Journal of Finance and Investment Analysis, vol.1, no.2, 2012, 1-39
ISSN: 2241-0988 (print version), 2241-0996 (online)
International Scientific Press, 2012

Measuring the degree to which probability weighting affects risk-taking Behavior in financial decisions

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Abstract

The paper investigates the importance of probability weighting in financial decisions and examines the degree to which risk-taking behavior deviates from expected utility theory in the presence of probability weighting. A group of professional traders participates in an experiment, whose data are used to calculate risk and uncertainty premiums. This framework allows measuring and disentangling the impact of probability weighting on risk perceptions and behavior. Several findings emerge. Professional traders exhibit probability weighting which has a substantial and heterogeneous effect on behavior. Probability weighting affects traders' perceptions of their own risk attitude more intensely than it affects their actual behavior. Finally, risk-averse or risk-seeking behavior is more intense under conditions of uncertainty than it is under conditions of risk. These findings

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Article Info: *Received* : February 1, 2012. *Revised* : March 1, 2012
Published online : May 31, 2012

are consistent with previous studies, but provide new insights on several dimensions of trading decisions, and offer insights into market movements.

JEL classification numbers: D03, D81, G02

Keywords: probability weighting, behavior, risk premium, risk perception, traders

1 Introduction

The traditional framework to investigate behavior is the expected utility theory. However, experimental evidence has demonstrated its assumptions are often violated when decisions are made under conditions of risk (Schoemaker [1]; De Bondt and Thaler [2]; Starmer [3]; Hirschleifer [4]; Barberis and Thaler [5]). As a consequence, researchers have developed alternative theories to explain choice. In financial applications prospect theory developed by Kahneman and Tversky [6] and Tversky and Kahneman [7] appears to offer the most promising non-expected utility theory for explaining decision making (Barberis and Thaler [5]). Prospect theory differs from the expected utility paradigm in that choice is influenced by probability weighting and loss aversion. Probability weighting reflects the notion that decision makers use transformed probabilities rather than objective probabilities to make choices. Loss aversion posits that decisions are made in terms of gains and losses rather than final wealth, and individuals react differently to gains and losses. The choice model under prospect theory has two fundamental components: a weighting function that reflects a non-linear transformation of probability, and a value function that incorporates loss aversion.

Several studies suggest that probability weighting plays an important role in behavior. Tversky and Kahneman [7] discuss a fourfold pattern of decision making frequently found in empirical work, i.e. risk aversion for gains and risk seeking for losses at high probabilities, and risk seeking for gains and risk aversion for losses at low probabilities. This pattern cannot be explained solely by a value function; probability weighting must be incorporated (Tversky and Kahneman [7]). In financial settings Fox et al. [8] conduct a laboratory experiment with professional traders in stock options markets and find that their decisions exhibit probability weighting. Langer and Weber [9] demonstrate that probability weighting can make individuals behave differently than their risk preferences suggest. They show behavior characterized by risk aversion for gains and risk seeking for losses, as implied by a typical value function, can change dramatically when probability weighting is taken into account. Further, they provide evidence that models incorporating probability weighting are more consistent with observed behavior, which is also in line with Blavatskyy and Pogrebna [10], Davies and Satchell [11], and Mattos et al. [12].

Despite the importance of probability weighting in decision making, no attempt has been made to measure the degree to which behavior of real decision makers can change in its presence. A number of studies use laboratory experiments to elicit weighting functions and estimate their parameters. While estimated parameters provide information on the magnitude of deviation from objective probabilities, they do not offer a measure of how risk-taking behavior changes in the presence of probability weighting. In addition, previous studies fail to address important issues. Apart from Fox et al. [8], no studies have performed experiments with professional traders to obtain their value and weighting functions. This is an important point since experiments with students and real decision makers can yield distinct results (Haigh and List [13]; Alevy et al., [14]).

The paper investigates the importance of probability weighting among professional traders and examines the degree to which risk aversion is modified in the presence of probability weighting. We use a group of fifteen proprietary traders in the CME Group and a novel method focusing on risk and uncertainty premiums. This approach is based on Davies and Satchell [15], who theoretically investigate risk premiums to describe the degree of risk aversion. In the present study the approach is used to empirically explore the importance of probability weighting using real decision makers. Traders participate in an experiment, whose outcomes provide information about their risk attitude and degree of probability weighting. The tradeoff method adopted by Abdellaoui [16] and Abdellaoui et al. [17] is used to elicit value and weighting functions under risk (when probabilities of uncertain events are known) and uncertainty (when probabilities of uncertain events are unknown). Based on their elicited value and weighting functions, risk and uncertainty premiums are calculated to identify the impact of probability weighting on behavior. Three premiums are calculated: expected utility (EU) premium, standard premium and behavioral premium. The EU premium is the traditional risk premium which assumes that probabilities are treated linearly. The standard premium considers the effect of probability weighting on risk attitude and reflects whether individuals perceive themselves to be risk averse or risk seeking. The behavioral premium illustrates actual behavior when probability weighting and the value function influence decisions.

This paper contributes to the literature in two ways. First, it gathers data from experiments with real decision makers (professional traders) to discuss trading behavior and uses them to empirically investigate the degree to which probability weighting affects trading decisions. The framework of risk and uncertainty premiums offers a novel approach that allows measuring and disentangling the impact of probability weighting on risk perceptions and behavior. Second, results provide insights on several dimensions of how behavior deviates from expected utility theory due to probability weighting. These findings can help understand individual trading behavior and provide insights into market movements.

2 Theoretical Framework

Prospect theory is used to investigate trading behavior. The choice model is based on a function $V(x_i)$ with two components (equation 1): a value function $v(x_i)$ and a probability weighting function $w(p_i)$, where x is the argument of the value function, and p is the objective probability distribution of x.

$$V(x_i) = \sum_{i=1}^{n} v(x_i) \cdot w(p_i) \qquad (1)$$

The value function measures value in terms of gains and losses (changes in wealth) with respect to a reference point. The shape that typically arises from prospect theory is s-shaped, allowing for risk-averse behavior (concavity) in the domain of gains (x>0), and risk-seeking behavior (convexity) in the domain of losses (x<0) (Figure 1).[3] Risk seeking in the loss domain has empirical support and arises from the idea that individuals dislike losses to such a degree (loss aversion) that they are willing to take greater risks to make up their losses.

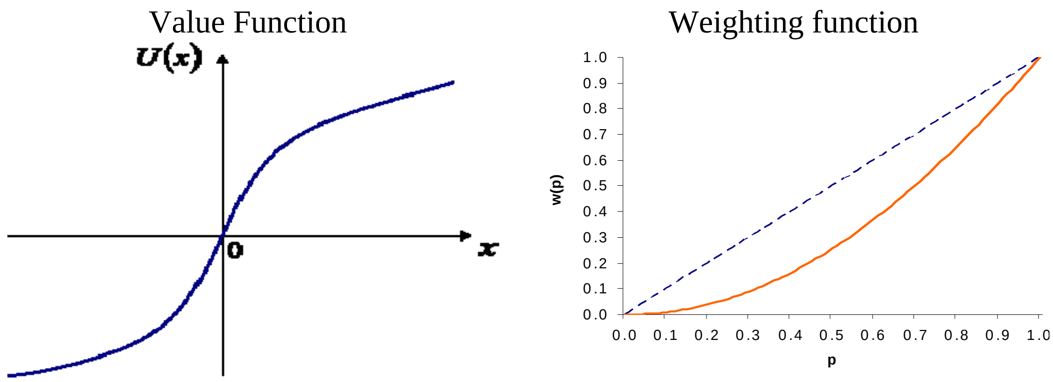

Figure 1: Prospect Theory's value and weighting functions

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[3] Figure 1 assumes that the reference point is zero.

A second component of prospect theory is a probability weighting function, which was developed from observations that individuals do not treat probabilities linearly. Empirical evidence shows probabilities can be overweighed or underweighted, meaning individuals make decisions based on perceived probabilities that are either larger or smaller than really exist. For example, Figure 1 shows the weighting function of a person who consistently underweighs probabilities, meaning that $w(p) < p$ for the whole probability scale.[4] If the individual is able to clearly distinguish probabilities and use them objectively, there is no curvature in the weighting function, represented by the linear dotted line in Figure 1. In this situation, $w(p_i) = p_i$ in equation (1) and risk-taking behavior is determined solely by the risk preferences in the value function. However, when objective probabilities are not used, then $w(p_i) \neq p_i$ and decisions are based on transformed probabilities and the value function.

The effect of the weighting function in decision making depends on its structure and strength. For instance the weighting function in Figure 1 depicts an individual who underestimates the likelihood of uncertain events and thus believes that probabilities are smaller than actual. In this situation a person is less willing to take risks. Now, consider the value function in Figure 1, which shows risk aversion for gains and risk seeking for losses. In this situation the weighting function enhances the risk aversion for gains and reduces (or eliminates) the risk seeking for losses. Consequently, in the presence of probability weighting actual behavior can differ from what might be expected based on the risk attitude observed in the value function.

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[4] In empirical studies, a variety of shapes have been identified.

3 Previous Studies

Empirical evidence suggests probability weighting is an important determinant of individual behavior. In financial investment settings several studies show how it can lead to patterns of behavior which differ from those based solely on risk and loss aversion. Evidence also exists that models incorporating probability weighting yield results consistent with observed behavior. Levy and Levy [18] investigate whether risk aversion characterizes investors and the effect of probability weights on risk premium. They conclude that risk aversion is not present over the entire wealth domain, and behavior may be explained either by risk attitude or the presence of a probability function. They argue that even if individuals are risk averse, they can still act as risk-seeking investors due to probability weighting. In some situations, their results indicate that probability weights can enhance risk aversion.

Blavatskyy and Pogrebna [10] and Langer and Weber [9] introduce probability weighting to extend the analysis of the effect of myopic loss aversion on investment decisions. Blavatskyy and Pogrebna [10] demonstrate probability weighting can make investors increase the proportion of risky assets in their portfolios, which is the opposite conclusion reached by Berkelaar et al. [19] and Hwang and Satchell [20] who considered just the effect of myopic loss aversion. Hence in this situation probability weighting leads investors to buy more risky assets as opposed to buy less risky assets when only myopic loss aversion is considered. Similarly, Langer and Weber [9] find that myopic loss-averse investors who also transform probabilities may decide to increase rather than decrease the proportion of risky assets in their portfolios.

Weighting functions for professional options traders have been investigated by Fox et al. [8]. They conduct two experiments and their findings indicate investors exhibit probability weighting. The first experiment focuses on pricing and matching prospects over gains with known objective probabilities. Their results yield a linear weighting function which indicates investors price risky prospects by their expected actuarial value according to expected utility theory. A second experiment involves pricing prospects over gains with unknown probabilities and assessing the probabilities of uncertain events. The results for both decision weights and judged probabilities reveal subadditivity, meaning investors' weighting functions are not linear and expected utility theory is violated in the presence of uncertain prospects. Hence, when investors evaluate prospects weighting functions are affected by whether probabilities are known or unknown.

The reviewed studies illustrate an extensive literature that shows probability weighting is an important component of decision making. A natural extension is to explore how much probability weighting affects risk-taking behavior, and Hilton [21] and Davies and Satchell [15] propose a theoretical framework to perform this task using risk premiums. The next section presents investor data used to investigate the importance of probability weighting and the extent to which behavior is modified in its presence. This is followed by a section which discusses procedures based on Hilton [21] and Davies and Satchell [15] that are used to measure the effect of probability weighting.

4 Research Method and Data

4.1 Subjects and experimental procedure

Decision making is investigated in a sample of fifteen proprietary traders. They are all male, have a college degree and trade agricultural contracts at the CME Group. Their age ranges from 23 to 54 years old, with an average (median) age of 31.8 (31.0). The most experienced subject has been trading for 30 years, while the least has 5 months of market experience. The average (median) trading experience is 7.2 (5) years.

Among the traders, twelve trade futures and options, two trade only futures, and one trades only options. In terms of trading platform, eight trade only in the pit, two trade only electronic, and five trade both pit and electronic. Finally, six traders trade only corn, two trade only soybeans, two trade only soybean oil, one trades only wheat, three trade corn and soybeans, and one trades corn, soybeans, wheat, soybean oil and soybean meal. Even though they work under the same trading group, they trade independently and only for their own portfolios. The trading group provides technical support, training and offers suggestions. The managers of the group are former traders and are available to review trades and discuss strategies. Traders are free to trade as they want, but managers try to emphasize discipline and steer them towards responsible risk management. Profits are used to pay transaction and overhead costs.

All traders participated in a framed field experiment conducted between December of 2006 and May of 2007. Framed field experiments are defined as experiments with nonstandard subject pool and field context (Harrison and List [22]).[5] In this study professional traders are the nonstandard subjects and their natural work environment provides field context. The experiment was conducted in the form of computer-based sessions in the same trading room where traders work, and they knew they were participating in an experiment. Traders were seated in front of a personal computer and answered choice questions that appeared on the screen. The experiment was conducted after their regular trading hours, so that there would be no distractions and they could focus on the questions. Each trader participated in two sessions, the first for the experiment under conditions of risk and the second for the experiment under conditions of

[5] Harrison and List [22] propose a terminology with four types of experiments: conventional lab experiments, artefactual field experiment, framed field experiment, and natural field experiment. Conventional lab experiments are the most traditional type, employing a standard subject pool (students), abstract framing and imposed set of rules. Artefactual field experiments improve on conventional lab experiments by using nonstandard subjects. Framed field experiments improve on artefactual field experiments by adding field context. Natural field experiments are the most innovative type as they use nonstandard subjects who perform the experimental tasks in their own environment, but subjects do not know they are in an experiment.

uncertainty. The experiment allowed generating data sets of value and probability points, which were used to fit value and weighting functions as described in the next sections.

4.2 Elicitation of value and weighting points

The tradeoff method proposed by Wakker and Deneffe [23] is used to elicit value and weighting points in the gain and loss domains. The first step is to determine probability p, reference outcomes R and R^*, and the starting outcome x_0. Those values are set by the experimenter such that $x_0 > R > R^*$, and they are held fixed through the whole experiment. The design of the experiment is critical for a good assessment of values and probability weights (Hershey et al., [24]). The choices related to the decision context and also the dimension of outcomes and probabilities are made based on conversations with the manager of the traders participating in the experiment, along with the experimental procedures adopted by Abdellaoui [16]. The experiment should be as close as possible to the subjects' environment; hence in the current study it reflects trading decisions commonly experienced in futures markets. Traders are asked to choose between two trading strategies $(x_i, p; R)$ and $(x_{i+1}, p; R^*)$ yielding different monetary outcomes, where x_i, R, x_{i+1}, and R^* represent possible gains or losses and p is the probability associated with the outcomes. Given x_{i-1}, x_i is elicited such that the subject is indifferent between prospects $(x_{i-1}, p; R)$ and $(x_i, p; R^*)$. Based on numbers discussed with the manager of the trading group participating in this study, small traders usually make gains (losses) in a range between US$800 and US$1,000 per trade, while large traders can make (lose) up to US$15,000 per trade. Therefore, in the initial step of the elicitation procedure x_0 is set to $1,000 (–$1,000), which then increases (decreases) from x_1 (x_{-1}) through x_n (x_{-n})

according to each trader's choices during the experiment. The values of R and R^* are set to \$500 (–\$500) and \$0, respectively.

The elicitation of each outcome in the sequence $x_1,...,x_n$ is obtained through an iterative procedure in which elicited outcomes are derived from observed choice rather than assessed by subjects. After the sequence of outcomes $x_1,...,x_n$ is obtained it is possible to use the same procedure to elicit probabilities $p_1,\ldots,p_{n-1}$. In the probability elicitation process subjects are asked a new series of choice questions, and probability p_i is determined such that the subject is indifferent between the certain outcome x_i and a prospect $(x_i, p_i; x_0)$. The process to assess probabilities is also based on an iterative procedure in which elicited probabilities are derived from observed choice. In the experiment under risk two sequences of ten outcomes are elicited: $x_1, x_2,..., x_{10}$ in the gain domain, and $x_{-1}, x_{-2},..., x_{-10}$ in the loss domain. Additional sequences of nine probabilities are assessed: $p_1, p_2,\ldots, p_9$ in the gain domain, and $p_{-1}, p_{-2},\ldots, p_{-9}$ in the loss domain. So for each trader in each domain there are ten pairs of outcomes and value points $(x_i, v(x_i))$ to identify their value functions, and nine pairs of probabilities and weights $(p_i, w(p_i))$ to identify their weighting functions.

To explore decision-making under uncertainty, the experimental procedure follows Abdellaoui et al. [17]. It is similar to the procedure described above, except that probabilities are not provided. Gains and losses are affected by the occurrence of uncertain events E_i representing some occurrence with which traders are familiar. Further, an extra step is added to elicit probability functions since participants need to make their own assessment of the probabilities of those events. Thus subjects first need to judge the probability of the uncertain event, generating a choice-based probability which will differ for each individual. Then choice-based probabilities are used to elicit weighting functions. Based on Abdellaoui et al. [17] and conversations with the trading manager of the group participating in this study, two types of events are used. For the elicitation of $v(x_i)$ event E is "USDA report is bullish", while for the elicitation of $w\left(q\left(E_j\right)\right)$ event E is the percentage change of the Dow Jones Industrial Average (DJIA) stock index over the next six months. Four elementary events are defined based on historical performance of the DJIA: $\Delta DJIA < -4\%$, $-4\% < \Delta DJIA < 0\%$, $0 < \Delta DJIA < 4\%$, and $\Delta DJIA > 4\%$. Five other events are also defined from all unions of elementary events that result in contiguous intervals, yielding a total of nine events. The output of this experiment is two sequences of ten outcomes: $x_1, x_2, ..., x_{10}$ in the gain domain, and $x_{-1}, x_{-2}, ..., x_{-10}$ in the loss domain; and two sequences of nine choice-based probabilities: $q(E_1), q(E_2), \ldots, q(E_9)$ in the gain domain, and $q(E_{-1}), q(E_{-2}), \ldots, q(E_{-9})$ in the loss domain. So for each trader and in each domain there are ten pairs of outcomes and values $(x_i, v(x_i))$ to assess their value functions, and ten pairs of probabilities and weights $(q(E_j), w(q(E_j)))$ to assess their weighting functions.

The elicitation procedure described above allows identifying the presence of probability weighting. Parametric procedures can be used to fit value and weighting functions to the data and measure the impact of probability weighting on decisions using the framework of risk premiums.

4.3 Risk premiums

Risk premiums are used to explore the effect of probability weighting on behavior. Risk premium is defined as the sure amount of money that an individual would require to be indifferent between an uncertain prospect x and a sure amount $EV(x) - r$, where $EV(x)$ is the expected value of prospect x and r is the risk premium. Following the ideas of Hilton [21] and Davies and Satchell [15], we consider prospect theory's function $V(x_i)$ and a value function v. Risk premium then is calculated as the solution to $V(x) = v(EV(x) - r)$ and therefore can be represented as $r = EV(x) - v^{-1}(V(x)) = EV(x) - CE(x)$, which is equivalent to the difference between the expected value of x and its certainty equivalent $CE(x)$. Intuitively, it refers to the amount of money that investors are willing to forego to avoid the risk associated with an uncertain prospect. A positive risk premium is associated with risk aversion since an individual requires a sure amount of money to take risk. In contrast, a negative risk premium is associated with risk seeking as an individual is willing to pay to take risk.

In the calculation of risk premiums a power value function with a reference point separating gains and losses is adopted (equation 2). Assuming a prospect x that yields outcomes x_1 with probability p and x_n with probability *1-p*, the two components of the risk premium are given by $EV(x) = px_1 + (1-p)x_n$ and $CE(x) = v^{-1}(V(x)) = v^{-1}(pv(x_1) + (1-p)v(x_n))$ .Initially we calculate expected utility (EU) risk premiums, assuming no probability weighting. EU premiums are expressed in equation (3) for gains (r_G^{EU}) and equation (4) for losses (r_L^{EU})(see Appendix for details of the calculation).

$$v(x) = \begin{cases} x^{\alpha} & x > 0 \\ -\lambda(-x)^{\beta} & x \leq 0 \end{cases} \tag{2}$$

$$r_G^{EU} = EV_G(x) - CE_G(x) = px_1 + (1-p)x_n - \left[px_1^{\alpha} + (1-p)x_n^{\alpha}\right]^{1/\alpha} \tag{3}$$

$$r_L^{EU} = EV_L(x) + CE_L(x) = px_1 + (1-p)x_n + \left[p(-x_1)^{\beta} + (1-p)(-x_n)^{\beta}\right] \tag{4}$$

In a prospect theory framework two additional risk premiums–standard and behavioral–can be developed based on Hilton [21] and Davies and Satchell [15]. The standard risk premium assumes that probability weighting is incorporated in the $CE(x)$ component but not in the $EV(x)$ component. It shows how individuals perceive their own risk preferences relative to the objective expected value of the prospect.

The weighting function $w(p)=\left[-\theta \exp(-\ln p)^{\delta}\right]$ proposed by Prelec [25] is adopted, where p is the probability and θ and δ are respectively the elevation and curvature parameters of the function. Standard risk premiums are developed for gains $\left(r_G^S\right)$ and losses $\left(r_L^S\right)$ using equations (5) and (6), where the superscript *w* in certainty equivalents indicates that probability weights are incorporated in their calculation.

$$r_G^s = EV_G(x) - CE_G^w(x) = px_1 + (1-p)x_n - \left[w(p)x_1^{\alpha} + w(1-p)x_n^{\alpha}\right]^{1/\alpha} \tag{5}$$

$$r_L^s = EV_L(x) + CE_L^w(x) = px_1 + (1-p)x_n + \left[w(p)(-x_1)^{\beta} + w(1-p)(-x_n)^{\beta}\right]^{1/\beta} \tag{6}$$

The behavioral risk premium assumes that probability weighting is incorporated in both $EV(x)$ and $CE(x)$ components, and shows risk behavior, where the evaluation of the prospect x is measured against a probability weighted expected value of x. Using Prelec [25]'s weighting function, behavioral risk premiums are calculated for gains $\left(r_G^B\right)$ and losses $\left(r_L^B\right)$ using equations (7) and (8), where the superscript *w* in expected values and certainty equivalents indicate the presence of probability weighting in their calculation.

$$r_G^B = EV_G^w(x) - CE_G^w(x) = w(p)x_1 + w(1-p)x_n - \left[w(p)x_1^{\alpha} + w(1-p)x_n^{\alpha}\right]^{1/\alpha} \tag{7}$$

$$\begin{aligned} r_L^B &= EV_L^w(x) + CE_L^w(x) \\ &= w(p)x_1 + w(1-p)x_n + \left[w(p)(-x_1)^{\beta} + w(1-p)(-x_n)^{\beta}\right]^{1/\beta} \end{aligned} \tag{8}$$

If probability weighting is relevant in explaining behavior, then the three risk premiums will differ. In particular, the difference between the behavioral risk premium and the other risk premiums provides a reflection of how much probability weighting influences actual behavior. The difference between behavioral and standard risk premiums indicates the degree to which an individual's actions contradict their beliefs about their own risk attitude. For instance, a person may believe himself to be risk averse but still act in a risk-seeking manner. The difference between behavioral and EU risk premiums represents how much actual behavior deviates from what is predicted by expected utility theory because of probability weighting.

The three risk premiums are calculated for each trader from the data obtained in the framed field experiment under conditions of risk. Points x_1 and x_n are the first and last points of the value function elicited in each experiment. The coefficients α and β of the value function are estimated by fitting a power function to the elicited points. The transformed probabilities $w(p)$ and $w(1-p)$ are also generated in the experiment, and coefficients δ and θ are estimated by fitting Prelec [25]'s function to the elicited probability points.

Since the magnitudes of premiums depend on an individual's risk attitude and the distribution of outcomes, premiums calculated under different situations cannot be compared in absolute terms. Consequently the effect of probability weighting on behavior is assessed by examining proportional risk premiums—the risk premiums expressed as a proportion of the expected value of the prospect $(p,\$1{,}000;\ 1-p,x_n)$. Proportional risk premiums (PRP) are calculated as $PRP_i^j = r_i^j / EV_i$, where $j =$ EU, standard, behavioral and $i =$ gain, loss. In the gain (loss) domain proportional risk premiums are positive (negative) for risk-averse individuals, negative (positive) for risk-seeking individuals, and zero for risk- neutral individuals.[6]

The effect of probability weighting on proportional risk premiums is explored through the difference between proportional behavioral premium and proportional EU premium, which can be decomposed into two factors: the difference between behavioral and standard risk premiums $(PRP_i^B - PRP_i^S)$ and

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[6] By construction, $EV_G > 0$ and $EV_L < 0$.

the difference between standard and expected utility risk premiums $\left(PRP_i^S - PRP_i^{EU}\right)$ (equation 9).

$$PRP_i^B - PRP_i^{EU} = \left(PRP_i^B - PRP_i^S\right) + \left(PRP_i^S - PRP_i^{EU}\right) \tag{9}$$

The difference between the proportional behavioral and EU risk premiums $(PRP_i^B - PRP_i^{EU})$ provides a measure of how much actual behavior would deviate from what is predicted by expected utility theory because of probability weighting. The factor $\left(PRP_i^B - PRP_i^S\right)$ identifies the degree to which an individual's actions would contradict a belief about his own risk attitude. The factor $\left(PRP_i^S - PRP_i^{EU}\right)$ identifies the degree to which an individual's perception of his risk attitude is consistent with that predicted by expected utility theory. For example, consider a person with a $PRP_G^{EU} = 0.05$ which implies a risk-averse individual is willing to give up 5% of expected value to avoid risk. If this individual exhibits $PRP_G^S = 0.09$, he perceives himself to be more risk averse than expected utility would suggest since he is willing to give up 9% of the expected value to avoid risk. Now consider $PRP_G^B = 0.05$, indicating this individual would actually give up 5% of the expected value to avoid risk, which is the same value predicted by expected utility theory. In this case the impact of probability weighting emerges only in his perceptions about his risk attitude, with $PRP_i^B - PRP_i^{EU} = 0$, $PRP_i^B - PRP_i^S = -0.4$ and $PRP_i^S - PRP_i^{EU} = 0.04$. Despite perceiving himself to be more risk averse than indicated by expected utility theory, he would behave consistent with expected utility.

4.4 Uncertainty premiums

Proportional uncertainty premiums (EU, standard and behavioral) are also calculated for each trader in the gain and loss domains. The method to calculate uncertainty premiums is the same as explained in the previous section, except x_1, x_n, α, β, $w(p)$, and $w(1-p)$ for each trader in equations (3) through (8) are based on a data set obtained from the experiment under uncertainty. Thus the differences between uncertainty and risk premiums arise from distinct value and probability points elicited in each experiment, which reflect diverse behavior under conditions of risk and uncertainty.

5 Results

5.1 Value and weighting functions under risk

Despite considerable heterogeneity across traders, the results indicate the importance of prospect theory. Estimation of value functions under risk reveals that traders are essentially risk averse for gains and risk seeking for losses. The means of the estimated parameters of the value function are respectively 0.87 and 0.89 in the gain and loss domains, denoting concavity for gains and convexity for losses (Table 1). More specifically, in the gain domain twelve of fourteen traders show concave functions, while in the loss domain ten of fourteen traders display convex functions (Appendix II).[7] Elicited value functions suggest traders follow the standard structure in prospect theory, but behavior also depends on the weighting function. Our results show that traders generally exhibit an inverse s-shaped weighting function, considering the mean values for the elevation (θ) and curvature (δ) parameters in both domains (Table 1). In particular, nine in the gain domain and eleven in the loss domain exhibit an inverse s-shaped curve

[7] Answers to elicitation questions were invalid for trader 9 (gains) and 12 (losses). Therefore fourteen functions were elicited for each domain in the experiment, even though there were fifteen traders in the sample. This problem also affects the calculation of risk premiums for these two traders.

(Appendix II).[8] These findings already indicate the presence of probability weighting in decisions under risk and uncertainty, and provide a sense of over- and underweighting. But the magnitude of probability weighting vary across traders, as can be seen by the elevation and curvature parameters in Appendix II, with probability weighting being generally more intense as these parameters are further from one. Risk and uncertainty premiums can be used as an additional measure of the impact of probability weighting on decisions in the context of how much profit an individual would be willing to forgo in order to avoid risk or uncertainty.

Table 1: Summary statistics for estimated parameters of the value and weighting functions under risk

	Value function (a)		Weighting function (b)			
	gains (α)	losses (β)	elevation (θ)		curvature (δ)	
			gains	losses	gains	losses
mean	0.87	0.89	1.06	0.93	0.73	0.72
st. dev.	0.26	0.23	0.49	0.35	0.48	0.32
25th perc.	0.75	0.72	0.81	0.66	0.46	0.61
median	0.81	0.83	1.00	0.97	0.73	0.73
75th perc.	0.88	1.04	1.34	1.04	0.90	0.84

(a) A power function is estimated as shown in equation 2. In the gain domain it is concave (convex) if α is less (greater) than 1. In the loss domain it is concave (convex) if β is greater (less) than 1. Both mean and median adjusted R^2 range between 0.98 and 0.99, and both mean and median MSE range between 0.04 and 0.06.

(b) The weighting function follows Prelec [25]'s functional form: $w(p) = \left[-\theta \exp(-\ln p)^{\delta}\right]$. Both mean and median adjusted R^2 range between 0.92 and 0.98, and both mean and median MSE range between 0.08 and 0.14.

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8 In the gain domain, the remaining traders exhibit s-shaped curves (two traders), concave curves indicating complete overweighting of probabilities (two traders) and convex curves indicating complete underweighting of probabilities (two traders). In the loss domain, each of the remaining four traders exhibits an s-shaped curve, a concave curve, a convex curve, and a straight line.

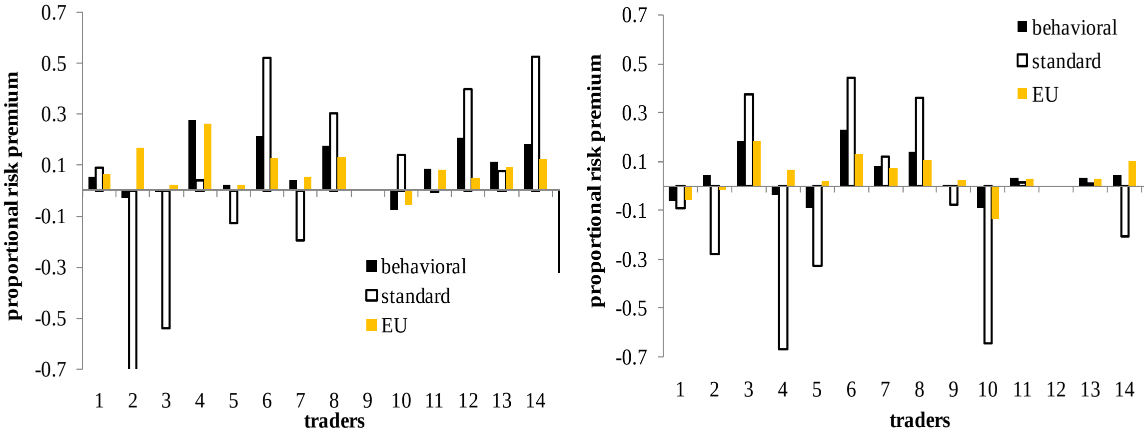
5.2 Proportional risk premiums

Three proportional risk premiums are calculated: expected utility (EU) premium, standard premium and behavioral premium. As discussed earlier, risk premiums represent the amount of money that a trader is willing to forego to avoid a prospect yielding x_1 with probability p and x_n with probability $1-p$, where x_1 and x_n represent monetary values elicited for each traderin the experiment. Proportional risk premiums are calculated for each probability p from 0.01 to 0.99 in increments of 0.01.[9]Figure2 shows premiums for gains and losses for each trader averaged across all probabilities in the interval $[0.01, 0.99]$.[10] Using a t test and the null hypothesis that mean premiums are equal to zero, behavioral and EU premiums for all traders are statistically distinguishable from zero at 5%. With regards to standard premiums, the null hypothesis only fails to be rejected for trader 4 and 11 in the gain domain and trader 11 and 13 in the loss domain. Focusing first on EU and behavioral premiums, both suggest that traders are mainly risk averse for gains and risk seeking for losses. Behavioral (EU) premiums indicate that ten (twelve) traders are risk averse in the gain domain, while nine (ten) traders are risk seeking in the loss domain. However, their magnitudes differ, implying the presence of probability weighting can cause the strength of risk aversion or risk seeking to vary from what expected utility theory predicts. For example, EU premium indicates that trader 6 would forego 21.1% of expected value to avoid risk in the gain domain, while the behavioral premium suggests he would actually forego only 12.6% of expected value to avoid risk (Figure 2).Contrasting behavioral and standard premiums also helps identify the effect of probability weighting on behavior by comparing how a trader actually

[9] Probabilities 0 and 1 are not used because assumptions of probability weighting functions imply w(0)=0 and w(1)=1.

[10]Premiums calculated for each individual probability are not presented for brevity but are available upon request.

behave to how they perceive they would behave. The presence of probability weighting has a stronger impact on standard premiums, which show a larger magnitude than the other premiums. Returning to the previous example of trader 6 in the gain domain, the standard premium suggests he perceives he would forego 52.2% of his expected value to avoid risk, which is larger than both EU and behavioral premiums.



(a) Gains: positive (negative) premiums indicate risk aversion (seeking). Losses: positive (negative) premiums indicate risk seeking (aversion).
(b) All premiums are statistically distinguishable from zero at 5% (t test), except for standard premium for traders 4 and 11.
(c) All premiums are statistically distinguishable from zero at 5% (t test), except for standard premium for traders 11 and 13.

Figure 2: Proportional risk premiums – averages across probabilities (a), Gains (b), Losses (c)

Table 2 presents the difference between behavioral and EU premiums (B–EU) and its decomposition into the differences between behavioral and standard premiums (B–S) and standard and EU premiums (S–EU) based on equation (9). All differences are calculated within the interval $[0.01, 0.99]$ and then averaged across all probabilities. A t test is adopted to test the null hypothesis that mean differences between premiums are equal to zero. The null hypotheses can be rejected at 5% in almost all cases, with the exception of B-EU for trader 3 (losses) and trader 4 (gains), and B-S and S-EU for traders 11 (losses) and 13 (gains and losses) (Table 2). Failure to reject the null hypothesis implies that probability weighting has no impact on average risk taking. In the gain domain positive (negative) differences between premiums indicate less (more) risk taking. In the loss domain positive (negative) differences between premiums indicate more (less) risk taking. Three main findings emerge. First, the effect of probability weighting in terms of more or less risk taking seems to be almost evenly split in the gain domain and leans towards more risk taking in the loss domain. The difference B–EU indicates less (more) risk taking for six (seven) traders in the gain domain, and for five (eight) in the loss domain. Second, the difference between behavioral and EU premiums (B–EU) is relatively small compared to its two components B–S and S–EU. Third, the differences between behavioral and standard premiums (B–S) and standard and EU premiums (S–EU) tend to have opposite signs. These last two points suggest the strongest impact of probability weighting happens to traders' perception of their own risk attitude. Although they generally perceive themselves to be much more risk averse or risk seeking than expected utility indicates, their actual behavior is relatively closer to expected utility predictions. For example, in the gain domain trader 3 believes himself to be more risk taking than expected utility theory suggests (S–EU=-0.565), but behaves with more risk aversion than he believes to have (B–S=0.538). The magnitude of these effects is similar, meaning the deviation of actual behavior from expected utility due to probability weighting is relatively small (B–EU=-0.027).

Table 2: Differences in proportional risk premiums – averages across probabilities (a)

Trader	Gains (b)			Losses (b)		
	B–EU	B–S	S–EU	B–EU	B–S	S–EU
1	-0.008*	-0.032*	0.024*	-0.005*	0.029*	-0.034*
2	-0.196*	2.434*	-2.630*	0.056*	0.321*	-0.265*
3	-0.027*	0.538*	-0.565*	-0.001	-0.193*	0.192*
4	0.012	0.236*	-0.224*	-0.106*	0.630*	-0.736*
5	-0.004*	0.149*	-0.153*	-0.108*	0.239*	-0.347*
6	0.085*	-0.311*	0.396*	0.103*	-0.209*	0.312*
7	-0.012*	0.239*	-0.251*	0.012*	-0.038*	0.050*
8	0.047*	-0.128*	0.175*	0.036*	-0.219*	0.255*
9	n/a	n/a	n/a	-0.018*	0.080*	-0.098*
10	-0.016*	-0.211*	0.195*	0.043*	0.553*	-0.510*
11	0.004*	0.086*	-0.082*	0.007*	0.017	-0.010
12	0.162*	-0.187*	0.349*	n/a	n/a	n/a
13	0.025*	0.037	-0.012	0.005*	0.026	-0.021
14	0.058*	-0.346*	0.404*	-0.056*	0.250*	-0.306*
15	-0.230*	-0.442*	0.212*	0.005*	0.355*	-0.350*
Number of traders who exhibit (c):						
less risk taking	6	6	6	5	4	8
more risk taking	7	7	7	8	8	4
same risk taking	1	1	1	1	2	2

(a) The null hypothesis that differences between premiums are equal to zero is tested with a t test. The * indicates the null hypothesis can be rejected at 5%.

(b) B–EU: difference between behavioral and EU premiums, B–S: difference between behavioral and standard premiums, S–EU: difference between standard and EU premiums.

(c) Gains: positive (negative) difference indicates less (more) risk taking. Losses: positive (negative) difference indicates more (less) risk taking. If the difference is found to be statistically equal to zero, it is considered that there is no change in risk taking.

The effect of probability weighting is further investigated for different ranges of probability, since previous research indicates that behavior can change at different levels of probability. An example is the fourfold pattern, showing that both risk aversion and risk seeking can happen in the gain and loss domains depending on the probabilities involved (Tversky and Kahneman [7].[11] Other examples are Etchart-Vincent [26] and Etchart-Vincent [27], who find evidence that behavior at small probabilities differs from that at high probabilities.[12] Table 3 shows the differences between proportional risk premiums, B–EU and its decomposition into B–S and S–EU. All differences are calculated within four intervals– $[0.01, 0.25]$, $[0.26, 0.50]$, $[0.51, 0.75]$, $[0.76, 0.99]$ –and then averaged across all probabilities within each interval. As discussed previously, these probabilities refer to the prospect $(p, \$1{,}000;\ 1-p, x_n)$ where x_n varies across traders but is always positive and greater than $1,000 in the gain domain (for losses x_n is more negative than –$1,000). Hence higher probability p means higher chances of getting the smallest gain (loss) x_n. A t test is adopted to test the null hypothesis that average differences within each interval are equal to zero, and results indicate the null hypothesis can be rejected at 5% in 320 of the 336 intervals. The differences between premiums in Table 3 indicate that the magnitude of the impact of probability weighting can vary and even switch signs for different probabilities. For example, in the gain domain trader 2 shows B–EU becoming more negative as the intervals move towards higher probabilities. This result suggests that probability weighting makes trader 2 take more risk than expected utility predicts, and this effect becomes more pronounced as probabilities increase. In the loss domain trader 1 shows S–EU switching signs as the intervals

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[11]In the gain domain risk aversion (seeking)is found at high (low) probabilities. In the loss domain risk seeking (aversion) is found at high (low) probabilities.

[12]Etchart-Vincent [26] finds evidence that the magnitude of losses affects probability weighting at small probabilities, but not at high probabilities. Etchart-Vincent [27] also finds that the payoff structure of gambles affects probability weighting at moderate and high probabilities, but not at small probabilities.

move towards higher probabilities. The difference between standard and EU premiums is positive for the two lower intervals and negative for the two higher intervals, implying he believes himself to be relatively more risk seeking (averse) than expected utility predicts when probabilities are lower (higher). Here, Table 3, in Appendix

5.3 Value and weighting functions under uncertainty

The mean value of the estimated parameter of the power function indicates concavity for gains and losses, suggesting traders are risk averse in both domains (Table 4). However, there is also large heterogeneity across traders, and the mean value in the loss domain is highly influenced by trader 9 (Appendix II).[13]

In general, traders exhibit concave value functions in the gain domain (twelve of fifteen traders) and convex value functions in the loss domain (nine of fifteen traders) (Appendix II). Again, value functions elicited in the experiment suggest that most traders follow the standard behavior suggested by prospect theory, with risk aversion for gains and risk seeking for losses. Estimation of weighting functions under uncertainty reveals a similar pattern compared to the findings under risk with respect to its inverse s-shape, as suggested by mean values of the elevation and curvature parameters (Table 4). However, in the gain (loss) domain only seven (five) of fifteen traders exhibit inverse s-shaped curves (Appendix II). Further, estimation results show larger degree of probability weighting under uncertainty, since estimated elevation and curvature parameters under uncertainty are farther from 1 compared to values found under risk (Table 4). In particular, many traders' weighting functions (five for gains and seven for losses) showed a

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[13]If the mean is calculated without trader 9 in the loss domain, the average value function is convex for losses.

low sensitivity to changes in probability. Consequently they tend to give similar weights to different probabilities, accounting for nearly horizontal curves in their weighting functions as indicated by curvature parameters close to zero (Appendix II). Finally, as identified for situations under risk, individual results under uncertainty also show large heterogeneity across traders. As discussed previously, these differences can have distinct impacts in the calculation of uncertainty premiums.

Table 4: Summary statistics for estimated parameters of the value and weighting functions under uncertainty

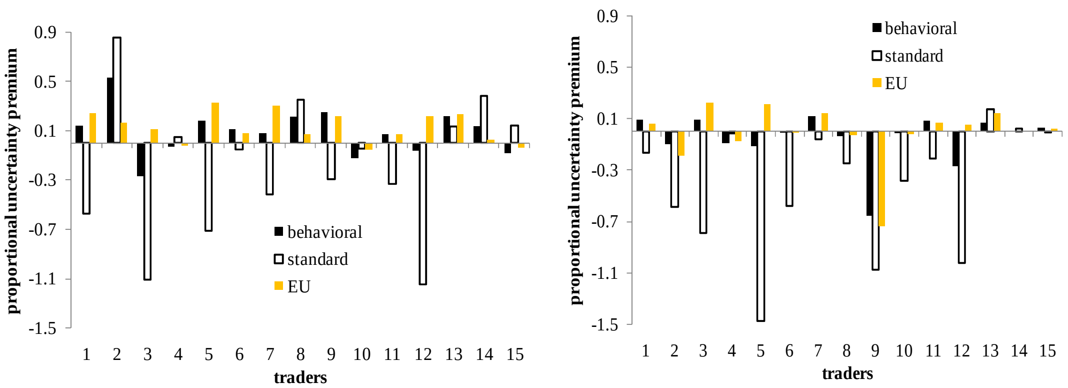
	Value function (a)		Weighting function (b)			
	gains (α)	losses (β)	elevation (θ)		curvature (δ)	
			gains	losses	gains	losses
mean	0.72	1.11	0.91	0.74	0.26	0.45
st. dev.	0.27	0.80	0.53	0.31	0.39	0.70
25^{th} perc.	0.47	0.74	0.52	0.51	0.00	0.00
median	0.67	0.93	0.78	0.78	0.03	0.09
75^{th} perc.	0.81	1.10	1.17	0.90	0.32	0.63

(a) A power function is estimated as in equation 2. In the gain domain it is concave (convex) if α is less (greater) than 1. In the loss domain it is concave (convex) if β is greater (less) than 1. Both mean and median adjusted R^2 are 0.99, and both mean and median MSE are 0.04.

(b) The weighting function follows Prelec [25]'s functional form: $w(p) = \left[-\theta \exp(-\ln p)^{\delta}\right]$. Both mean and median adjusted R^2 range between 0.97 and 0.99, and both mean and median MSE range between 0.03 and 0.09.

5.4 Proportional uncertainty premiums

The proportional uncertainty measures are calculated for the expected utility (EU) premium, standard premium and behavioral premium. Their definitions are the same as discussed for risk premiums. Figure 3 shows premiums for gains and losses for each trader averaged across all probabilities in the interval $[0.01, 0.99]$. Using a t test and the null hypothesis that mean premiums are equal to zero, behavioral and EU premiums for all traders are statistically distinguishable from zero at 5%. With regards to standard premiums, the null hypothesis only fails to be rejected for trader 6, 9 and 10 in the gain domain and trader 1, 14 and 15 in the loss domain. In general, the qualitative results are the same as in the experiment under risk. Both behavioral and EU premiums suggest that traders are mainly risk averse for gains and risk seeking for losses, but the magnitudes of premiums can vary. Behavioral (EU) premiums indicate that ten (twelve) traders are risk averse in the gain domain, while seven (ten) traders are risk seeking in the loss domain (Figure 3). Further, deviations from expected utility theory appear to happen more strongly in traders' own perception of their risk attitude (standard premiums) than in their actual behavior (behavioral premiums).



(a) Gains: positive (negative) premiums indicate risk aversion (seeking). Losses: positive (negative) premiums indicate risk seeking (aversion).
(b) All premiums are statistically distinguishable from zero at 5% (t test), except for standard premium for traders 6, 9 and 10.
(c) All premiums are statistically distinguishable from zero at 5% (t test), except for standard premium for traders 1, 14 and 15.

Figure 3: Proportional uncertainty premiums – averages across probabilities (a), Gains (b), Losses (c)

The difference between behavioral and EU uncertainty premiums (B–EU) and its decomposition using equation (9) are also calculated within the interval $[0.01, 0.99]$, and then averaged across all probabilities. Similar to risk premiums, three main findings can be drawn here.[14] Two of them are qualitatively the same as in the experiment under risk: the differences B–EU are relatively small compared to B–S and S–EU, and the differences B–S and S–EU tend to have opposite signs. These two points imply the strongest impact of probability weighting happens on traders' perception on their own risk attitude also under uncertainty. Finally, one finding differs from the experiment under risk. The effect of probability weighting on actual behavior seems to lean towards more risk taking in the gain domain and less risk taking in the loss domains. The difference B–EU indicates less (more) risk taking for five (nine) traders in the gain domain, and for eight (five) in the loss domain.

The analysis of the effect of probability weighting for different levels of probability also reveals similar results to the experiment under risk. Differences between proportional uncertainty premiums calculated within the same four probability intervals as before, and then averaged across all probabilities within each interval, indicate that the magnitude of the impact of probability weighting can vary and also switch signs for different probabilities.[15]

5.5 The effect of probability weighting under risk and uncertainty

Our findings show the effect of probability weighting is stronger under uncertainty than under risk. Figure 4 exhibits differences between behavioral and EU premiums (B–EU) in the two experiments.

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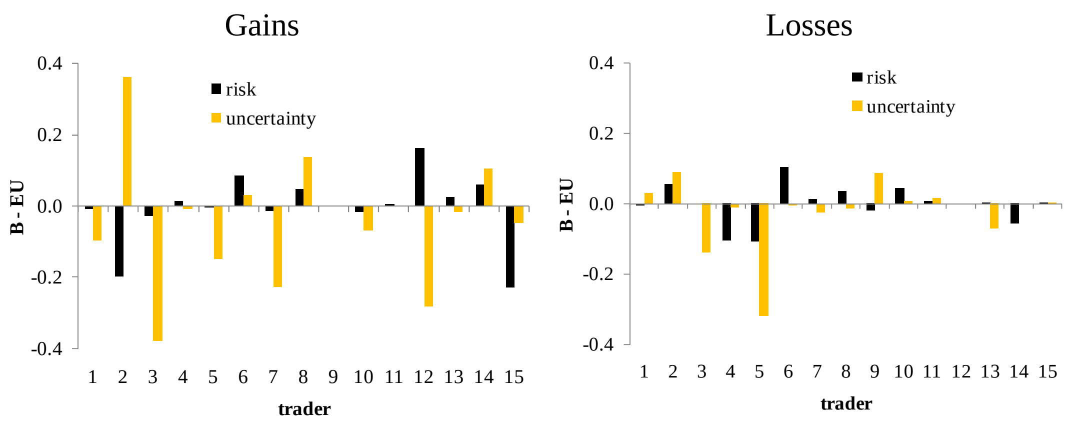
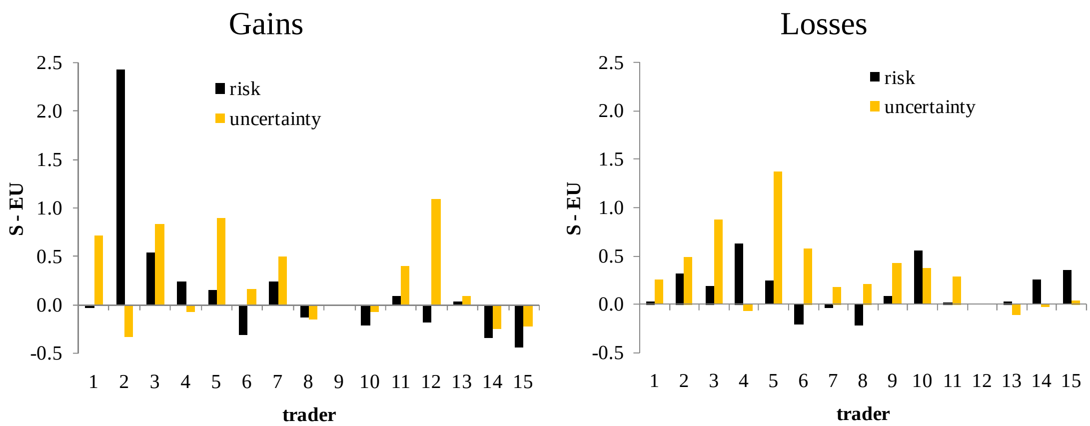
[14]Since most results are qualitatively similar to the experiment under risk, calculations of uncertainty premiums are not presented for brevity but are available upon request.
[15] These calculations are also not presented for brevity but are available upon request.



(a) The null hypothesis that the average (B–EU) under risk is equal to the average (B–EU) under uncertainty is tested with Welch F-test. Results show it can be rejected at 1% for all traders, except trader 9 in the gain domain and traders 9 and 15 in the loss domain.

Figure 4: Difference between behavioral and EU premiums (B–EU) under risk and uncertainty (a)



(a) The null hypothesis that the average (S–EU) under risk is equal to the average (S–EU) under uncertainty is tested with Welch F-test. Results show it can be rejected at 1% for all traders, except traders 14 and 15 in the gain domain and trader 10 in the loss domain.

Figure 5: Difference between standard and EU premiums (S–EU) under risk and uncertainty (a)

The null hypothesis that the average (B–EU) under risk is equal to the average (B–EU) under uncertainty is tested with a Welch F-test. The null hypothesis can be rejected at 1% for all traders, except trader 9 in the gain domain and traders 9 and 15 in the loss domain. Results indicate that the magnitudes of deviations from expected utility theory are generally larger under uncertainty than they are under risk, and they also seem to be more pronounced for gains than for losses. Figure 4 also shows the direction of the effect of probability weighting can change depending on the environment. The sign of B–EU is different under risk than it is under uncertainty for four (six) traders in the gain (loss) domain. Similar findings can be seen for the effect of probability weighting on traders' perception on their own risk attitude. Figure 5 exhibits differences between standard and EU premiums (S–EU).The null hypothesis that the average (S–EU) under risk is equal to the average (S–EU) under uncertainty is also tested with a Welch F-test. The null hypothesis can be rejected at 1% for all traders, except trader 14 and 15 in the gain domain and trader 10 in the loss domain. Again, these differences tend to be larger under uncertainty than under risk, and the direction of the effect of probability weighting also can change depending on the environment; the sign of S–EU differs across experiments for five (six) traders in the gain (loss) domain.

6 Discussion and Conclusions

The study empirically investigates the impact of probability weighting on financial decisions using a group of professional traders and a novel approach based on risk and uncertainty premiums. Despite the relatively small sample size in the experiment, our framework applied to real decision makers offers informative results.

Professional traders exhibit probability weighting in their choices. This is consistent with the experiment conducted by Fox et al. [8] under different market conditions and using different types of securities. The fact that both studies separated by time and differences in the markets examined find that probability weighting is an important determinant of financial decisions emphasizes its significance in understanding the nature of risk and the resultant risk-return behavior using prospect theory.

Probability weighting also has a substantial impact on behavior. Many situations exist in which premiums change sign when probability weighting is introduced. For instance, risk aversion (risk seeking) changes to risk seeking (risk aversion) in the presence of probability weighting. In other situations probability weighting enhances dramatically the intensity of risk aversion or risk seeking. Further, behavior is not homogenous across probabilities. The magnitude and direction of deviations from expected utility theory can vary depending on the level of probabilities. This result is in line with previous research which finds evidence of distinct behavior at small and large probabilities (Harbaugh et al. [28]; Etchart-Vincent [26]; Etchart-Vincent [27]). Harbaugh et al. [28], for example, find that individuals are risk averse over small-probability gains but risk seeking over high-probability gains. Conversely, they find risk aversion over high-probability losses and risk seeking over small-probability losses. Even though our discussion is framed in terms of deviations from expected utility theory, it supports the notion that behavior changes over different levels of probability.

Probability weighting affects traders' perceptions of their own risk attitude more intensely than it affects their actual behavior. Standard premiums are generally of larger magnitude than behavioral premiums, meaning EU premiums tend to be closer to behavioral premiums than to standard premiums. This suggests traders believe themselves to be more risk averse or risk seeking than their actual behavior shows, which implies their behavior is closer to expected utility theory than they perceive it to be. Here it is important to note this finding may be related to the environment in which our traders work. The trading group encourages its traders to trade with discipline and responsible risk management, which may attenuate the impact of probability weighting on behavior even though it is still pronounced in traders' perceptions. This idea is consistent with studies which find that market experience (here gained through either traders' own experience or obtained from former traders) reduces deviations from expected utility theory (List [29] and [30]; Feng and Seasholes [31]).It is also in line with results by Liu et al. [32] in that deviations from expected utility theory tend to be smaller among traders who place orders combining calls, puts and the underlying asset, which are essentially the types of trades used by traders studied here. In addition, Zaloom [33] and [34] points out the importance of discipline and self-control in trading, highlighting that knowing when to place a trade and how much to trade are important skills for traders. It is possible that traders learn these skills through discussions with former traders available to help them in the trading group.

Finally, risk-averse or risk-seeking behavior is more intense under conditions of uncertainty than it is under conditions of risk. This finding is consistent with previous studies including Tversky and Fox [35], who find that the effect of probability weighting is more pronounced under uncertainty than risk. They argue that departures from expected utility theory are amplified by ambiguity. Similarly, Fox et al. [8] find that investors who participate in their experiments tend to follow expected utility theory in decisions where objective probabilities are known, but depart from expected utility theory in decisions involving a subjective assessment of probabilities. Clearly, larger deviations from expected utility theory emerge when individuals need to make their own assessments about the likelihood of events.

Overall, the findings support the existence of bias and heuristics when investors make decisions under conditions of risk and uncertainty. It also supports the usefulness of the tradeoff method and behavioral risk premiums to gather experimental data to empirically investigate the importance of probability weighting. By combining procedures developed by Hilton [21] and Davies and Satchell [15], we provide a useful measure of the degree that actual behavior deviates from expected utility behavior.

The results also provide insights on the effect of probability weighting in financial decisions, which is important not only to understand market movements but also in evaluating other situations. For instance, Fehr and Tyran [36] consider the interaction between rational and irrational agents and discuss evidence that even a small degree of individual irrationality (such as probability weighting) can cause large deviations from aggregate predictions in rational models. Here, we find a high degree of heterogeneous behavior across investors, which suggest the nature and magnitude of individual irrationality may be highly diverse, making it quite difficult to predict its effect on aggregate market behavior. Importantly, understanding individual behavior also is of value in its own right in many settings. For instance, a manager of professional traders may need to understand individual investor behavior to properly train and advise them. In this context, our measures can provide an indication of the value of reducing the effect of probability weighting on trading decisions.

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Appendix I

Assume a prospect x that yields outcomes x_1 with probability p and x_n with probability *1-p*. Considering the absence of probability weighting $(w(p)=p)$ and a power value function with a reference point separating gains and losses as in equation 10, the expected utility (EU) premium can be calculated as in equations 11 through 14 for the gain domain and equations 15 through 18 for the loss domain. The extension to behavioral and standard premiums is performed simply by replacing p by $w(p)$ as needed.

$$v(x)=\begin{cases} x^{\alpha} & x>0 \\ -\lambda(-x)^{\beta} & x\le 0 \end{cases} \tag{10}$$

$$V(x)=v\left(EV(x)-r_G^{EU}\right) \tag{11}$$

$$pv(x_1)+(1-p)v(x_n)=v\left(px_1+(1-p)x_n-r_G^{EU}\right) \tag{12}$$

$$px_1^{\alpha}+(1-p)x_n^{\alpha}=\left(px_1+(1-p)x_n-r_G^{EU}\right)^{\alpha} \tag{13}$$

$$r_G^{EU}=px_1+(1-p)x_n-\left(px_1^{\alpha}+(1-p)x_n^{\alpha}\right)^{1/\alpha} \tag{14}$$

$$V(x)=v\left(EV(x)-r_L^{EU}\right) \tag{15}$$

$$pv(x_1)+(1-p)v(x_n)=v\left(px_1+(1-p)x_n-r_L^{EU}\right) \tag{16}$$

$$p\left[-\lambda(-x_1)^{\beta}\right]+(1-p)\left[-\lambda(-x_n)^{\beta}\right]=-\lambda\left\{-\left[p(-x_1)+(1-p)(-x_n)-r_L^{EU}\right]^{\beta}\right\} \tag{17}$$

$$r_L^{EU}=px_1+(1-p)x_n+\left[p(-x_1)^{\beta}+(1-p)(-x_n)^{\beta}\right]^{1/\beta}. \tag{18}$$

The premiums are calculated from the data obtained in the experiment with traders. Points x_1 and x_n are the first and last points elicited in the experiment. The first point is always 1,000 but the last point depends on how each trader makes choices during the experiment. In the experiment under risk x_n ranges from 4,200 to 41,900 for gains and from –2,100 to –31,500 for losses. In the experiment under uncertainty it goes from 4,500 to 38,800 for gains and –1,000 to –36,200 for losses.

Appendix II

Table 5: Estimated parameters of value and weighting functions

Trader	Value function (a)		Weighting function (b)			
	gains (α)	losses (β)	elevation (θ)		curvature (δ)	
			gains	losses	gains	losses
Risk						
1	0.77	1.16	1.08	0.98	1.29	0.80
2	0.74	1.31	0.09	0.52	0.00	0.53
3	0.93	0.69	0.33	1.54	1.87	1.47
4	0.58	0.75	0.83	0.39	0.43	1.04
5	0.89	0.62	0.80	0.65	0.67	0.75
6	0.81	0.73	1.73	1.46	0.73	0.65
7	0.87	0.83	0.75	1.07	0.77	0.88
8	0.78	0.83	1.26	1.43	0.73	0.91
9	–	0.71	1.00	0.83	0.09	0.70
10	1.19	1.27	1.42	0.66	1.17	0.59
11	0.82	0.93	0.92	1.01	0.75	0.63
12	0.63	–	1.29	1.00	0.49	0.00
13	0.72	0.91	0.95	0.97	0.62	0.73
14	0.81	0.66	1.98	0.70	1.03	0.77
15	1.60	1.08	1.39	0.67	0.32	0.34
Uncertainty						
1	0.47	0.85	0.53	0.83	0.00	0.00
2	0.70	1.85	2.48	0.57	0.28	0.30
3	0.45	0.51	0.37	0.47	0.00	0.00
4	1.11	1.29	1.14	1.11	1.00	1.00
5	0.40	0.50	0.50	0.30	0.00	0.00
6	0.67	0.98	0.78	0.43	0.19	0.43
7	0.47	0.78	0.50	0.79	1.00	1.00
8	0.78	1.09	1.21	0.81	0.02	0.00
9	0.65	3.74	0.76	0.81	0.00	0.00
10	1.25	1.10	0.99	0.56	0.04	0.00
11	0.79	0.81	0.65	0.76	0.03	0.09
12	0.46	0.54	0.38	0.33	0.00	0.00
13	0.61	0.70	0.88	1.44	0.92	2.58
14	0.83	1.00	1.20	0.99	0.01	0.58
15	1.13	0.93	1.24	0.97	0.36	0.69

(a) A power function is estimated following equation 2. In the gain domain it is concave (convex) if parameter is less (greater) than 1. In the loss domain it is concave (convex) if parameter is greater (less) than 1.
(b) The weighting function follows Prelec [25]'s functional form $w(p) = \left[-\theta \exp(-\ln p)^{\delta}\right]$.

Table 3: Average differences in proportional risk premiums within probability intervals (a)

Trader	Behavioral –EU premiums (b) probability intervals				Behavioral – standard premiums (b) probability intervals				Standard – EU premiums (b) probability intervals			
	0.01-0.25	0.26-0.50	0.51-0.75	0.76-0.99	0.01-0.25	0.26-0.50	0.51-0.75	0.76-0.99	0.01-0.25	0.26-0.50	0.51-0.75	0.76-0.99
Gains												
1	-0.005*	-0.009*	-0.002*	-0.020*	0.041*	0.048*	-0.047*	-0.179*	-0.047*	-0.057*	0.045*	0.159*
2	-0.069*	-0.153*	-0.250*	-0.318*	0.079*	0.517*	1.548*	7.807*	-0.148*	-0.670*	-1.798*	-8.125*
3	-0.014*	-0.035*	-0.041*	-0.016*	0.161*	0.521*	0.868*	0.604*	-0.175*	-0.556*	-0.908*	-0.621*
4	0.079*	0.043*	-0.036*	-0.039*	-0.144*	-0.078*	0.131*	1.069*	0.223*	0.121*	-0.167*	-1.108*
5	-0.002*	-0.006*	-0.010*	-0.001	-0.034*	0.014*	0.168*	0.461*	0.032*	-0.020*	-0.178*	-0.462*
6	0.060*	0.111*	0.122*	0.047*	-0.202*	-0.329*	-0.365*	-0.348*	0.262*	0.439*	0.487*	0.395*
7	-0.004*	-0.012*	-0.023*	-0.007	-0.008*	0.063*	0.245*	0.673*	0.004*	-0.075*	-0.268*	-0.680*
8	0.038*	0.060*	0.055*	0.035*	-0.126*	-0.187*	-0.171*	-0.023	0.163*	0.248*	0.226*	0.058*
9	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
10	-0.006*	-0.028*	-0.043*	0.016*	-0.020*	-0.140*	-0.335*	-0.357*	0.013*	0.113*	0.292*	0.373*
11	0.007*	0.005*	-0.006	0.007*	-0.052*	-0.037*	0.069*	0.373*	0.059*	0.042*	-0.074*	-0.366*
12	0.139*	0.191*	0.184*	0.137*	-0.212*	-0.248*	-0.208*	-0.072*	0.351*	0.439*	0.392*	0.210*
13	0.026*	0.030*	0.015*	0.029*	-0.101*	-0.093*	0.022	0.331*	0.126*	0.122*	-0.007*	-0.302*
14	0.032*	0.097*	0.138*	-0.038	-0.108*	-0.295*	-0.427*	-0.563*	0.139*	0.392*	0.565*	0.525*
15	-0.206*	-0.256*	-0.240*	-0.219*	-0.504*	-0.595*	-0.497*	-0.161*	0.298*	0.339*	0.257*	-0.058
Losses												
1	-0.006*	-0.007*	-0.002*	-0.008*	-0.051*	-0.058*	0.015	0.215*	0.045*	0.051*	-0.017*	-0.223*
2	0.051*	0.059*	0.062*	0.052*	0.130*	0.227*	0.379*	0.560*	-0.079*	-0.168*	-0.317*	-0.508*
3	-0.007*	0.035*	0.094*	-0.133*	0.039*	-0.044*	-0.256*	-0.527*	-0.046*	0.080*	0.350*	0.394*
4	-0.075*	-0.127*	-0.144*	-0.077*	0.147*	0.409*	0.778*	1.208*	-0.221*	-0.536*	-0.922*	-1.285*
5	-0.096*	-0.121*	-0.122*	-0.094*	0.095*	0.188*	0.301*	0.375*	-0.192*	-0.308*	-0.423*	-0.469*
6	0.084*	0.130*	0.122*	0.075*	-0.190*	-0.262*	-0.251*	-0.132*	0.274*	0.392*	0.373*	0.207*
7	0.008*	0.015*	0.013*	0.010*	-0.042*	-0.069*	-0.057*	0.018*	0.050*	0.084*	0.070*	-0.008
8	0.021*	0.048*	0.062*	0.012	-0.088*	-0.197*	-0.274*	-0.319*	0.109*	0.246*	0.336*	0.332*
9	-0.017*	-0.018*	-0.020*	-0.015*	-0.010*	0.018*	0.103*	0.215*	-0.008*	-0.036*	-0.123*	-0.230*
10	-0.002*	0.020*	0.068*	0.091*	-0.040*	0.076*	0.435*	1.793*	0.038*	-0.056*	-0.367*	-1.702*
11	0.008*	0.009*	0.005*	0.008*	-0.119*	-0.129*	-0.016	0.346*	0.126*	0.138*	0.021	-0.338*
12	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a

13	0.005*	0.006*	0.003*	0.007*	-0.070*	-0.074*	0.013	0.243*	0.075*	0.081*	-0.010	-0.236*
14	-0.039*	-0.067*	-0.083*	-0.032*	0.014*	0.103*	0.286*	0.613*	-0.054*	-0.170*	-0.369*	-0.644*
15	-0.002*	0.003*	0.012*	0.008*	-0.124*	-0.005	0.330*	1.257*	0.122*	0.008	-0.318*	-1.248*

(a) The null hypothesis that differences between premiums are equal to zero is tested with a t test. The * indicates the null hypothesis can be rejected at 5%.
(b) Gains: positive (negative) difference indicates less (more) risk taking. Losses: positive (negative) difference indicates more (less) risk taking.