve equals ½. For gains, utility is convex [concave] if the area under the curve is smaller [larger] than ½. For losses, utility is convex [concave] if the area under the curve is larger [smaller] than ½.

The parametric method estimated the utility function by the power (constant relative risk aversion (CRRA) family, x^α, the most commonly used parametric family in decision theory. For gains [losses], $\alpha \geq 1$ corresponds to convex [concave] utility and $\alpha \leq 1$ to concave [convex] utility. Estimation was by nonlinear least squares. To test for robustness, we also analyzed the results under the exponential (constant absolute risk aversion) and under the expo-power (Abdellaoui, Barrios, & Wakker, 2007; Saha, 1993) families. We also performed a mixed-effects estimation in which each individual parameter was estimated as the sum of a fixed effect, common to all participants, a group-specific effect, and an individual-specific random effect. These robustness checks led to the same conclusions. They are also reported in Section D of the online appendix.

Loss aversion

There are several definitions of loss aversion. Our main findings are based on the definition of

[5] One subject violated monotonicity so that x_5^- was not the largest loss and x_5^+ was not the largest gain. For this subject we normalized losses x_j^- to $x_j^- / \{\min_{i=1,\dots,5} x_i^-\}$ and gains to x_j^+ to $x_j^+ / \{\max_{i=1,\dots,5} x_i^+\}$.

Kahneman & Tversky (1979), which says, intuitively, that losses loom larger than absolutely commensurate gains. We checked for robustness using the definition of Köbberling & Wakker (2005), which defines loss aversion as the kink at the reference point, but this led to similar results and the loss aversion indices of Kahneman & Tversky (1979) and Köbberling & Wakker (2005) were highly correlated. These results are in Section D of the online appendix.

Kahneman & Tversky (1979) defined loss aversion as $-U(-x) > U(x)$ for all $x > 0$. To measure loss aversion coefficients according to this definition, we computed $-U(-x_j^+)/U(x_j^+)$ and $-U(x_j^-)/U(-x_j^-)$ for $j = 1, \dots, 5$, whenever possible.[6] We determined $U(-x_j^+)$ and $U(-x_j^-)$ through linear interpolation when they could not be observed directly (which happened when $-x_j^+$ did not belong to the standard sequence of losses or when $-x_j^-$ did not belong to the standard sequence of gains). Some participants occasionally violated stochastic dominance. Then utility could not be estimated and the loss aversion coefficient was treated as missing. In total, 175 out of 620 (28%) possible loss aversion coefficients were missing. A subject was classified as loss averse if all values of $-U(-x)/U(x)$ exceeded 1, as loss neutral if all values of $-U(-x)/U(x)$ were equal to 1, and as gain seeking if all values of $-U(-x)/U(x)$ were less than 1.[7]

Probability weighting

We used linear interpolation to measure $U(x_p^+)$ and $U(x_p^-)$, $p = 0.05, 0.33, 0.50, 0.67, 0.95$. We also performed a parametric estimation of the probability weighting function using Prelec's (1998) two-parameter specification $w(p) = \exp(-\delta(-\ln(p))^\gamma)$. In this specification, the γ-parameter measures the decision maker's sensitivity to variation in probabilities, with higher values indicating more sensitivity, and the δ-parameter measures the elevation of the probability weighting function, with higher values indicating for gains more pessimism (contributing to risk aversion) and for losses more optimism (contributing to risk seeking). Estimation was by nonlinear least squares. To test for robustness, we also analyzed the results under the Goldstein Einhorn weighting function (Goldstein & Einhorn, 1987). This led to the same conclusions. The results of the Goldstein Einhorn function are in Section D of the online appendix.

[6] These computations required that $-x_j^+$ was contained in $[x_5^-, 0)$ and $-x_j^-$ in $(0, x_5^+]$. If they were not then we treated them as missing.

[7] We also used a more lenient rule, which allowed for response errors and classified participants as loss averse, loss neutral, or gain seeking if the above inequalities held for more than half of the observations. This did not affect the conclusions.

Cross-validation

To test for overfitting we performed two cross-validation tests, one using the standard leave-one-out cross validation (LOOCV) and the other using a leave-but-three-out cross validation (L3OCV). Cross-validation involves partitioning the data into two subsets, a training set on which the analysis is performed and a complementary set on which the analysis is validated. This analysis is repeated for different training and validation sets and the results are averaged over the analyses. In LOOCV the validation set consists of just one observation. In L3OCV the training set consists of the minimum number of observations to obtain the parameter values deterministically.

The cross-validation analyses indicated that our estimates of utility and the probability weighting function for gains were robust and our main conclusions remained valid. For the probability weighting function for losses, the results were less reliable especially using L3OCV for the measures of curvature. The results of the cross-validation analyses are reported in Section G of the online appendix.

4. Results

4.1. Consistency

To get an impression of the quality of the data, we included several consistency checks. First, we repeated the third choice of the choice-based elicitation procedure in 8 questions, selected randomly for each participant. Participants made the same choice in 81.3% of the repeated choices (81.1% for the professionals and 81.5% for the recreational players). This is high compared to other choice experiments where reversal rates up to 33% are common (Stott, 2006; Wakker, Erev, & Weber, 1994). Second, at the end of the gain sequence, we elicited x_2^+ again. The correlation between the original measurement and the repeated measurement of x_2^+ was high: Kendall's τ was 0.77 for the professionals and 0.81 for the recreational players. We also computed the absolute difference between the original and the repeated measurement of x_2^+ as a proportion of x_2^+.[8] The median relative absolute deviation was equal to 16%. It was 25% for the professionals and 7.6% for the recreational players (Mann-Whitney test, $p = 0.02$).

[FIGURE 2 HERE]

[8] The absolute deviation is not informative because the trade-off method cannot control the elements of the standard sequences and hence the stimuli differed across participants.

4.2 The utility for gains and losses

Figure 2 shows the utility for gains and losses for the professional (Panel A) and for the recreational hockey players (Panel B) using the median data. The utility functions were close and, consistent with Kahneman & Tversky's (1979) assumption, they were concave for gains and convex for losses. Furthermore, the utility functions were steeper for losses than for gains, reflecting loss aversion. The estimated CRRA coefficients (based on the median normalized data) confirm that utility was concave for gains and convex for losses (t-test, all $p < 0.01$). Utility was slightly more concave for the professionals (z-test, $p < 0.01$) and equally convex for losses in the two groups (z-test, $p = 0.38$).

[INSERT FIGURES 3 AND 4 HERE]

Figures 3 and 4 show the cumulative distributions of the area under the individual utility functions for gains and losses. Figure 3 shows that a clear majority of both the professional and the recreational hockey players had concave utility for gains (area > 0.5). The distribution function for the professionals lies under the function of the recreational players, which is consistent with slightly more concave utility for the professional players. However, a Kolmogorov-Smirnov test revealed that the distributions did not differ for the professional and the recreational players ($p = 0.27$)

Figure 4 shows that most professional and recreational hockey players had convex utility for losses (area > 0.5). The cumulative distribution functions nearly coincide, which is consistent with comparable curvature of utility in the two groups (Komogorov-Smirnov test, $p = 0.94$)

[TABLE 2 HERE]

Table 2 shows the classification of the participants according to the shape of their utility function. We could not reject the null that the classifications were the same for the professionals and the recreational players (Fisher's exact test, p = 0.69). The most common pattern was S-shaped utility: 60% of the participants had concave utility for gains and convex utility for losses. By contrast, only 16% of the participants behaved according to the traditional assumption in decision theory that utility is concave throughout.

[FIGURE 5 HERE]

4.3. Loss Aversion

Figure 5 displays the relationships between the medians of x_j^+ and $-x_j^-$ for the professional and for the recreational players. Loss aversion in the sense of Kahneman & Tversky (1979) requires that $x_j^+ > -x_j^-$ for all j. Figure 5 clearly shows that this held (Wilcoxon test, all $p < 0.001$). A simple estimate of the degree of loss aversion is obtained by regressing the x_j^+ on $\left(-x_j^-\right)$. The $\beta's$ in Figure 5 display the coefficients from these regressions. Both $\beta's$ were statistically different from one (t-test, p < 0.001) and the values were close to the loss aversion coefficients observed by Tversky & Kahneman (1992) and others (Fox & Poldrack, 2014). Figure 5 also shows that the degree of loss aversion was the same for the professionals and the recreational players (z-test, p = 0.30).

[FIGURE 6 HERE]

Figure 6 shows the cumulative distributions of the individual loss aversion coefficients for the professional and the recreational players. It is clear that most players were loss averse. The distributions were similar and did not differ between professional and recreational players (Kolmogorov-Smirnov test, p = 0.22).

4.4. Probability weighting

Figure 7 displays the probability weighting functions for gains and losses for the professional (Panel A) and for the recreational hockey players (Panel B) using the median data. While utility and loss aversion were nearly the same for the professional and the recreational players, Figure 7 shows that the probability weighting functions differed, particularly for gains. Professionals overweighted all gain probabilities much more than the recreational players did. In the terminology of prospect theory, the professionals were much more optimistic than the recreational players about the probability of a gain (Wakker, 2010). For losses, the recreational players were close to linear probability weighting (i.e. expected utility), but the professional players underweighted larger probabilities of losses. In other words, the professionals were also more optimistic than the recreational players for larger losses.

[FIGURE 7 HERE]

Statistical analysis confirmed the above impressions. For gains, all probability weights were higher in the professional group than in the recreational group (Mann-Whitney test, all $p \leq 0.02$), with the exception of probability 0.95. For losses, we found more underweighting of probability 0.67 for the professionals (Mann-Whitney test, $p = 0.03$), but for the other probabilities we found no differences.

Figure 7 also shows the estimated parameters of the Prelec two-parameter weighting function based on the pooled data. For gains, δ^+ was lower for the professionals, which is consistent with more optimism (z-test, $p < 0.01$). The γ^+-parameters reflected that the professionals were marginally less sensitive to changes in probability than the recreational players (z-test, $p = 0.06$). For losses, the difference in optimism was insignificant (z-test, $p = 0.31$), but, again, the professionals were marginally less sensitive to changes in probability (z-test, $p = 0.05$).

The parameter estimates in the recreational group were close to those observed by Bleichrodt & Pinto (2000), Stott (2006), and Abdellaoui, Diecidue, & Öncüler (2011) suggesting that the results for the recreational group were consistent with what is usually observed and that the professionals were more optimistic, particularly for gains.[9]

A more detailed picture is obtained by looking at the individual data. Figures 8 and 9 show the cumulative distributions of the individual estimates of the elevation parameters δ^+ and δ^-. Figure 8 confirms that the professionals were more optimistic for gains than the recreational players. Their cumulative distribution of δ^+ was above that of the recreational players indicating that the professionals were more optimistic for gains. The distributions differed significantly (Kolmogorov-Smirnov test, $p = 0.02$). For losses, the cumulative distributions were much closer and not significantly different (Kolmogorov-Sirnov test, $p = 0.50$).

Figures 10 and 11 show the cumulative distributions of the individual estimates of the curvature parameters γ^+ and γ^-. The cumulative distributions of γ^+ were close suggesting comparable sensitivity to likelihood information for gains (Kolmogov-Smirnov test, $p = 0.46$). However, Figure 11 shows that the professionals displayed less curvature for losses than the recreational players, which is in line with more underweighting of the probability of likely losses. However, the difference was not significant (Kolmogorov-Smirnov test, $p = 0.17$).

[9] Abdellaoui, Baillon, Placido, & Wakker (2011) found comparable sensitivity to changes in probability as we observed in the recreational group. They observed less optimism than what we observed for the professionals, but more than what we found in the recreational group. A reason may be that they asked their participants to simultaneously evaluate risky prospects and ambiguous prospects. It is well known that such simultaneous evaluations make risky prospects appear more attractive (Chow & Sarin, 2001; Fox & Tversky, 1995) leading to more optimism.

5. Follow-up study

While the original experiment suggested that the professional and recreational hockey players differed in terms of optimism, it left several questions open. First, the difference in observed optimism may have been caused by differences in cognitive abilities (even though the samples were comparable in terms of education and both the professionals and the recreational players were highly educated: 89% of the professionals and 97% of the recreational players had a college degree). Several studies suggest that better cognitive performance correlates positively with risk tolerance (Frederick, 2005, Benjamin, Brown, & Shapiro, 2013; Burks, Carpenter, Goette, & Rustichini, 2009; Dohmen, Falk, Huffman, & Sunde, 2010). Moreover, individuals with greater cognitive skills tend to display fewer cognitive biases (Stanovich & West, 1998; Stanovich, 1999).

A second open question is where the difference in optimism comes from. For example, empirical evidence indicated a relation between overconfidence and (excessively) daring strategies and Murad, Sefton, & Starmer (2016) observed that more overconfident subjects displayed more probabilistic risk seeking. It might be that the difference in optimism that we observed was due to a difference in overconfidence. A similar question is whether the difference in optimism is related to personality traits that are associated with risk taking.

To address these two questions, we designed a follow-up study. As the professional players were preparing for the European Championships (which they won), we could not interview them personally and we could not repeat the main experiment. However, they were willing to fill out a short survey. We also approached the participants in the recreational sample again.

The survey started with two questions about past and current education and a question whether they possessed stocks (as an indication of risk taking). We then asked the three questions of Frederick's (2005) cognitive reflection test (CRT), which measures cognitive ability. To measure overconfidence, we asked the participants for each of the three CRT questions to estimate the chance that their answer was correct. To relate risk attitudes to personality traits, we asked the participants to fill out the venturesomeness and impulsiveness parts of the I_7 questionnaire (Eysenck, Pearson, Easting, & Allsopp, 1985) using the Dutch translation of Lijffijt, Caci, & Kenemans (2005). We did not include the empathy part of the I_7 as it is unrelated to risk taking (in the original I_7 the empathy questions served as filler questions) and we had to keep the survey short.

5.1. Results

Three professional players did not return the questionnaire. Their results in the original experiment were similar to those who did return the questionnaire and we obtained the same conclusions in the original experiment if we excluded these three respondents. All recreational players returned the questionnaire. Hence, the analysis of the follow-up study used the responses of 28 professional and 31 recreational players.

[TABLE 3 HERE]

Table 3 shows the descriptive statistics of the follow-up survey. To test for differences between the professional and the recreational sample, we performed a minimum distance non-bipartite matching (Rosenbaum, 2005). This technique takes into account multitesting and correlations between covariates. Details are in Section A of the online appendix. Based on Rosenbaum's (2005) exact test, we could not reject the null hypothesis that the multivariate distributions of the professionals and the recreational players were the same ($p = 0.96$).

We measured overconfidence by the difference between the average confidence in giving the correct answer and the average proportion of correct answers. The professionals and the recreational players were both overconfident and the extent of overconfidence was the same in the two groups. The average overconfidence scores were 0.17 for the professionals and 0.13 for the recreational players (both different from 0, $p < 0.01$). We could not reject the null hypothesis that they were the same (Mann-Whitney test, $p = 0.74$).[10]

To control for the effect of the variables of Table 3, we regressed our measures of optimism from the main experiment, δ^+ and δ^-, on these variables and a dummy for being a professional hockey player. We used seemingly unrelated regression (SUR) to account for the correlated nature of the errors. Because δ^+ and δ^- were regressed on the same individuals, unobservable factors in each regression could be correlated. SUR estimates the parameters of both regressions simultaneously, so that the parameters of each regression also take account of the information provided by the

[10] Some studies have argued that miscalibrated confidence judgments could be due to a biased selection of questions (Gigerenzer, Hoffrage, & Kleinbölting, 1991; Klayman, Soll, González-Vallejo, & Barlas, 1999. However, we are interested in the question whether the observed difference in optimism between professional and recreational players could be explained by differences in overconfidence. Given that the professionals and the recreational players faced the same questions and did not differ in terms of education and cognitive abilities, we believe that our conclusion that the observed difference in optimism was not caused by a difference in overconfidence is justified.

other regression. This leads to more efficient parameter estimates.

Table 4 shows the estimation results. For gains, the professionals were still significantly more optimistic than the recreational players even after controlling for the variables in Table 3. For losses we observed no difference in optimism between professionals and recreational players. Optimism for losses was positively related to stock holding and negatively related to venturesomeness.

[TABLE 4 HERE]

We also regressed utility curvature, loss aversion, and sensitivity to changes in probability on the set of covariates, but found no differences except that higher education led to more sensitivity to changes in probability. These estimation results are in Section B of the online Appendix.

6. Discussion

Professional hockey players were substantially more optimistic than recreational players. This held particularly for gains. For losses we observed some tendency to underweight larger probabilities, but this failed to reach statistical significance. The difference in optimism for gains was unrelated to differences in overconfidence, venturesomeness, and impulsivity. Together these findings suggest that success in sports could be related to differences in risk preferences: successful athletes concentrate on the small probability of success and less on the much larger probability of failure compared to those who do not become professional. However, it should be kept in mind that our study only established an association between success in sports and optimism and no causal relationship. Success in sports might be due to differences in optimism but the relationship may also run the other way round with success in sports leading to a change in perspective of probability and chance.

We observed no differences in utility curvature and loss aversion between the professional and the recreational players. This suggests, perhaps surprisingly, that success in sports is not associated with attitudinal differences towards money outcomes or towards gains and losses.

A reason why the professionals overweighted the probability of success is that the best outcome of a prospect is more salient to them. Salience is a well-known concept in cognitive psychology and refers to the phenomenon that if one choice attribute attracts more attention than other attributes, this attribute will be weighted disproportionately in subsequent choices. Psychologists view salience detection as a key mechanism that people use to focus their limited cognitive resources (Kahneman, 2011; Taylor & Thompson, 1982). Economists have also recently paid increasing attention to salience and to the question how it can be included in economic models (e.g. Bordalo, Gennaioli, & Shleifer, 2012).

A common notion in decision theory is that behavioral biases lead to suboptimal outcomes and should be corrected. Our findings qualify this view and suggest that optimism, which is usually perceived as a bias (Wakker, 2010), may be associated with better outcomes. In this, our study complements Kaniel, Massey, & Robinson (2010), who found that dispositional optimists experience significantly better job search outcomes and are more likely to be promoted than pessimists with the same skills, and Graham, Harvey, & Puri (2013) who found that CEOs are more optimistic than lay people and CFOs working in the same company. Kaniel, Massey, & Robinson (2010) found that optimism was, at least in the short run, caused by inaccurate beliefs. Our study suggests that there is more to optimism than just inaccurate beliefs, as probabilities were objectively given in our study. Perhaps, optimistic people better cope with setbacks, which makes it more likely that they will succeed. The finding of Puri & Robinson (2007) that dispositional optimists tend to work harder is consistent with this explanation. If this explanation is correct then it has interesting implications. Measuring optimism should then perhaps be part of the assessment procedure of, for example, managers hiring new employees, banks deciding on whether to finance a new startup, and universities deciding on whether a candidate should be admitted to a program. Similarly, to the extent that optimism can be trained, developing a more optimistic outlook may be a useful part of training and teaching programs.

An alternative explanation of our findings could be what Krumer, Shavit, & Rosenboim (2011) coin athletes' win-at-all-costs approach. There is much evidence for this approach in sports psychology. Krumer, Shavit, & Rosenboim (2011) use it to explain why professional athletes tend to concentrate more on the present. In our study, it might explain why professionals concentrate on the probability of winning. Krumer, Shavit, & Rosenboim (2011) mention that one of the factors that motivate professionals to win at all costs is their short career. This motive may be less important for the professional hockey players in our study as they were well-educated and for most hockey players the end of their hockey career marks the beginning of a new, usually well-paid career outside hockey. Moreover, the win-at-all-costs approach might also suggest a difference in loss aversion between professional and recreational players, which we did not observe.

Because we used large losses, all choices were hypothetical. No subject is willing to participate in an experiment where he can lose a lot of money. Because all but a few questions involved losses, we could not play out one of the gain questions for real either, as participants would know which questions would not be played out for real. The literature on the importance of real incentives is mixed. Most studies found that there was little or no effect of using real instead of hypothetical choices for the kind of tasks that we asked our participants to perform, except that hypothetical responses tend to be noisier (Bardsley et al., 2010). Dohmen et al. (2011) concluded that even a simple (hypothetical) qualitative survey measure gave behaviorally valid measurements of risk attitudes, which predicted risk-taking behavior in incentivized experiments. We believe that the benefits of being able to use (larger) losses clearly outweighed the limitation that questions were hypothetical. On the other hand, there is some evidence that incentivized confidence measurements produce less overconfidence than non-incentivized measurements (Blavatskyy, 2009; Hollard, Massoni, & Vergnaud, 2015; Murad, Sefton, & Starmer, 2016).[11]

Our elicitation process was chained. A possible danger of using chained measurements is that error propagation may affect the results. Abdellaoui et al. (2016) performed an extensive simulation study to test whether error propagation could affect their method and they found that the effects were negligible. Other simulation studies also concluded that the effects of error propagation on measurements by the trade-off method were small (Abdellaoui, Vossmann, & Weber, 2005; Bleichrodt & Pinto, 2000; Bleichrodt, Cillo, & Diecidue, 2010). We performed three analyses to test for the effects of error propagation. All tests indicated that the chained nature of our measurements did not affect our conclusions. First, we repeated the abovementioned simulation studies using our data and confirmed that the effects of error propagation were minor (see Section E of the online appendix). Second, we repeated the parametric analyses accounting for serial correlation in the error terms. We assumed that the error terms followed an AR(1) process $\epsilon_t + \rho\epsilon_{t-1} = u_t$ with u_t normally distributed with expectation 0 and variance σ^2 and estimated this model using generalized least squares (Gallant, 1975). The generalized least squares estimates were similar to the ones reported in the paper (see Section E of the online appendix). Finally, we measured the probability weights using only the (non-chained) stage 4 responses assuming linear utility (which was a good approximation for most of our participants). Again, this did not affect our conclusions.

Our analysis assumes that the professional and recreational hockey players behaved according to prospect theory and that probability weighting exists. In fact, because we only use binary prospects in our elicitations, the model we assume is consistent with many theories of decision under risk that allow probabilities to be transformed.[12] However, there exist models that do not assume probability transformation and that explain the observed behavioral patterns through other

[11] By contrast, Clark & Friesen (2009) found little if any effect of incentives on calibration.

[12] For example, original prospect theory (Kahneman & Tversky, 1979), rank-dependent utility (Quiggin, 1981; Quiggin, 1982), prospective reference theory (Viscusi, 1989), and disappointment aversion theory Delquié & Cillo, 2006; Gul, 1991) are all consistent with binary prospect theory.

concepts. An example is the priority heuristic (Brandstätter, Gigerenzer, & Hertwig, 2006).

Our paper assumes that each decision maker acts according to a single utility and probability weighting function. Previous research has shown that measured risk attitudes depend on the instruments and stimuli that are used and that utility and probability weighting functions may not be unique (e.g. Loomes & Pogrebna, 2014; Stewart, Reimers, & Harris, 2014). It is clearly desirable to investigate whether our results can be replicated with different instruments and stimuli. Unfortunately, such replications are not easy. The value of our paper is derived from the unique sample of elite athletes that we could use for the analysis. Access to such elite athletes is difficult and the time they have available is limited. Even though we had good contacts with the Dutch hockey team[13] it turned out to be impossible to repeat our measurements in the follow-up study.

One way to extend our research is by studying decisions under ambiguity. For simplicity, we have assumed that probabilities were objectively given, but in many real-world situations probabilities are unknown or ambiguous. Studying optimism under ambiguity complicates the measurements as it requires measuring subjective beliefs in addition to utility, probability weighting, and loss aversion.

Another interesting follow-up question would be to explore whether differences in optimism can explain why some people opt for risky careers. For example, Lovallo and Camerer (1999) explain the decision to become an entrepreneur with excessive optimism about one's likelihood to succeed. Previous evidence has shown that differences in risk attitudes can explain such choices but it is as yet unknown which components of risk attitudes have most explanatory power. Our data suggest that prospect theory may be of help in better explaining these choices and confirm Lovallo and Camerer's conjecture that the observed differences are primarily related to differences in optimism.

7. Conclusion

We measured the risk preferences of 31 professional players of the Dutch national hockey team and compared those with a matched group of 31 recreational players. The professionals were significantly more optimistic for gains than the recreational players. This optimism was unrelated to differences in cognitive abilities, overconfidence, venturesomeness, and impulsivity. It suggests that

[13] David van Ass's father was the coach of the Dutch national team at the time of the interviews and his brother plays in the team.

being successful in sports and optimism are related and that optimism is a judgmental bias that may be associated with improved rather than suboptimal outcomes.

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Table 1: Four-stage procedure to measure prospect theory

The third column shows the quantity that was assessed in each of the four stages of the procedure. The fourth column shows the indifferences that were elicited and the fifth their implications. The sixth column shows the stimuli used in the experiment.

		Assessed quantity	Indifference	Implication	Fixed variables
Stage 1		L	$G_p L \sim 0$	$U(x_1^+) = -U(x_1^-)$	$G =$ €5000 $p = ½$
		x_1^+	$x_1^+ \sim G_p 0$		
		x_1^-	$x_1^- \sim L_{1-p} 0$		
Stage 2	Step 1	$\mathcal{L}$	$x_1^+{}_p\mathcal{L} \sim \ell_{1-p} 0$	$U(x_j^+) - U(x_{j-1}^+)$ $= U(x_1^+) - U(0)$	$\ell = -€750$ $j = 2, \ldots, 5$
	Step 2 to 5	x_j^+	$x_j^+{}_p\mathcal{L} \sim x_{j-1}^+{}_p\ell$		
Stage 3	Step 1	$\mathcal{G}$	$\mathcal{G}_p x_1^- \sim g_p 0$	$U(x_j^-) - U(x_{j-1}^-)$ $= U(x_1^-) - U(0)$	$g =$ €750 $j = 2, \ldots, 5$
	Step 2 to 5	x_j^-	$\mathcal{G}_p x_j^- \sim g_p x_{j-1}^-$		
Stage 4	Gains	x_p^+	$x_p^+ \sim x_5^+{}_p 0$	$U(x_p^+)/U(x_5^+)$ $= w^+(p)$	$p = \begin{cases} 0.05 \\ 0.33 \\ 0.50 \\ 0.67 \\ 0.95 \end{cases}$
	Losses	x_p^-	$x_p^- \sim x_5^-{}_p 0$	$U(x_p^-)/U(x_5^-)$ $= w^-(p)$	

Table 2: Classification of participants according to the shape of their utility function

The table classifies the participants according to the shape of their utility function based on the area under the normalized utility function. Panel A displays the results for the Professional group. Panel B displays the results for the recreational group.

Gains	Concave	Convex	Total
Concave	6	19	25
Convex	3	3	6
Total	9	22	31

Gains	Concave	Convex	Total
Concave	4	18	23
Convex	3	6	8
Total	7	24	31

Table 3: Descriptive statistics follow-up survey

Variable	ALL	Professionals N=28	Recreational N=31
Mean age	24.12	24.46	23.81
Education			
College	93%	89%	96%
Other	7%	11%	4%
Holding Stocks	29%	21%	35%
Mean CRT Score	2.36	2.21	2.48
Mean confidence in CRT	94%	91%	96%
Impulsiveness	7.83	7.79	7.87
Venturesomeness	9.58	9.39	9.74

Table 4: SUR estimation on the measures of optimism δ^{+} and δ^{-} (full set of covariates)

	Gains	**Losses**
Professional (0/1)	-0.432*	-0.041
	(2.43)	(0.25)
Age	0.008	0.020
	(0.23)	(0.61)
Lower education	-0.176	-0.297
	(0.54)	(1.02)
Stocks (0/1)	-0.001	0.443*
	(0.01)	(2.53)
CRT (0/1/2/3)	-0.137	0.080
	(1.03)	(0.66)
Confidence (0-100%)	0.356	-0.809
	(0.26)	(0.67)
Impulsiveness (0-19)	-0.043	0.018
	(1.45)	(0.67)
Venturesomeness (0-16)	0.007	-0.125**
	(0.15)	(3.21)
Constant	1.327	2.173
	(0.88)	(1.59)
Observations	57	57

Absolute value of z-statistics in parentheses, * significant at 5% level; ** significant at 1% level. Higher values of δ^{+}indicate less optimism, higher values of δ^{-} indicate more optimism.

Figure 1: Probability weighting

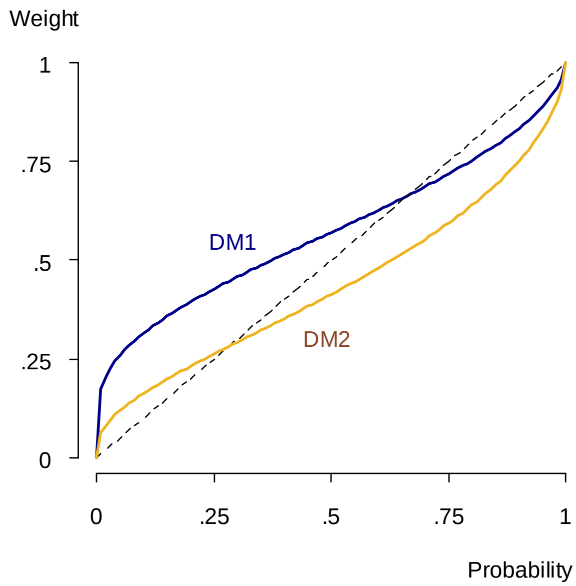
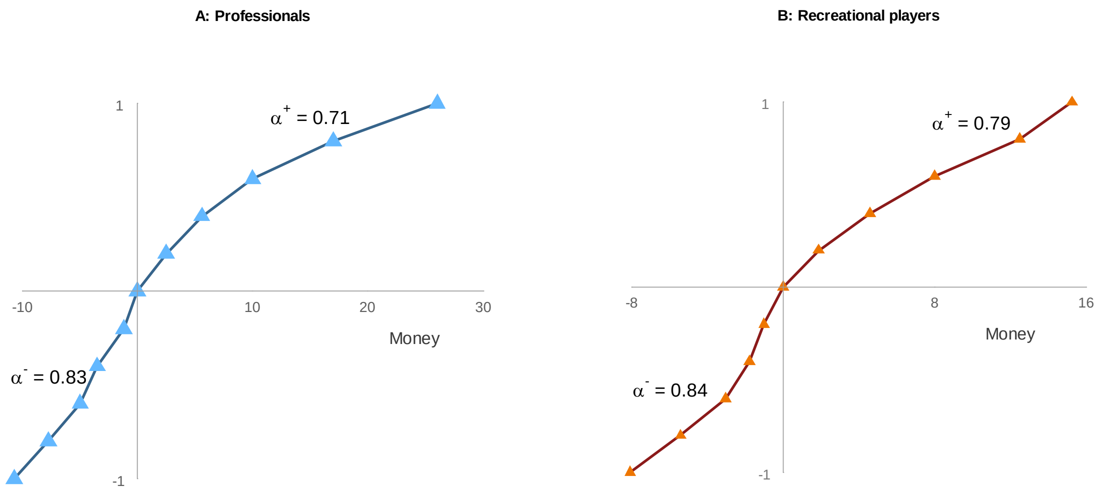


Figure 2: The utility for money based on the median data.
(Money in thousands €)



Note: α^{+} [α^{-}] indicates the estimated CRRA coefficient for gains [losses] based on the median data.

Figure 3: Cumulative distribution of the area under the individual utility functions for gains

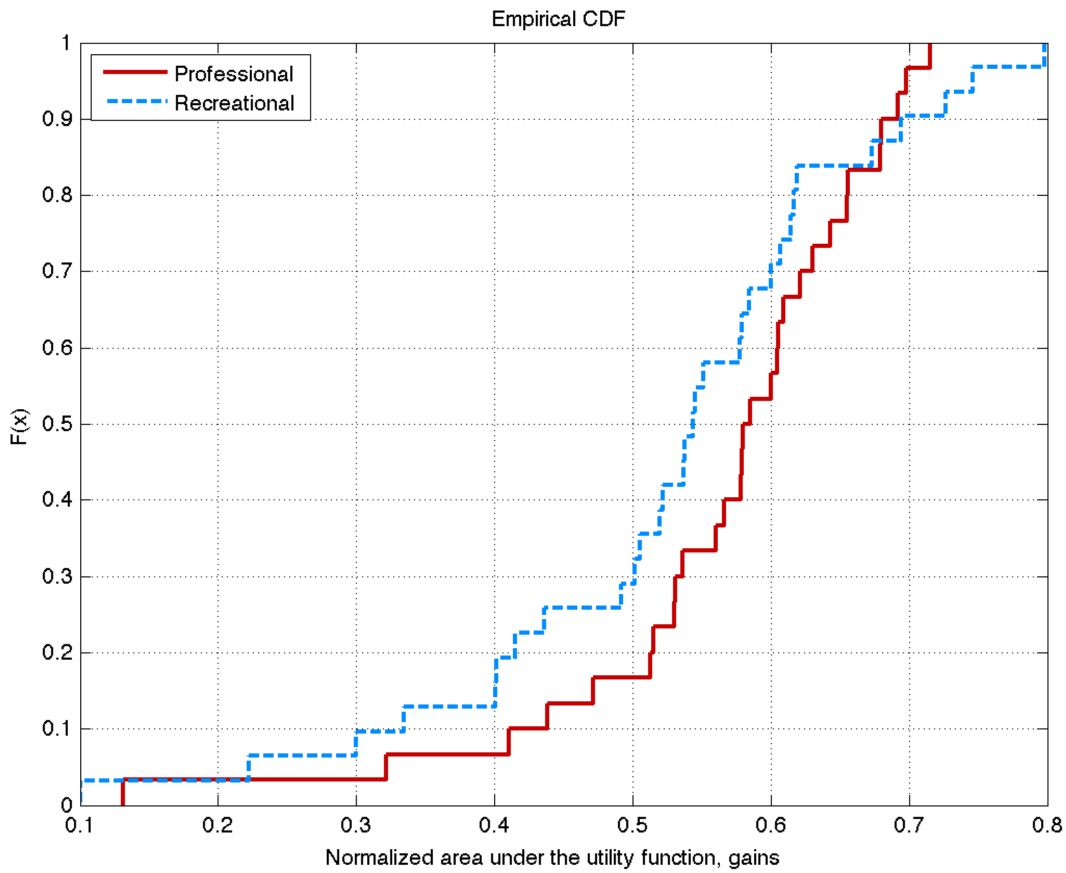


Figure 4: Cumulative distribution of the area under the individual utility functions for losses

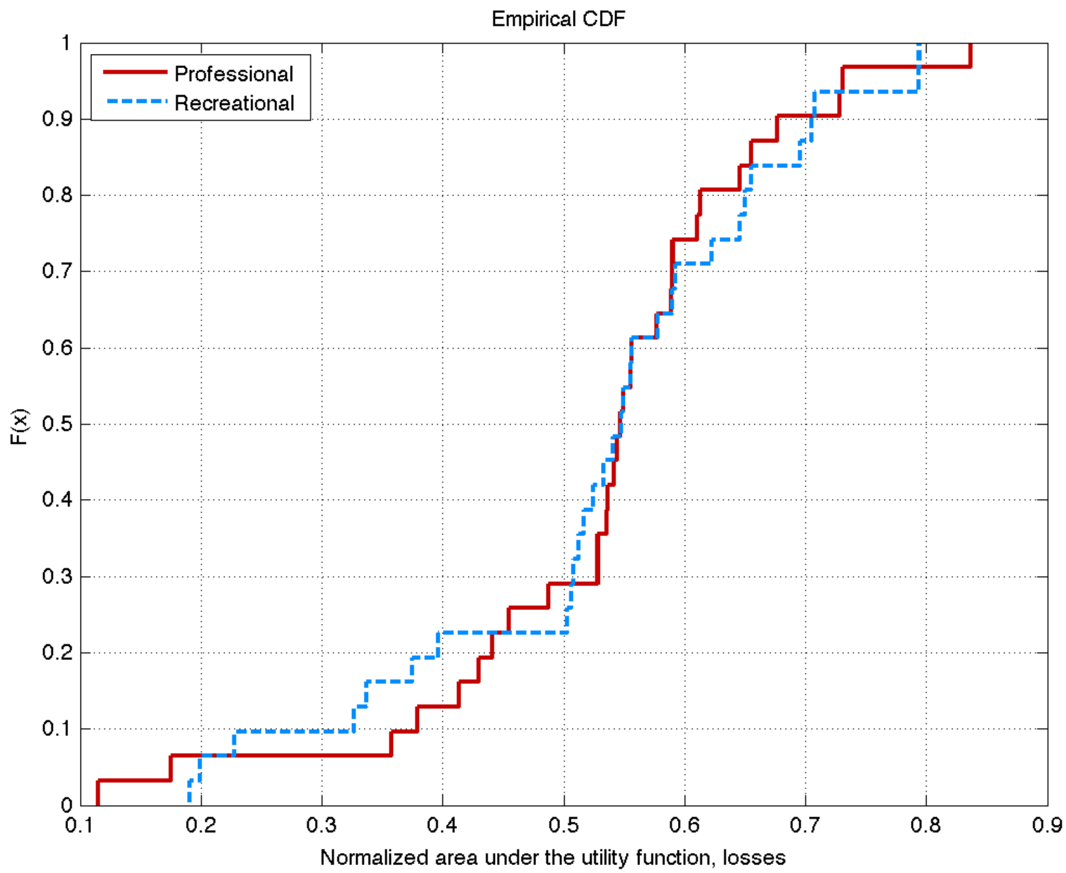
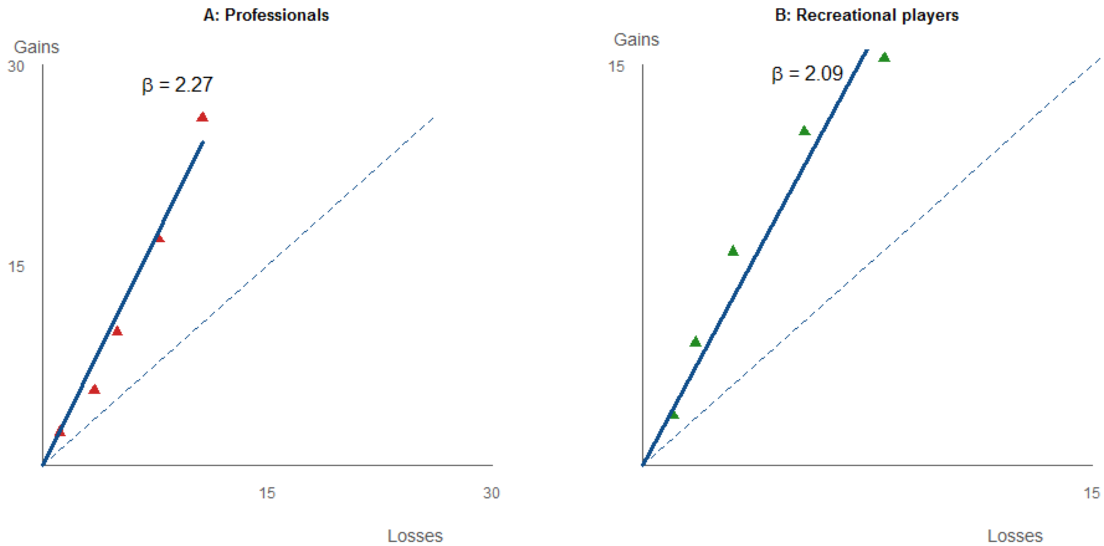


Figure 5: Median gains and median losses with the same absolute utility.
(Gains and losses in thousands €)



Note: Panel A displays the median gains and losses for the professional group, Panel B for the recreational group. The dashed line corresponds to the case where gains and losses of the same absolute utility would be equal (no loss aversion). The straight line with slope β corresponds to the best fitting linear equation.

Figure 6: Cumulative distribution of the individual loss aversion coefficients

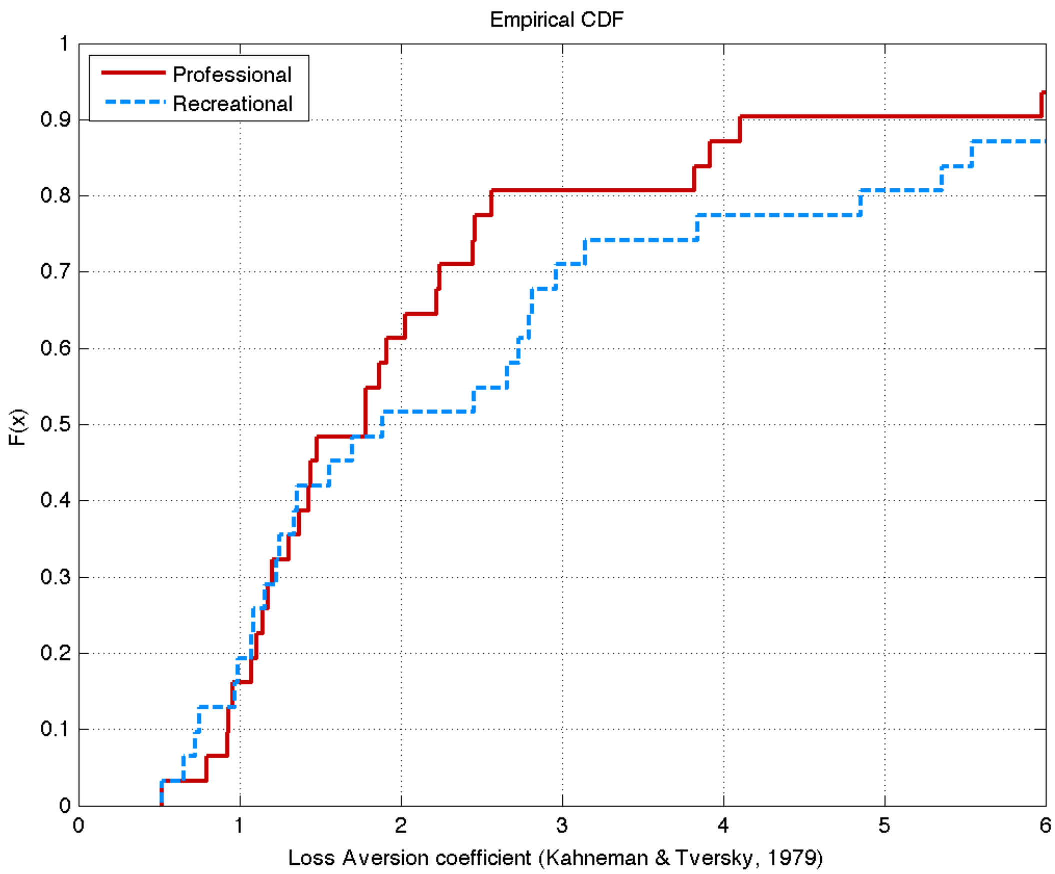
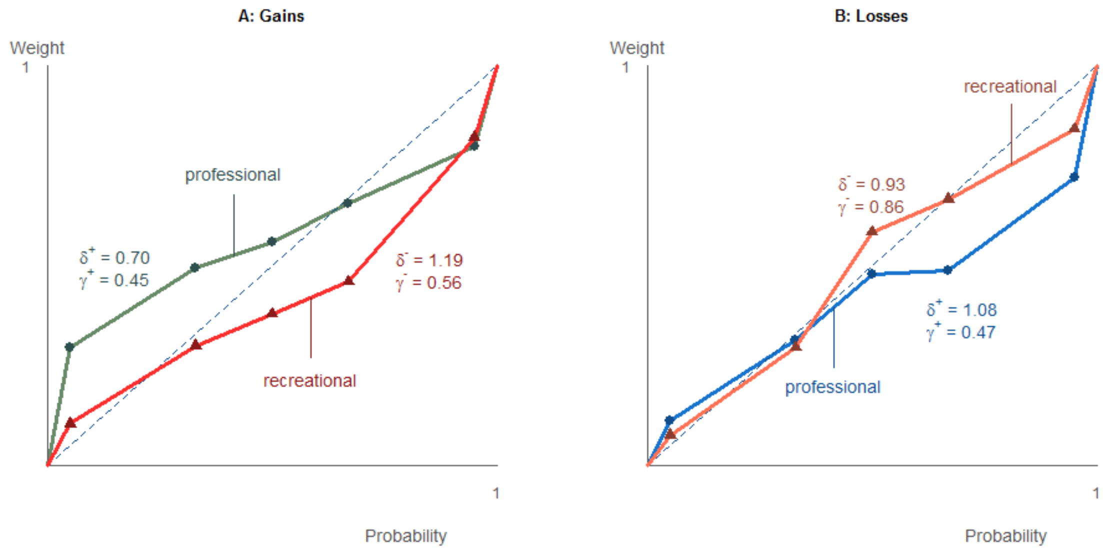


Figure 7: Probability weighting functions
(median data)



Note: Panel A displays the probability weighting functions for gains for the professional and the recreational players and Panel B for losses. The dashed line corresponds to no probability distortion. The δ^+ [δ^-] and γ^+[γ^-]-parameters are the elevation and curvature parameters for gains [losses] of Prelec's (1998) probability weighting function.

Figure 8: Cumulative distribution of the individual elevation coefficients for gains

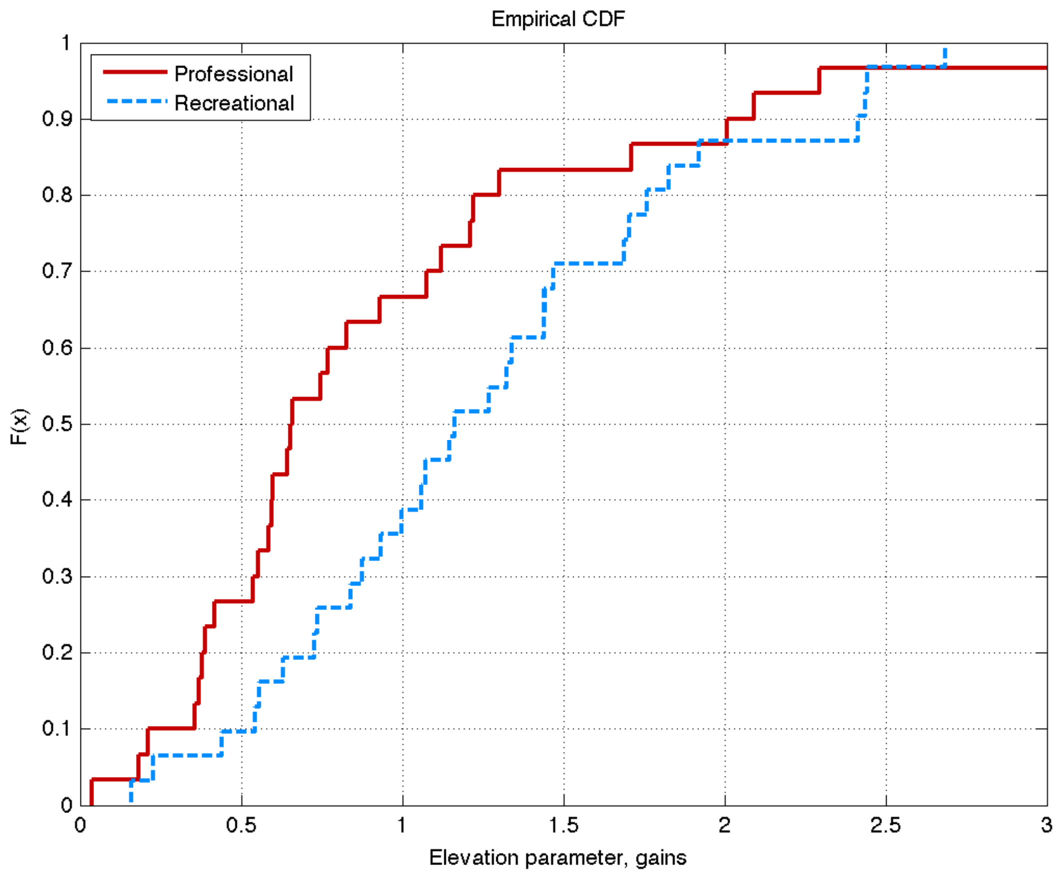


Figure 9: Cumulative distribution of the individual elevation coefficients for losses

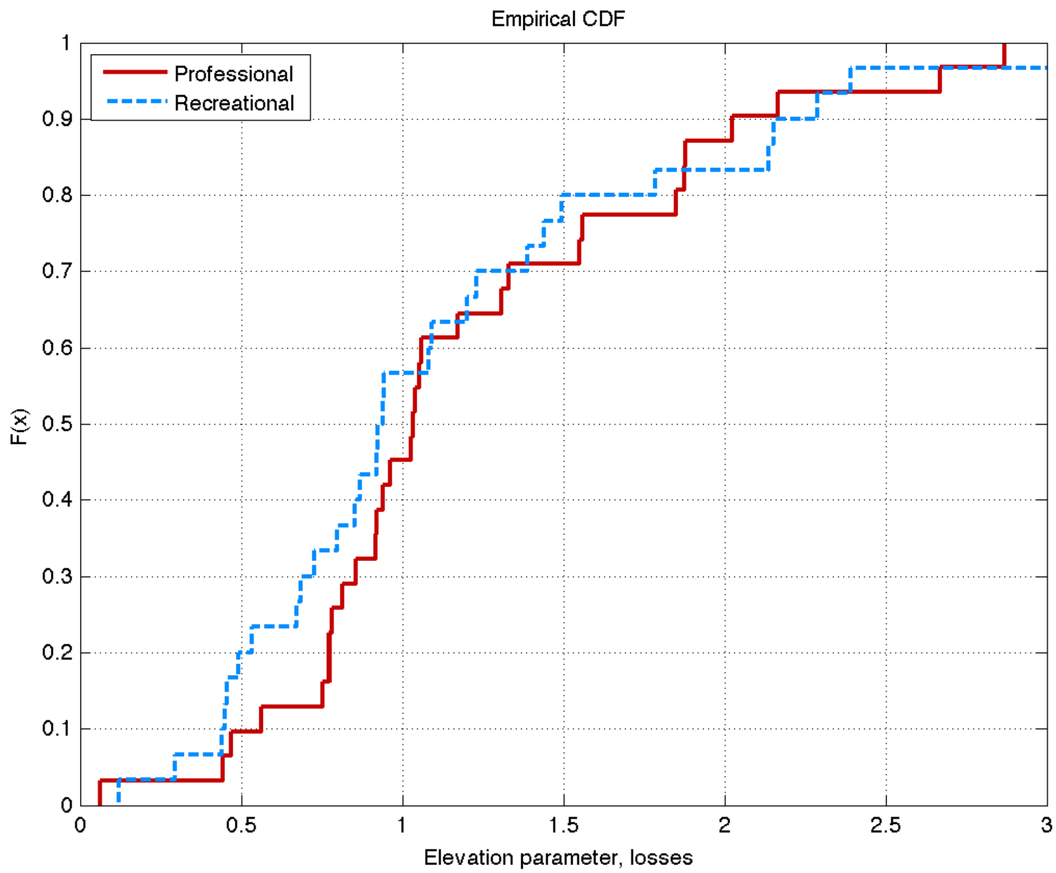


Figure 10: Cumulative distribution of the individual curvature coefficients for gains

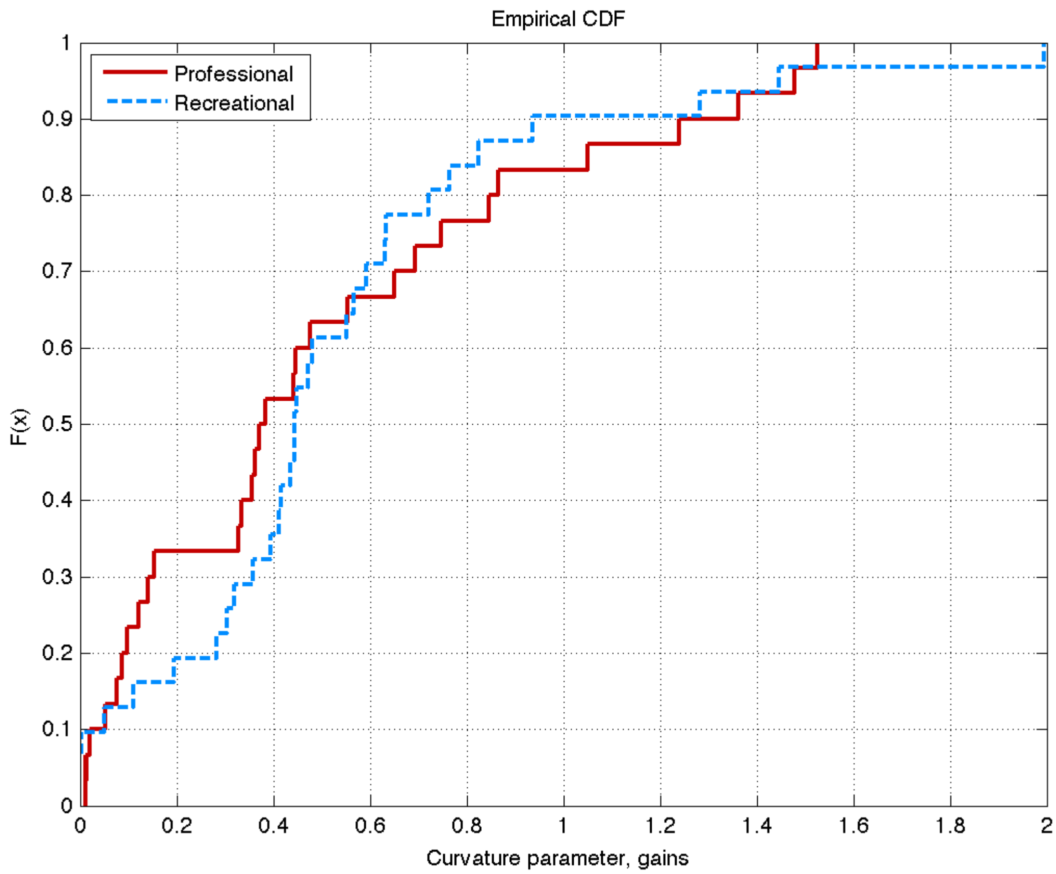
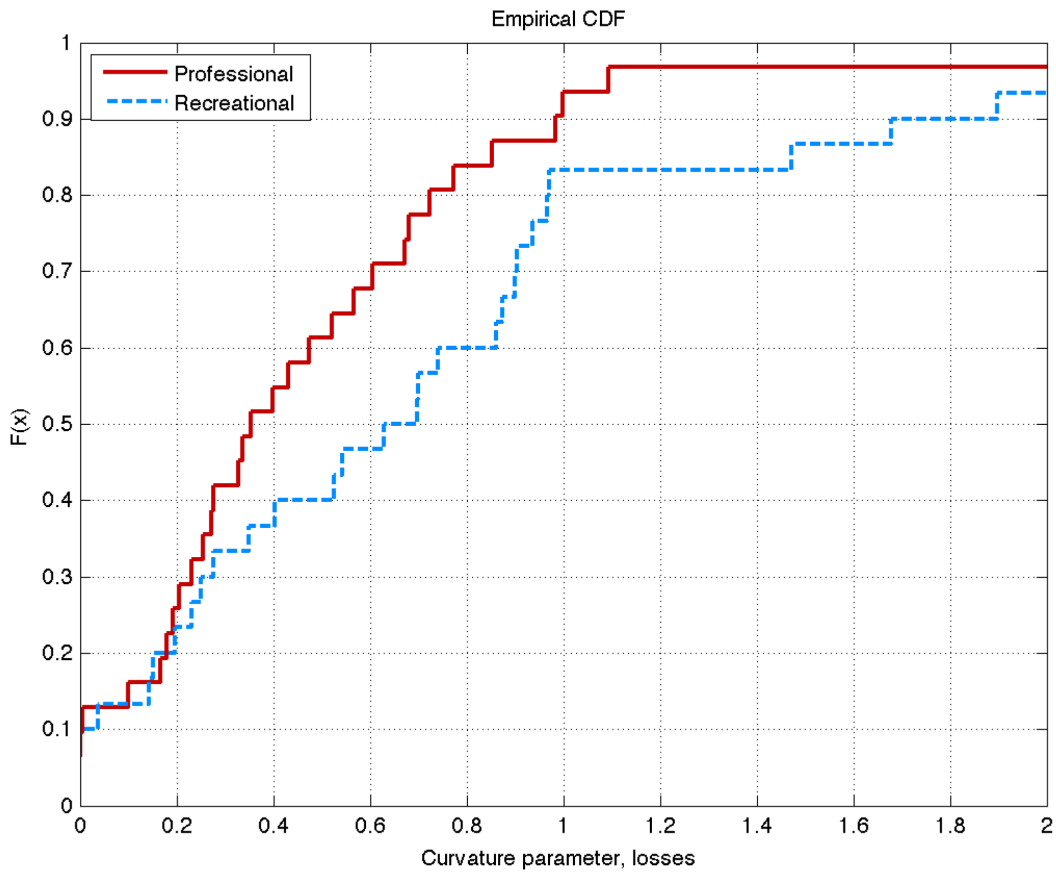


Figure 11: Cumulative distribution of the individual curvature coefficients for losses



Appendix.

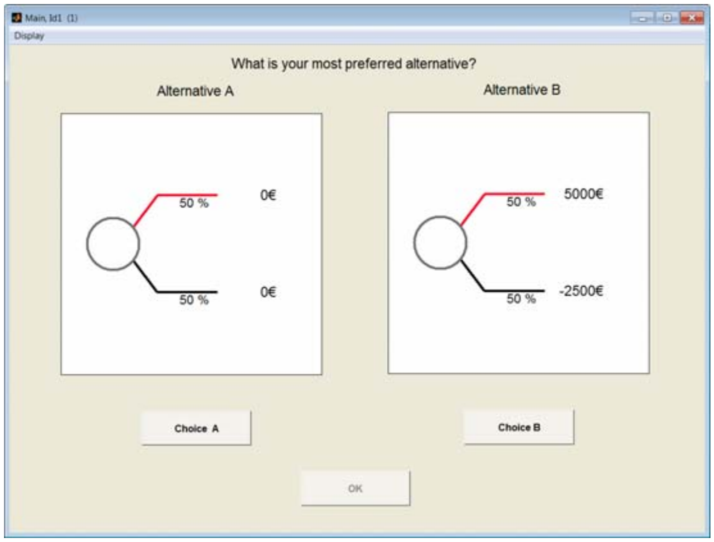


Figure A1: Example of a choice participants faced during the experiment

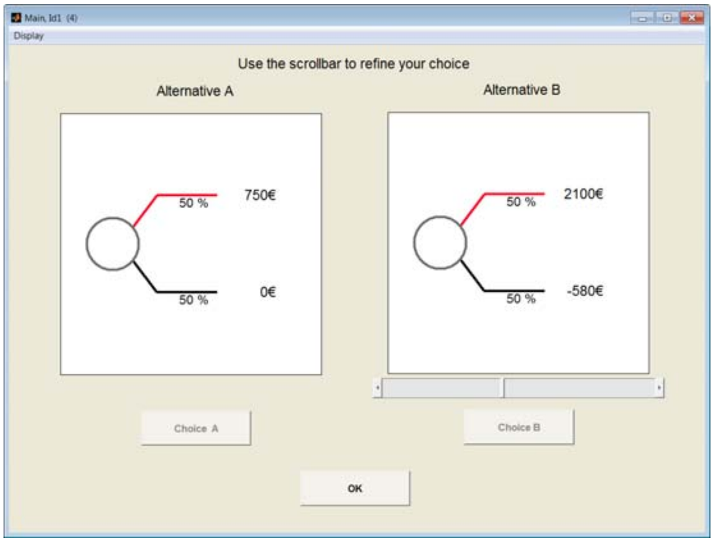


Figure A2: The use of the scrollbar

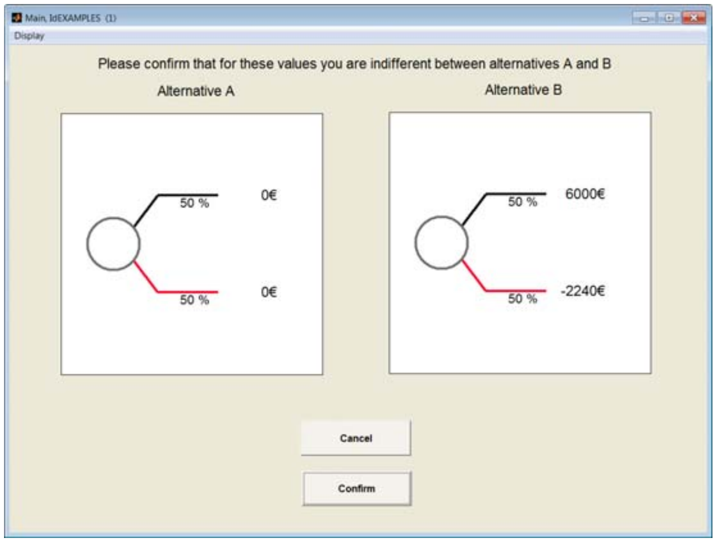


Figure A3: Confirmation screen

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