Insights into Trader Behavior:
Risk Aversion and Probability Weighting

by

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Insights into Trader Behavior: Risk Aversion and Probability Weighting

The objective of this study is to investigate how professional traders in futures and options markets behave under risk and uncertainty. Our preliminary findings suggest that most traders exhibit concave utility functions for gains and convex utility functions for losses, while their weighting functions are inverse s-shaped. However, differences in magnitude of the risk aversion parameters and the degree of probability weighting can lead to distinct behavior even if the shapes of utility and weighting functions are the same. Further, the typical pattern of prospect theory is more prevalent under risk but not as much under uncertainty. More combinations of shapes for utility and weighting functions are found under uncertainty, suggesting that different types of behavior emerge when people need to make their own assessments about the likelihood of events. Finally, our results are consistent with evidence of loss aversion and disposition effect found in studies of trading behavior in futures markets.

Keywords: trader behavior, risk aversion, probability weighting

INTRODUCTION

The standard decision-making framework is based on the rationality assumption which implies that choice results from a maximization process. Agents receive new information and update their beliefs using Bayes' law, and make their choices consistent with Savage's idea of subjective expected utility (Barberis and Thaler, 2003). Two types of studies have been conducted to investigate the validity of the rationality assumption. One is based on either aggregate market data or individual trading records, and researchers search trading data for evidence of behavior inconsistent with standard theory, including loss aversion, the disposition effect, and overconfidence. Another line of research is based on laboratory and field experiments, and researchers elicit preferences and beliefs in order to investigate whether or not they fit standard expected utility theory. Both types of research have found evidence that the rationality assumption is often violated (Schoemaker, 1982; De Bondt and Thaler, 1995; Starmer, 2000; Hirschleifer, 2001; Barberis and Thaler, 2003).

Building on this evidence, a new research agenda has emerged which combines rational and less than rational agents to explain limits to arbitrage, asset mispricing, and other facts which cannot be understood in the standard framework (Benartzi and Thaler, 1995; Barberis, Huang and Santos, 2001; Berkelaar, Kouwenberg, and Post, 2004; Gomes, 2005). Most financial work is based on prospect theory and incorporates several violations to standard theory (Barberis and Thaler, 2003). Camerer and Loewenstein (2004) suggest that behavioral models should replace simplified models based on rationality as long as they prove to be tractable and useful in explaining behavior and making predictions.

A challenge to this new research agenda is to model individual behavior correctly, which implies accurate specifications of functional forms for prospect theory's utility and weighting functions.

Utility and weighting functions can only be elicited through field or laboratory experiments. All functional forms and parameters adopted in these theoretical models were derived from experiments conducted with students, leading to the question of whether real decision makers who evaluate prospects as part of their professional activity violate expected utility to the same degree (Holt and Villamil, 1986). In experiments with students and professional dealers, Burns (1986) and Haigh and List (2005) noticed strategic differences in the behavior of the two groups. Only Fox, Rogers, and Tversky (1996) and Haigh and List (2005) have conducted experiments with professional traders in futures and options markets, and their findings indicate that traders' behavior is consistent with loss aversion and probability weighting. However, they have neither estimated functional forms nor investigated both utility and weighting functions simultaneously. Since behavior towards risk are determined by both utility and weighting functions (Kahneman and Tversky, 1979), the actual behavior of futures and options traders using both dimensions of prospect theory remains to be investigated. Recent studies suggest that substantive changes can arise when multiple dimensions of the behavioral literature are considered (Blavatskyy and Pogrebna, 2005; Davies and Satchell, 2005; Langer and Weber, 2005). For example, compared to myopic loss aversion case, probability distortion was found to have an opposite effect on investment decisions, in some cases completely offsetting the effect of loss aversion (Blavatskyy and Pogrebna, 2005). The elicitation of utility and weighting functions based on professional traders may allow more accurate definition of functional forms and parameters to build theoretical models, leading to more complete models of trading behavior which capture both investors' preferences and beliefs.

The objective of this paper is to study how professional traders in futures and options markets behave in situations of risk and uncertainty. The procedure of this investigation is based on laboratory experiments to elicit value and weighting functions. Mixed prospects will be used such that behavior in the domains of gains and losses can be determined. Specific functional forms will be fitted to the elicited points in the utility and probability space, and their parameters will be estimated.

This study contributes to the literature in several ways. For the first time the behavior of futures and options traders will be explored using laboratory experiments combined with field data from individual trading records. Such combination should allow sharper and more convincing inference on economic behavior since experiments and field data can provide complementary perspectives (Harrison and List, 2004). The combined analysis will allow us to disentangle several dimensions of behavior (loss aversion, probability weighting, risk aversion) and relate them to individual characteristics of the traders and also to their performance in the market.

THEORETICAL FRAMEWORK

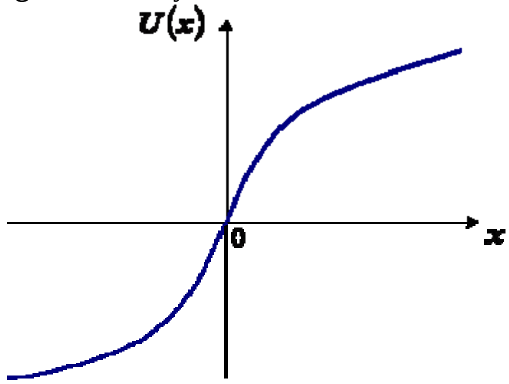
Prospect theory is used to investigate trader behavior. This choice model is based on a function $v(x)$ with two components (equation 1): a value function $U(x)$ and a probability weighting function $w(F(x))$, where x is the argument of the value function, and $F(x)$ is the objective cumulative probability distribution of x (Rieger and Wang (2006)).

$$v(x) = \int U(x) \cdot \frac{d}{dx} w(F(x))\ dx \tag{1}$$

Utility function

The utility function takes into account that framing of alternatives systematically yields different preferences, as agents react differently to gains and losses. The function also allows for risk-averse behavior (concavity) in the domain of gains $(x > 0)$, and risk-seeking behavior (convexity) in the domain of losses $(x < 0)$. Risk-seeking in the domain of losses has empirical support and arises from the idea that individuals dislike losses so much (loss aversion) that they would be willing to take greater risks in order to make up for their losses. Therefore, the typical shape of the value function that arises from prospect theory is the inverse s-shape, i.e. concavity for gains and convexity for losses (Figure 1).

Figure 1: Utility function



A power specification is the most-commonly used functional form to represent preferences over gains/losses. The power function in (2) is strictly increasing and unbounded in *x*. It exhibits constant relative risk aversion. In the gain domain $(x \geq 0)$ it is concave for $0 < \alpha < 1$, linear for $\alpha = 1$, and convex for $\alpha > 1$. In the loss domain $(x < 0)$ it is concave for $\beta > 1$, linear for $\beta = 1$, and convex for $0 < \beta < 1$.

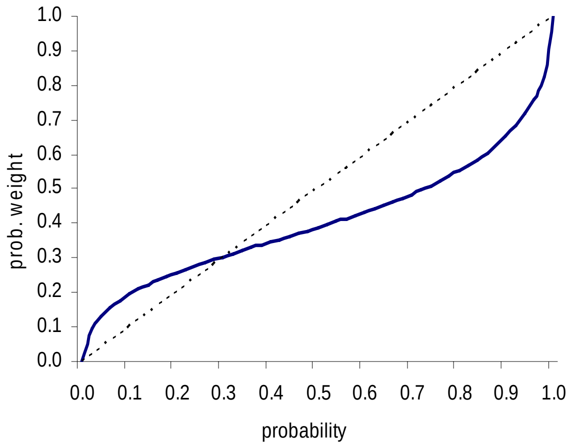
$$U(x) = \begin{cases} x^{\alpha} & , \ x \geq 0 \\ -(-x)^{\beta}, & x < 0 \end{cases} \tag{2}$$

Blondel (2002) fits linear, power and exponential functions to experimental data. His findings indicate that power and exponential functions provide significantly better fits than the linear function, with the power function performing slightly better than the exponential form. Stott (2006) also uses experimental data to fit several functional forms. His findings suggest that power and logarithmic forms provide the best fit, while quadratic and linear specifications show the worst fit. His comparison of the power and exponential functions indicates that the latter specification performs better.

Weighting function

A second component of prospect theory is the probability weighting function, which was developed from empirical observation that individuals do not treat probabilities linearly. Empirical evidence shows that it is difficult to discriminate probabilities near endpoints of the probability scale, which makes weighting functions more curved near endpoints and causes the typical s-shaped functions (Figure 2). If the individual is able to distinguish clearly each probability and assess them objectively, there is no curvature in the weighting function and it is linear as the dotted line in Figure 2. This concept is also related to diminishing sensitivity, i.e. individuals are more sensitive to changes in probability near a reference point such as the end points of the probability scale.

Figure 2: Weighting function



Prelec (1998) proposes the functional form in (3) to represent the weighting function $w(p)$, which is an increasing function of probability p[1]. It is characterized by a unique parameter γ defining the curvature of the probability curve. Curvature reflects the ability of the decision maker to discriminate between probabilities. When $0<\gamma<1$ the probability function is regressive and inverse s-shaped, i.e. first $w(p)>p$ (small probabilities are overweighed) and the function is concave, and then $w(p)<p$ (large probabilities are underweighed) and the function is convex. For $\gamma>1$ the probability function is S-shaped which implies that small probabilities are underweighed and high probabilities are overweighed. Probability overweighting means that probabilities receive large weights when people make decisions, making uncertain events more attractive. On the other hand, probability underweighting implies that probabilities receive little weight, making uncertain events less attractive. Therefore, probability overweighting (underweighting) enhances (diminishes) the attractiveness of gains and aversion to losses.

$$w(p)=\left[-\exp(-\ln p)^{\gamma}\right] \qquad (3)$$

[1] Other functional forms exist in the literature, but Prelec's one-parameter function has been found to be parsimonious and accurate in explaining behavior (Gonzalez and Wu, 1999; Stott, 2006).

The inverse s-shaped weighting function combined with the s-shaped utility function leads to the commonly found fourfold pattern of risk attitudes in empirical studies. This pattern implies risk aversion for large-probability gains and small-probability losses, and risk seeking for small-probability gains and large-probability losses. The intuition behind this behavior is that overweighting of small probabilities enhance the attractiveness of (aversion to) small-probability gains (losses), leading to risk seeking (aversion) behavior for small probabilities, overriding the risk aversion (seeking) attitude implied by the concave (convex) value function over small gains (losses). Similarly, underweighting of large probabilities diminishes the attractiveness of (aversion to) large-probability gains (losses), leading to risk aversion (seeking) behavior for large probabilities which reinforces the risk aversion (seeking) attitude implied by the concave (convex) value function over large gains (losses).

PREVIOUS STUDIES

Utility functions

Most studies which conduct laboratory experiments to estimate functional forms use the power specification, and almost all previous studies are based on experiments with students. These studies show a wide variety of behavior for gains and losses, suggesting that a generalization cannot be clearly made. However, concavity for gains and convexity for losses tend to be found more often than other shapes. In general, experimental studies with known objective probabilities suggest that utility functions are predominantly concave for gains and convex for losses, although there seems to be stronger evidence of concavity for gains than of convexity for losses. This form is consistent with loss aversion and the s-shaped curve from prospect theory. Only Abdellaoui et al. (2005) conduct laboratory experiments with unknown probabilities to elicit utility functions. They also find that utility functions for gains are mainly concave, but they fail to find strong evidence of convexity for losses. The median estimates for the parameter of the power function are usually close to 1, particularly for losses, suggesting that the curvature is not very pronounced.

Some studies recruit real decision makers to participate in laboratory experiments. Pennings and Smidts (2003) assess utility functions of hog farmers and find some heterogeneity in their results. Among all the hog farmers, 38.8% exhibit concave a utility function, 30.1% have an s-shaped function and 27.4% show a convex function. These results are consistent with studies with students to a certain extent, since concavity over gains and convexity over losses seem to be the shapes most frequently found.

Only two studies conduct laboratory experiments with professional traders. Haigh and List (2005) assess utility functions in an investigation of the presence of myopic loss aversion among professional traders. An individual is myopically loss averse if he weighs losses more heavily than gains of equal size and evaluates gains and losses separately rather than pooling the returns into a lifetime portfolio. They conduct experiments with professional traders and a control group of undergraduate students based on bets in a lottery with known objective probabilities following two treatments. In one treatment feedback is given to subjects after each round of the experiment, while in the other treatment feedback is provided after three rounds. The results show that both traders and students exhibit myopic loss aversion, which is more pronounced among traders than students. Their findings suggest that traders' utility functions over losses are steeper than over gains. However, it is not possible to infer the shape of the utility functions from their experiment.

Fox et al. (1996) find linear utility functions in two experiments with professional options traders. In the first experiment traders are presented with complete and incomplete prospects with known probabilities. Then they are asked to report the missing value in the incomplete prospect which would make them indifferent between the two prospects. In the second experiment traders are asked to report the minimum value for which they would sell a prospect with unknown probabilities. The linearity in utility functions found by Fox et al. (1996) may be explained by the small values used in their experiments, which range from zero to US$150. Further, their linear utility functions are only related to the gain domain. As opposed to Haigh and List (2005) who consider gains and losses in their experiment, Fox et al. (1996) only use prospects over gains.

Therefore, little research has been done on the elicitation of utility functions for professional traders. The two studies in this field suggest that their utility functions are linear for gains, and steeper for losses than for gains.

Weighting functions

Empirical evidence tends to support the inverse s-shaped probability function, which implies $0 < \gamma < 1$ in (3). Most experimental studies investigate weighting functions using laboratory experiments with students, and their results often find support for inverse s-shaped curves. Di Mauro and Maffioletti (2004) explore the fourfold pattern of decision making, 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. They find that their subjects exhibit the fourfold pattern both under risk and uncertainty, which is a behavior consistent with an inverse s-shaped weighting function. Other studies use data collected from experiments with students to estimate functional forms (Gonzalez and Wu, 1999; Abdellaoui, 2000; Kilka and Weber, 2001; Etchart-Vincent, 2004; Abdellaoui et al., 2005). They find evidence of inverse s-shaped curves which hold for different functional forms for gains and losses under risk and uncertainty.

Few studies investigate probability weighting in experimental frameworks using real decision makers rather than students. Donkers et al. (2002) use a sample of Dutch households and find evidence of inverse s-shaped weighting functions, which is often found in experiments with students. Humphrey and Verschoor (2004) conduct experiments with the main income earner of households in rural farming communities in Uganda, India and Ethiopia. Their findings support the existence of s-shaped weighting functions, as opposed to the inverse s-shaped functions typically found. They further raise the question whether their relatively uneducated subject sample from developing countries may show preferences which are systematically different from what is often observed among college students.

Finally, weighting functions for professional options traders are investigated by Fox et al. (1996) using two experiments. The first experiment is focused on pricing and matching prospects over gains with known objective probabilities, and the results yielded a linear weighting function which indicates that traders price risky prospects by their expected actuarial value according to expected utility theory. The second experiment involves pricing prospects over gains with unknown probabilities and assessing the probabilities of uncertain events. This implies a distinction between decision weights derived from preferences and degree of belief expressed by direct judgments of probabilities. The results for both decision weights and judged probabilities reveal subadditivity, meaning that traders' weighting functions are not linear and expected utility theory is violated in the presence of uncertain prospects.

Therefore, Fox et al. (1996) find different weighting functions depending whether probabilities are known or unknown when traders evaluate prospects. Even though this conclusion only holds for the domain of gains, since losses are not included in their experimental design, it contrasts to results obtained in experiments with students in which weighting functions are found to be inverse s-shaped regardless probabilities are known or unknown.

RESEARCH METHOD

Experimental design

The experiment is conducted with a group of traders who trade futures and options contracts in the Chicago Board of Trade (CBOT). Most of them trade grains, and there are both pit traders and screen traders in the group (with a slight predominance of pit traders). Before the experiment subjects are asked to answer a short survey to identify individual characteristics such as age, education, and years of experience in the market. After that subjects receive instructions and then asked to start the experiment. The experiment is conducted in the form of computer-based sessions. Subjects are seated in front of a personal computer and answer choice questions that appear on the computer screen.

The tradeoff method proposed by Wakker and Deneffe (1996) is used to elicit utility and weighting functions in the domains of gains and losses. This method is designed to elicit a sequence of outcomes $X_1,...,X_n$ that are equally spaced in terms of utility, and it draws inferences from indifferences between two-outcome gambles (Appendix). The focus on decision-making under risk and experimental procedure follow Abdellaoui (2000). Initially two sequences of ten outcomes are elicited: $X_1, X_2,..., X_{10}$ in the domain of gains, and $X_{-1}, X_{-2},..., X_{-10}$ in the domain of losses. Further two sequences of nine probabilities are assessed: $p_1, p_2, \ldots, p_9$ in the domain of gains, and $p_{-1}, p_{-2}, \ldots, p_{-9}$ in the domain of losses. So for each trader in each domain there are ten pairs of outcomes and utility points $\left(X_i, U\left(X_i\right)\right)$ to assess their utility functions, and nine pairs of probabilities and weights $\left(p_i, w(p_i)\right)$ to assess their weighting functions.

The reliability of subjects' responses is tested for each of the four sequences elicited in the experiment. At the end of the experiment for the two sequences of outcomes subjects are confronted once again with the choice questions previously used to elicit X_2 and X_7 (X_{-2} and X_{-7}) to determine if they express the same preferences. Similarly, at the end of the experiment for the two sequences of probabilities subjects are also confronted again with the choice questions previously used to elicit p_3 and p_{-3}. Further, they are confronted with new choice questions to elicit p_5 and p_{-5}. Rather than eliciting p_5 using prospects $\left(X_5, 1\right)$ and $\left(X_{10}, p_5; X_0\right)$, in the reliability check these probabilities are elicited using prospects $\left(X_5, 1\right)$ and $\left(X_6, p_5; X_4\right)$. The probabilities elicited through these two sets of choice question should be the same if subjects' choices are consistent.

An extension of the experiment deals with decision-making under uncertainty, and the experimental procedure in this part follows Abdellaoui et al. (2005). The procedure is very similar to the previous elicitation, except that probability p is now replaced by an uncertain event E representing some occurrence with which traders are familiar, and an extra step is added to elicit weighting functions. Now participants need to infer the probability of the event based on their own capabilities. Following Abdellaoui et al. (2005) and conversations with the manager of the trading group participating in this study, two types of events are used. For the elicitation of utility functions event E is "USDA report is bullish", while for the elicitation of probability weights 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 based on combinations of the elementary events, yielding a total of nine events $\left(E_1, \ldots, E_9\right)$. The output of the second experiment are two sequences of ten outcomes ($X_1, X_2, ..., X_{10}$ in the domain of gains, and $X_{-1}, X_{-2}, ..., X_{-10}$ in the domain of losses), two sequences of choice-based probabilities ($q(E_1), q(E_2), \ldots, q(E_9)$ in the domain of gains, and $q(E_{-1}), q(E_{-2}), \ldots, q(E_{-9})$ in the domain of losses) and two sequences of nine choice-based probability weights ($w(E_1), w(E_2), \ldots, w(E_9)$ in the domain of gains, and $w(E_{-1}), w(E_{-2}), \ldots, w(E_{-9})$ in the domain of losses). So for each trader and in each domain there are ten pairs of outcomes and utility points $\left(X_i, U\left(X_i\right)\right)$ to assess their utility functions, and ten pairs of probabilities and weights $\left(q(E_j), w(E_j)\right)$ to assess their weighting functions.

DATA

The data used to estimate utility and weighting functions under risk consists of pairs of outcomes X_i and respective utilities $U(X_i)$, and pairs of probabilities p_i and respective weights $w(p_i)$. For each trader there are ten observations $(X_i, U(X_i))$ to estimate equation (2), and nine observations $(p_i, w(p_i))$ to estimate equation (3). Similarly, the data used to estimate these functions under uncertainty also consists of pairs of outcomes X_i and respective utilities $U(X_i)$, and subjective probabilities $q(E_i)$ (rather than objective probabilities) and respective weights $w(E_i)$. Thus, for each trader there are ten observations $(X_i, U(X_i))$ to estimate equation (2), and nine observations $(q(E_i), w(E_i))$ to estimate equation (3).

There are currently 15 traders in our sample, which means that the data collection process has not been finished yet. All 15 traders are male, have a college degree and trade agricultural contracts in the Chicago Board of Trade. Their age ranges from 23 to 54 years old, the average being 32 years old. The most experienced subject has been trading for 30 years, while the less experienced has only 5 months of experience in the market. The average trading experience is 7 years.

Among these 15 traders, 12 trade futures and options, 2 trade only futures, and 1 trades only options. In terms of trading platform, 9 trade only in the pit, 2 trade only electronic, and 4 trade both pit and electronic. Finally, 5 subjects trade only corn, 2 trade only soybeans, 2 trade only soybean oil, 1 trades only wheat, 4 trade corn and soybeans, and 1 trades wheat, corn, and the whole soy complex.

RESULTS

Only preliminary results are available at this point since only 15 traders have been interviewed.

Overall findings

Power utility functions and Prelec's weighting functions are estimated for each trader using standard nonlinear least squares regression[2]. From equation (2) α and β are the parameters of the power utility function in the domains of gains and losses respectively. In the gain domain the function is concave for $0 < \alpha < 1$, linear for $\alpha = 1$, and convex for $\alpha > 1$. In the loss domain it is concave for $\beta > 1$, linear for $\beta = 1$, and convex for $0 < \beta < 1$. In Table 1 summary statistics of individually estimated parameters indicate that most utility functions for gains are concave $(0 < \alpha < 1)$ both under risk and uncertainty. For losses convexity $(0 < \beta < 1)$ is dominant under risk and uncertainty, but the 75th percentiles above 1 indicate that concavity is not uncommon in

[2] The elicited outcomes for gains $(0, X_1, \ldots, X_{10})$ and losses $(X_{-10}, X_{-9}, \ldots, 0)$ are rescaled to unit intervals $[0,1]$ and $[-1,0]$ respectively.

this sample. From equation (3) γ is the curvature parameter of Prelec's weighting function. In both gain and loss domains the functions is inverse s-shaped if $0<\gamma<1$, linear if $\gamma=1$, and s-shaped if $\gamma>1$. All summary statistics in Table 1 suggest that weighting functions are mainly inverse s-shaped, since γ appears to be predominantly between 0 and 1.

Table 1: Estimated parameters of utility and weighting functions for each individual

	Power utility function *		Prelec weighting function **	
	gains (α)	losses (β)	gains (γ)	losses (γ)
Risk				
mean	0.8662	0.8915	0.5601	0.6026
std deviation	0.2570	0.2290	0.3058	0.3424
25^{th} percentile	0.7460	0.7178	0.4170	0.4262
50^{th} percentile	0.8089	0.8308	0.6276	0.6688
75^{th} percentile	0.8837	1.0397	0.7278	0.8003
Adj. R^2				
average	0.9834	0.9782	0.9390	0.9136
median	0.9965	0.9948	0.9746	0.9391
MSE				
average	0.0514	0.0630	0.1344	0.1622
median	0.0348	0.0420	0.0989	0.1531
Uncertainty				
mean	0.7183	1.1120	0.4956	0.5141
std deviation	0.2684	0.8044	0.8527	0.6034
25^{th} percentile	0.4714	0.7394	0.0000	0.0000
50^{th} percentile	0.6747	0.9314	0.1540	0.4113
75^{th} percentile	0.8072	1.0954	0.6013	0.8452
Adj. R^2				
average	0.9923	0.9915	0.9080	0.9313
median	0.9965	0.9958	0.9738	0.9582
MSE				
average	0.0430	0.0440	0.1253	0.1440
median	0.0351	0.0381	0.0694	0.1204

* For gains, concave if $0<\alpha<1$, linear if $\alpha=1$, and convex if $\alpha>1$. For losses, concave if $\beta>1$, linear if $\beta=1$, and convex if $0<\beta<1$.

** For gains and losses, inverse s-shaped if $0<\gamma<1$, linear if $\gamma=1$, and s-shaped if $\gamma>1$.

Under risk, Table 1 suggests that most traders' utility functions are concave in the gain domain, denoting risk aversion over gains. Their weighting functions are inverse s-shaped for gains, which implies overweighting of small probabilities and underweighting of large probabilities.

This pattern of probability weighting enhances attraction of small-probability gains and diminishes attraction of large-probability gains. Hence probability weighting reduces risk aversion for small-probability gains and amplifies risk aversion for large-probability gains. In the loss domain the results suggest that utility functions are convex, which denotes risk seeking attitude over losses. Their weighting functions are inverse s-shaped, which enhances aversion to small-probability losses and diminishes aversion to large-probability losses. As a result, probability weighting reduces risk seeking for small-probability losses and amplifies risk seeking for large-probability losses.

According to the intensity of probability weighting the reduction in risk aversion for small-probability gains can turn into risk-seeking behavior, while the reduction in risk seeking for small-probability losses can turn into risk-averse behavior. This scenario would be consistent with the fourfold pattern found in empirical studies (Tversky and Kahneman, 1992), which suggests that individuals are risk seekers for small-probability gains and large-probability losses, and risk averse for large-probability gains and small-probability losses. The fourfold pattern implies that risk aversion (seeking) is prevalent in the gain (loss) domain except in the tail of the probability distribution.

Under uncertainty Table 1 also indicates that utility functions are mainly concave for gains and convex for losses, while weighting functions are inverse s-shaped. However, summary statistics in Table 1 suggest that this pattern is not as prevalent under uncertainty as it is under risk. The following discussion on individual results for each trader will focus on other behavior patterns which emerge from our experiments.

Experiment under risk: individual results

Table 2 presents the shape of utility and weighting functions inferred from individual estimates, and shows that 11 out of 15 traders exhibit concave-convex utilities (risk aversion over gains and risk seeking over losses) along with inverse s-shaped weighting functions as discussed earlier[3]. As opposed to the majority of the sample, two traders (10 and 15 in Table 2) are risk seekers (convex utilities) over gains and risk averse (concave utilities) over losses, but they still exhibit inverse s-shaped weighting functions for both gains and losses. In this case probability weighting enhances (diminishes) attraction of small-probability (large-probability) gains, leading to more (less) risk seeking over small-probability (large-probability) gains. Similarly, probability weighting enhances (diminishes) aversion to small-probability (large-probability) losses, which intensifies (attenuates) risk aversion over small-probability (large-probability) losses. Finally, there are also two traders (1 and 2 in Table 2) who exhibit risk aversion (concavity) over gains and losses. Like most subjects, trader 2 has inverse s-shaped weighting functions for gains and losses. Thus risk aversion over small-probability gains and large-probability losses is attenuated, while risk aversion over large-probability gains and small-probability losses is enhanced. In contrast to most individuals, trader 1 has an s-shaped weighting function. Therefore, his risk

[3] Trader 9 (12) did not provide valid answers for the elicitation of utility functions for gains (losses), but his answers relative to the loss (gain) domain are consistent with the loss (gain) segment of this pattern.

aversion over small-probability gains and large-probability losses is enhanced, while his risk aversion over large-probability gains and small-probability losses is attenuated.

Table 2: Individual results – experiment under risk

Trader #	Utility function		Weighting function	
	gains	losses	gains	losses
1	concave	concave	s-shaped	inverse s-shaped
2	concave	concave	inverse s-shaped	inverse s-shaped
3	concave	convex	inverse s-shaped	inverse s-shaped
4	concave	convex	inverse s-shaped	inverse s-shaped
5	concave	convex	inverse s-shaped	s-shaped
6	concave	convex	inverse s-shaped	inverse s-shaped
7	concave	convex	inverse s-shaped	inverse s-shaped
8	concave	convex	inverse s-shaped	inverse s-shaped
9	*	convex	inverse s-shaped	inverse s-shaped
10	convex	concave	inverse s-shaped	inverse s-shaped
11	concave	convex	inverse s-shaped	inverse s-shaped
12	concave	*	inverse s-shaped	inverse s-shaped
13	concave	convex	inverse s-shaped	inverse s-shaped
14	concave	convex	inverse s-shaped	inverse s-shaped
15	convex	concave	inverse s-shaped	inverse s-shaped

* shape could not be assessed due to inconsistent answers

Experiment under uncertainty: individual results

Concave-convex utilities (risk aversion over gains and risk seeking over losses) are also prevalent under uncertainty, but not to the same degree as they are under risk. There are 8 out 15 traders who exhibit this type of utility function under uncertainty (Table 3). Among these 8 traders, 6 exhibit inverse s-shaped weighting functions, which leads to the dominant behavior examined in the previous sections. In contrast, 2 traders show s-shaped weighting functions leading to an opposite behavior: enhanced risk aversion (seeking) in the tail of the gain (loss) segment of the probability distribution, and milder risk aversion (seeking) over large-probability gains (losses).

Another result shown by 3 traders is concave utility (risk aversion) along with inverse s-shaped weighting functions for both gains and losses. In the gain domain this behavior is characterized by improved risk aversion over large probabilities and diminished risk aversion in the tail of the distribution. In the loss domain risk aversion is smoother over large probabilities and larger in the tail.

A few other patterns are found for the remaining 4 traders (4 and 10, 14, and 15 in Table 3). Although concavity for gains and convexity for losses seem to dominate the results under uncertainty, in general there appears to be more diversity of risk attitudes under uncertainty (Table 3). In contrast, all but one weighting functions are inverse s-shaped in both gain and loss domains.

Table 3: Individual results – experiment under uncertainty

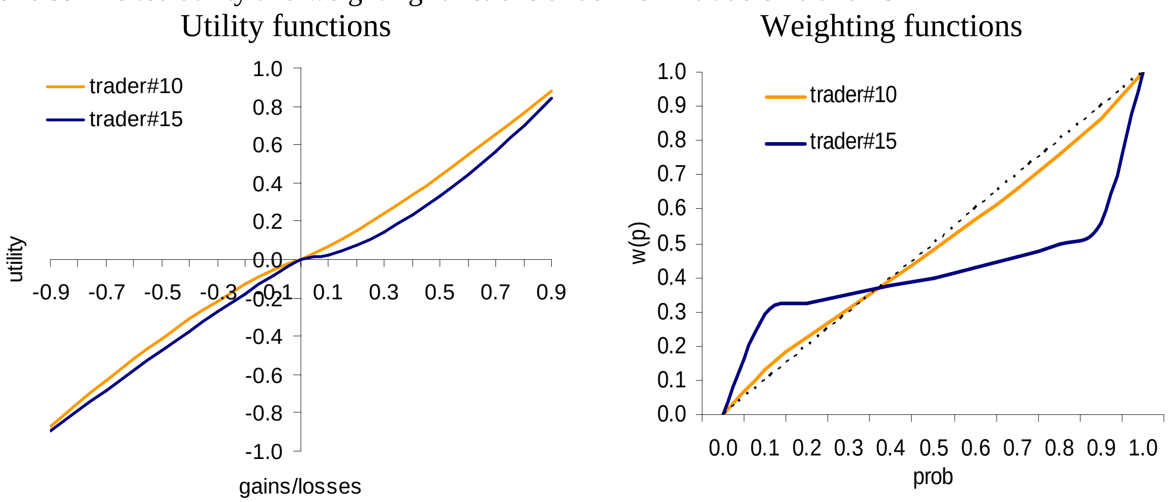
Trader #	Utility function		Weighting function	
	gains	losses	gains	losses
1	concave	convex	inverse s-shaped	inverse s-shaped
2	concave	concave	inverse s-shaped	inverse s-shaped
3	concave	convex	inverse s-shaped	inverse s-shaped
4	convex	concave	inverse s-shaped	inverse s-shaped
5	concave	convex	inverse s-shaped	inverse s-shaped
6	concave	convex	inverse s-shaped	inverse s-shaped
7	concave	convex	s-shaped	s-shaped
8	concave	concave	inverse s-shaped	inverse s-shaped
9	concave	concave	inverse s-shaped	inverse s-shaped
10	convex	concave	inverse s-shaped	inverse s-shaped
11	concave	convex	inverse s-shaped	inverse s-shaped
12	concave	convex	inverse s-shaped	inverse s-shaped
13	concave	convex	s-shaped	s-shaped
14	concave	linear	inverse s-shaped	inverse s-shaped
15	convex	convex	inverse s-shaped	inverse s-shaped

Subjects heterogeneity

Our findings indicate that utility functions are mainly concave for gains and convex for losses, while almost all weighting functions are inverse s-shaped. These results may suggest that our sample is homogenous and the 15 traders show similar behavior. Furthermore, one could question the importance of investigating utility and weighting functions together, since they appear to show similar results. However, the opposite conclusion emerges as individual results are investigated more closely. Although the overall shapes of utility and weighting functions are similar, the magnitude of their estimated parameters can lead to distinct behavior.

The results obtained for traders 10 and 15 illustrate these points. Figure 3 shows plots of estimated utility and weighting functions for both individuals in the experiment under risk. Both traders exhibit utility curves which are convex for gains and concave for losses, while their weighting curves are inverse s-shaped for gains and losses. The estimated parameters of their utility functions are similar, yielding almost identical curves in Figure 3. Hence, one could conclude that traders 10 and 15 should behave alike if one focus solely on utility curves, i.e. they are risk seekers over gains and risk averse over losses. But different conclusions are reached if probability weighting is also considered. Trader 10 exhibits little probability weighting, as can be seen by a weighting curve which is almost linear in Figure 3. In contrast, trader 15 reveals a high degree of overweighting for small probabilities and underweighting for large probabilities. In comparison with trader 10, this pattern makes trader 15 relatively more (less) risk averse over large (small)-probability losses, and relatively more (less) risk seeking over small (large)-probability gains. Since large probabilities are typically associated with relatively frequent events and small probabilities with relatively rare events, this example indicates that the degree of probability weighting exhibited by trader 15 reduces (amplifies) his risk-seeking (averse) behavior over gains (losses) often observed in the market. It also suggests an enhancement (reduction) of his risk-seeking (averse) behavior over gains (losses) in the tails of the probability distribution.

Figure 3: Elicited utility and weighting functions under risk – traders 10 and 15



The previous example illustrates two points. First, although the shapes of utility and weighting functions may be the same for two traders, their behavior does not necessarily need to be alike. Depending on the magnitude of risk aversion (seeking) implied by utility function and also the degree of probability weighting, actual behavior can be very different even if for curves exhibiting the same shapes. Second, it is important to investigate all dimensions of behavior together rather than only one in isolation. Even though two individuals may show similar risk attitudes as implied by their utility functions, their actual behavior may differ as distinct degrees of probability weighting come into play. Similarly, people with the same pattern of probability weighting may behave differently because of diverse risk attitudes.

CONCLUSION

The objective of this study is to investigate how professional traders in futures and options markets behave under risk and uncertainty. This is an on-going research since our current results are based on a small sample of traders and therefore they might change as our sample increases.

Our preliminary findings suggest that professional traders in futures and options markets behave according to prospect theory. There is evidence that most traders exhibit concave utility functions for gains and convex utility functions for losses, while their weighting functions are inverse s-shaped. However, this does not necessarily imply that most traders show similar behavior. Differences in magnitude of the risk aversion parameters and the degree of probability weighting can lead to distinct behavior even if the shapes of utility and weighting functions are the same. This point highlights the observation of Kahneman and Tversky (1979) that risk-taking behavior is determined jointly by utility and weighting functions, and not solely by the utility function.

There are also some differences in the results under risk and uncertainty. The typical pattern of prospect theory (concave-convex utilities and inverse s-shaped weighting functions) is more prevalent under risk but not as much under uncertainty. There are 11 traders with this type of pattern in the experiment under risk, and only 6 in the experiment under uncertainty. More combinations of shapes for utility and weighting functions are found in the experiment under uncertainty, suggesting that different types of behavior emerge when people need to make their own assessments about the likelihood of events. Recall that risk environment is defined as the daily activity of market which traders have learned to understand, and uncertainty environment is defined as the times when special events occur (e.g. release of USDA reports). Based on these definitions our findings suggest that there is a standard behavior pattern followed by most traders during regular trading sessions, but divergent behavior emerges when extraordinary or unanticipated events happen.

As we compare our results to other studies about professional traders, our findings contradict Fox et al. (1996) who encounter linear utility functions (risk neutrality) under both risk and uncertainty and linear weighting function (no probability weighting) under risk. However, we find inverse s-shaped weighting functions under uncertainty which coincides with their results. Recalling that Fox et al. (1996) only investigated gains, their findings suggest that traders are risk neutral under risk since both utility and weighting functions are linear, which contrast to our results. Under uncertainty their results lead to risk aversion over large probabilities and risk seeking over small probabilities, since their inverse s-shaped weighting function enhances (diminishes) attraction of small (large)-probability gains. The expected behavior emerging from their results is consistent to some patterns found in our experiments. However, our results differ in the sense that risk aversion and risk seeking behavior in Fox et al. (1996) emerge only from probability weighting, while in our study these two types of behavior are determined both by the utility and weighting functions.

Our results are consistent with evidence of loss aversion and disposition effect found in studies of trading behavior in futures markets (Heisler, 1994; Coval and Shumway, 2005; Locke and Mann, 2005; Haigh and List, 2005). These studies show that traders tend to be more cautious with winning positions and liquidate them faster, while they are more willing to take risks over losing positions as they try to make up for their losses. This observed behavior is in line with our findings of risk aversion over gains and risk seeking over losses. However, some points need to be acknowledged here. First, our experiments do not contemplate dynamic decisions and hence trading behavior in a sequence of decisions over time remains to be studied. Empirical evidence suggest that prospect theory may not be prevalent in a dynamic setting (Thaler and Johnson, 1990). Second, the evidence of loss aversion and disposition effect is conditioned on the empirical method adopted in the study, particularly on the time horizon chosen to evaluate gains and losses (Locke and Mann, 2005). Third, depending on the degree of probability weighting, the typical pattern of risk aversion over gains and risk seeking over losses may change for small-probability events (in the tails of the probability distribution). An inverse s-shaped weighting function reduces risk aversion (seeking) for small-probability gains (losses), but a high degree of probability weighting may also lead to risk seeking (aversion) over small-probability gains (losses). In this case, the disposition effect would hold only away from the tails of the probability distribution.

The next step of the research is to increase the sample of traders. A larger and more diversified sample of traders will allow us to verify the robustness of our current findings, and also explore their individual characteristics and how they affect their behavior. Finally, we will collect accounting data from all the traders and investigate how their behavior influence their performance in terms of risk and return in the market.

APPENDIX

The trade-off method is explained for the case of positive outcomes (gains), but its use for negative outcomes (losses) is straightforward. 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. Given X_{i-1}, X_i is elicited such that the subject is indifferent between prospects $(X_0, p; R)$ and $(X_1, p; R^*)$. 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. For example, as can be seen in Table 4, X_1 is the value that makes the subject indifferent between prospects $(X_0, p; R)$ and $(X_1, p; R^*)$. The next step is to elicit X_2 such that the subject is indifferent between prospects $(X_1, p; R)$ and $(X_2, p; R^*)$. Outcomes $X_3, \ldots, X_n$ can be elicited following the same steps.

Table 4: Tradeoff procedure to elicit sequence of outcomes X_1, …, X_n under risk

Step	Fixed values	Prospect A	Prospect B	Elicited outcome X_i	Utility $U(X_i)$
1	R, R^*, p, X_0	(X_0, p ; R)	(X_1, p ; R^*)	X_1	1/n
2	R, R^*, p, X_1	(X_1, p ; R)	(X_2, p ; R^*)	X_2	2/n
3	R, R^*, p, X_2	(X_2, p ; R)	(X_3, p ; R^*)	X_3	3/n
4	R, R^*, p, X_3	(X_3, p ; R)	(X_4, p ; R^*)	X_4	4/n
⋮	⋮	⋮	⋮	⋮	⋮
N	R, R^*, p, X_{n-1}	(X_0, p ; R)	(X_1, p ; R^*)	X_n	1

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 $(X_n, p_i; X_0)$, as illustrated in Table 5. Similar to the elicitation of outcomes, the process to assess probabilities is also based on an iterative procedure in which elicited probabilities are derived from observed choice.

Table 5: Tradeoff procedure to elicit sequence of probabilities P_1, …, P_{n-1} under risk

Step	Fixed values	Prospect A	Prospect B	Elicited probability p_i	Probability weight $w(p_i)$
1	X_0 , X_1 , X_n	X_1	(X_n, p_1 ; X_0)	p_1	1/n
2	X_0 , X_2 , X_n	X_2	(X_n, p_2 ; X_0)	p_2	2/n
3	X_0 , X_3 , X_n	X_3	(X_n, p_3 ; X_0)	p_3	3/n
4	X_0 , X_4 , X_n	X_4	(X_n, p_4 ; X_0)	p_4	4/n
⋮	⋮	⋮	⋮	⋮	⋮
n-1	X_0 , X_{n-1} , X_n	X_{n-1}	(X_n, p_{n-1} ; X_0)	p_{n-1}	n-1/n

The design of the experiment is critical for a good assessment of values and probability weights. Hershey, Kunreuther and Schoemaker (1982) discuss several steps for selecting an elicitation procedure in order to reduce the occurrence of bias. 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 (2000) and Abdellaoui et al. (2005). The experiment should be as close as possible to the subjects' environment, which means that in the current study it should reflect trading decisions commonly experienced in the CBOT markets. Traders are asked to choose between two trading strategies $\left(X_i, p; R\right)$ and $\left(X_{i+1}, p; R^*\right)$ 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. Based on numbers discussed with the manager of the trading group participating in this study, small traders usually make profits (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.

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