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Dynamic Decision Making in Agricultural Futures and Options Markets

by

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Dynamic Decision Making in Agricultural Futures and Options Markets

This paper investigates the dynamics of sequential decision-making in agricultural futures and options markets. Analysis of trading records of 12 traders identified considerable heterogeneity in individual dynamic trading behavior. Using risk measures derived from the deltas and vegas of trader's portfolios, we find nearly half the traders behavior is consistent with a house-money effect and the other half with loss aversion. These findings correspond closely to expected behavior inferred from elicited utility and probability weighting functions. The results call into question more aggregate findings that discount probability weighting to develop risk measures which support the notion of more uniform, less heterogeneous, behavior. Understanding behavior in a prospect theory context appears to call for investigation of both the probability weighting and utility functions. Our findings also suggest that strategies for loss-averse traders who consolidate gains and avoid using gains in risk-seeking market activities are effective.

Keywords: loss aversion, house-money effect, futures, options

INTRODUCTION

The effects of prior gains and losses on market choice have been the subject of recent behavioral research. Prospect theory, which is often used to explain individual behavior, suggests that individuals are risk averse over gains and risk seeking over losses. Despite a reliance on one-time decision framework (Thaler and Johnson, 1990; Ackert et al., 2006), evidence exists that traders take more risks after losses than after gains (Jordan and Diltz, 2004; Coval and Schumway, 2005). In contrast, Thaler and Johnson (1990) propose and provide evidence for an alternative view of sequential decision making, a house-money effect in which individuals take greater risk after gains than after losses. Weber and Zuchel (2005) argue that understanding how prior gains and losses affect current agent activity is important because it may result in systematic market behavior.

Only two studies have used actual trading records of professional traders to look into dynamic decision-making in futures and options markets. Coval and Shumway (2005) investigate the behavior of futures traders at the Chicago Board of Trade and find that their behavior is consistent with loss aversion, i.e. they tend to take more risk after losses and less risk after gains. Frisno et al. (2008) conduct a similar study using futures traders at the Sydney Futures Exchange. In contrast, Frisno et al. (2008) find evidence of a house-money effect, with traders taking more risk after gains and less risk after losses.

A fundamental issue in this area of research is the appropriate measure of profits and risk. While profits are relatively straightforward to measure, measuring risk in futures and options markets is complicated because it involves expectations about future price changes. Coval and Shumway (2005) and Frisno et al. (2008) measure risk by estimating the expected price change for a given moment during the trading day. The price change for each minute of the trading day is then multiplied by the size of a trader's position at the beginning of each minute to calculate the risk to which each trader is exposed. Their measure of risk does not allow traders to have different expectations about price changes. Since expected probability of price changes adopted to calculate each trader's risk comes from the same probability distribution all traders have the

same expectation about price changes. As a result, probability weighting, a critical component of prospect theory which allows traders to form price expectations based on their own assessment of likely occurrences, is not incorporated into the decision-making process.

However, empirical evidence suggests that people have different expectations, and probability weighting plays an important role in individual behavior. In financial settings Blavatskyy and Pogrebna (2005), Langer and Weber (2005), and Mattos et al. (2008) provide evidence that models incorporating probability weighting show results consistent with observed behavior. Further, Fehr and Tyran (2005) find evidence that even a small amount of individual irrationality (defined by prior outcomes affecting current decisions) can have large effects in aggregate, causing large deviations from rational aggregate behavior. Importantly, understanding individual behavior is of value in its own right in many settings. For instance, a manager of a group of professional traders may need to understand individual trader behavior to properly train and advise them.

The objective of this paper is to investigate the dynamics of sequential decision-making of agricultural futures and options traders. We use unique data from a group of 12 options traders. They are all male, have a college degree and trade agricultural contracts in the Chicago Board of Trade. Data consist of a time series of daily gains and losses in dollars based on the portfolios of each trader for the period January 3, 2006 to November 23, 2007. Daily measures of the riskiness of their individual portfolios (i.e., delta, gamma, vega, and theta) have also been developed. In addition, each trader also has participated in experiments to elicit their utility and weighting functions, providing information about their risk attitude and degree of probability weighting.

Since trading records contain profits made by each trader and individual risk measures, we can investigate how prior gains or losses affect current risk-taking behavior without making assumptions about probability weighting. We use elicited utility and weighting functions to examine the consistency between observed behavior, and to investigate how probability weighting affects risk-taking behavior in a sequential choice context. The results provide new insights on how prior outcomes affect current decisions and the role probability weighting plays.

THEORETICAL FRAMEWORK

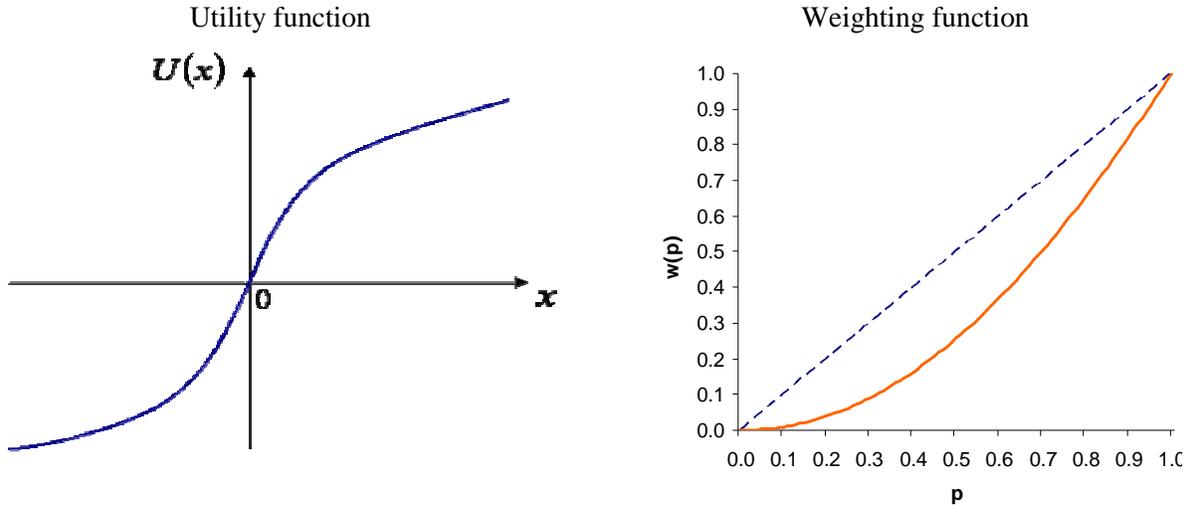
Prospect theory is used to investigate trading behavior. This choice model is based on a function $V(x_i)$ with two components (equation 1): a utility function $U(x_i)$ and a probability weighting function $w(p_i)$, where x is the argument of the utility function, and p is the objective probability distribution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

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

The utility function takes into account that framing of alternatives systematically yields different preferences, as agents react differently to gains and losses. The shape of the value function 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). 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: Utility and weighting functions



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 probabilities can be overweighted or underweighted, meaning individuals make decisions based on perceived probabilities that are either larger or smaller than they really are. For example, figure 1 shows the weighting function of a person who consistently underweights probabilities, meaning that $w(p) < p$ for the whole probability scale.¹

If the individual is able to clearly distinguish probabilities and assess them objectively, there is no curvature in the weighting function, represented by the linear dotted line in figure 1. In this situation we have $w(p_i) = p_i$ in equation (1) and risk-taking behavior is determined solely by the risk preferences in the utility function. However, when probabilities are not assessed objectively, then $w(p_i) \neq p_i$ and decisions are based on transformed probabilities and the utility function.

The effect of the weighting function in decision-making depends on its structure and strength. For instance the weighting function in figure 2 depicts an individual who underestimates the likelihood of uncertain events and thus believes that probabilities are smaller than they really are. In this situation a person would be less willing to take risks. Now, consider the utility function in figure 1, which shows risk aversion for gains and risk seeking for losses. In this situation the weighting function in figure 1 will enhance the risk aversion for gains and reduce (or eliminate) the risk seeking for losses. Consequently, actual behavior can differ from the risk attitude observed in the utility function in the presence of probability weighting.

¹ In empirical studies, a variety of shapes have been identified.

This framework can also be used to investigate dynamic behavior. While previous outcomes can affect behavior, the nature of the response can vary depending on how decision makers incorporate previous outcomes and whether risk attitudes change. When decision makers integrate the outcomes of sequential risky choices, the structure hypothesized by Kahneman and Tversky (1979) that prior losses increase risk-taking, and prior gains reduce it, holds. In effect, the structure of the utility function in figure 1 (convex in the loss domain and concave in the gain domain) leads investors to gamble and seek risk when faced with possible losses, and to avoid risk when gains are anticipated.

However, losses or gains may also change decision makers' willingness to take risks. Based on experimental observations, Thaler and Johnson (1990) find evidence that initial gains cause an increase in risk seeking. The intuition is that previous gains make losing in the next period somewhat less painful particularly, while previous losses make losing in the subsequent period more painful. They argue that this can occur because integration of subsequent outcomes is not necessarily sequential or automatic. In an experimental business context, Keasey and Moon (1996) also find prior gains shift behavior towards risk seeking, but no evidence that prior losses shift risk aversion. Barberis et al. (2001) use these findings to develop a model to explain the size of equity premiums and volatility, arguing that previous gains reduce investors' sensitivity to risk while previous losses, by making new losses more painful, increase risk aversion. Recently, Massa and Simonov (2005) in an analysis of actual investor behavior find empirical support for the notion that prior gains increase risk taking and prior losses reduce it.

PREVIOUS STUDIES

Only two studies have used actual trading records of professional traders to examine dynamic decision making. Coval and Shumway (2005) investigate the behavior of futures pit day-traders in the T-Bond market at the Chicago Board of Trade during 1998 and find that their behavior is consistent with loss aversion, a willingness to take more risk after losses and less risk after gains. Frisno et al. (2008) conduct a similar study using futures pit day-traders in the Share Price Index (SPI) market at the Sydney Futures Exchange between July 1997 and October 1999. In contrast, Frisno et al. (2008) find evidence of a house-money effect, with traders taking more risk after gains and less risk after losses.

Both studies use day-traders who do not carry open positions overnight. They are investigating traders with a short trading horizon, who open and close their positions within the same trading day. Therefore they split the trading day into morning and afternoon, and explore how morning profits affect the amount of risk taken by traders in the afternoon. A critical step in this research is the measurement of profits and risk. Profits are relatively straightforward to measure since they are the amount of money made or lost by each trader during a certain period. Measuring risk in futures and options markets is more complicated because it involves expectations about future price changes. Coval and Shumway (2005) and Frisno et al. (2008) measure risk by estimating the expected change in the value of a trader's position at a given moment during the trading day. Using a logit function, they examine the probability of potential price changes over the next minute as a function of the magnitude of price changes in the preceding 5 minutes and dummy variables for each 5-minute period during the trading day. The fitted values then are used to

construct an expected price change for each minute of the trading day. They note that their risk measure “roughly corresponds to a one standard deviation measure of price change risk associated with each 1-minute interval” (Coval and Shumway, 2005, p.10). The expected price change for each minute of the trading day is multiplied by the size of a trader’s position at the beginning of each minute to calculate the risk to which each trader is exposed. They call this measure the “total dollar risk”.

Since expected probability of price changes adopted to calculate each trader’s risk comes from the same probability distribution the measure implicitly assumes that all traders have the same expectation about price changes. Consequently the only difference between the each trader’s risk measure is the size of their positions. The “total dollar risk” also assumes that no trader exhibits probability weighting, i.e. they form expectations about future price change based on its objective probability distribution rather than on their own assessment of probabilities.²

Empirical evidence suggests that probability weighting is an important determinant of individual behavior. In financial investment settings Blavatsky and Pogrebna (2005) and Langer and Weber (2005) show how it can lead to patterns of behavior which differ from those based solely on risk and loss aversion. These authors also provide evidence that models incorporating probability weighting yield results consistent with observed behavior. In a hedging context, Mattos et al. (2008) show that probability weighting plays a major role in hedging decisions with futures contracts and has relatively more influence than loss aversion or risk aversion. Probability weighting always has an impact on hedging decisions, while risk and loss aversion only affects hedge ratios in the presence of probability weighting.

DATA

There are 12 traders in our sample, and all are male, have a college degree and trade agricultural contracts at the Chicago Board of Trade. Their age ranges from 25 to 54 years old, the average being 33.4 years old and the median being 32.5. The most experienced subject has been trading for 30 years, while the less experienced has only 6 months of experience in the market. The average trading experience is 8.6 years and the median is 6 years.

Among the 12 traders, 11 trade futures and options and 1 trades only options. In terms of trading platform, 8 trade only in the pit, and 4 trade both pit and electronic. Finally, 6 subjects trade only corn, 2 trade only soybeans, 2 trade only soybean oil, and 2 trade corn and soybeans. They trade independently and only for their own portfolios, and do not make trades for other people. Therefore they keep all the profits for themselves which are used to pay transaction and overhead costs.

Data consist of a time series of daily gains and losses in dollars based on the portfolios of each trader for the period January 3, 2006 to November 23, 2007. Daily measures of the riskiness of their individual portfolios (i.e., delta, gamma, vega, and theta) have also been developed. In

² Coval and Shumway (2005) and Frisno et al. (2008) also adopt other risk measures, namely the average trade size and the number of trades executed by each trader. Their results in terms of dynamic decision making do not change with these alternative risk measures.

addition, each trader also has participated in experiments to elicit their utility and weighting functions, providing information about their risk attitude and degree of probability weighting.

Delta, gamma, vega and theta denote how an options value change with respect to changes in the price of the underlying contract, volatility of the underlying contract, and time to maturity of the option. If these measures are equal to zero it means that the value of the option will not change regardless what happens to the price and volatility of the underlying contracts, or to time of maturity. The delta, gamma, vega, and theta of a portfolio can be calculated by adding the deltas, gammas, vegas, and thetas of all individuals assets in the portfolio. Ideally options traders try to keep the delta, gamma, vega, and theta of their portfolios equal to zero, which denotes that their aggregate position has no risk. Therefore they trade and rebalance their portfolios trying to keep their risk measures as close to zero as possible in order to reduce their risk. On the other hand, if they want to take more risk in the market they can simply incorporate options with higher delta, gammas, vegas and thetas in their portfolios.

We investigate whether traders take more or less risk after gains and losses using two risk measures: delta and vega. They represent the risk of changes in the underlying price and underlying volatility, respectively, and are selected because they are considered the most important measures by the traders in our sample. Our sample is composed of relatively long-term traders (as opposed to day traders used in previous studies) and hence they carry open positions for several days. Therefore we adopt a weekly time horizon in our empirical analysis and look at risk measures on Friday and cumulative profits over a Monday-to-Friday period.

RESEARCH METHOD

Following Coval and Shumway (2005) and Frisno et al. (2008), profits are standardized and risk measures are normalized to account for trader heterogeneity. The intuition is that different magnitudes of profits and risks are perceived differently by each trader. For example, a delta of 20 is probably seen as a large risk for a trader who usually keeps his delta around 10, but is likely to be perceived as a small risk for a trader whose portfolio's delta is often close to 30. This data transformation should not affect the results in terms of risk-taking behavior, and allows for more meaningful comparison across traders.

Sample means and standard deviations for profits, deltas and vegas are calculated for each trader. Then deltas and vegas are subtracted by trader-specific means and divided by trader-specific standard deviations, while profits are divided by trader-specific standard deviations. Profits are standardized rather than normalized based on the assumption that any positive profit is perceived as a gain and any negative profit is perceived as a loss. Alternatively, profits could have been normalized following the argument that traders' reference point is greater than zero in order to account for overhead and opportunity costs. Coval and Shumway (2005) and Frisno et al. (2008) conducted their analyses using both normalized and standardized profits which yielded qualitatively similar findings.

The effect of prior gains and losses on current risk-taking decisions are examined in two steps. In the first step delta and vega are regressed on the other risk measures (gamma and theta), changes in price and implied volatility of the underlying contract, and their lagged values (equations (1a) and (1b)). The intuition behind this procedure is that the four risk measures may be interrelated and are also affected by changes in price and volatility of the underlying contract, meaning that they can fluctuate even if the trader does not change his portfolio. For example, even if a portfolio is not rebalanced its delta and vega can change as long as the underlying price and volatilities change. So the first step consists of removing the “market effect” from delta and vega by estimating equations (1a) and (1b). This procedure is particularly important for our sample period, which includes recent sharp increases in prices and volatilities in commodity markets.

$$\begin{aligned} \text{delta}_t = & \alpha + \beta_1 \text{gamma}_t + \beta_2 \text{vega}_t + \beta_3 \text{theta}_t + \beta_4 \Delta p_t + \beta_5 \Delta \text{iv}_t \\ & + \gamma_1 \text{gamma}_{t-1} + \gamma_2 \text{vega}_{t-1} + \gamma_3 \text{theta}_{t-1} + \gamma_4 \Delta p_{t-1} + \gamma_5 \Delta \text{iv}_{t-1} + \varepsilon_t^{\text{delta}} \end{aligned} \quad (1a)$$

$$\begin{aligned} \text{vega}_t = & \alpha + \beta_1 \text{gamma}_t + \beta_2 \text{delta}_t + \beta_3 \text{theta}_t + \beta_4 \Delta p_t + \beta_5 \Delta \text{iv}_t \\ & + \gamma_1 \text{gamma}_{t-1} + \gamma_2 \text{delta}_{t-1} + \gamma_3 \text{theta}_{t-1} + \gamma_4 \Delta p_{t-1} + \gamma_5 \Delta \text{iv}_{t-1} + \varepsilon_t^{\text{vega}} \end{aligned} \quad (1b)$$

where Δp is the price change of the underlying contract and Δiv is the change in implied volatility of the underlying contract. The price change and implied volatility are also trader-specific, e.g. Δp and Δiv for an individual who trades soybean oil refer to price changes and implied volatility of soybean oil. If the individual is in the corn and soybeans markets Δp and Δiv refer to price changes and implied volatilities for corn and soybeans.

In the second step the residuals of (1a) and (1b), which represent the “net” delta and vega, are regressed on their lagged values and lagged profit (equations (2a) and (2b)). If $\beta_2 > 0$ in equations (2a) and (2b) traders tend to take more risk after gains ($\text{profit} > 0$) and less risk after losses ($\text{profit} < 0$), which is consistent with the idea of loss aversion from standard prospect theory. On the other hand, if $\beta_2 < 0$ it means that traders tend to take less risk after gains and more risk after losses, which is consistent with a house-money effect.

$$\varepsilon_t^{\text{delta}} = \alpha + \beta_1 \varepsilon_{t-1}^{\text{delta}} + \beta_2 \text{profit}_{t-1} + v_t \quad (2a)$$

$$\varepsilon_t^{\text{vega}} = \alpha + \beta_1 \varepsilon_{t-1}^{\text{vega}} + \beta_2 \text{profit}_{t-1} + v_t \quad (2b)$$

Equations (1a), (1b), (2a) and (2b) are estimated for each trader based on their specific risk measures and profits. In order to discuss and explore the presence of loss aversion or house-money effect we will rely on the set of estimated β_2 coefficients which indicate the effect of prior profits on delta and vega for each trader.

The second part of the analysis focuses on utility and weighting functions elicited through a computer experiment conducted with each trader. The tradeoff method was adopted in the experiment, and the details of the procedure are explained and discussed in Mattos et al. (2007).

This experiment provides a set of utility and weighting functions for gains and losses for each trader, which contains information about the risk attitude and degree of probability weighting for each trader when they are faced with gains and losses.

RESULTS

Trading records show mixed results in terms of behavior (table 1). There is evidence of a house-money effect (a willingness to take more risk after gains and less risk after losses, $\beta_2 > 0$) for six traders (1, 3, 4, 6, 7, 10), and evidence of loss aversion (less risk after gains and more risk after losses, $\beta_2 < 0$) for five traders (2, 8, 9, 11, 12). Results are inconclusive for trader 5 since the estimated coefficients of profit_{t-1} in the delta and vega equations were both statistically significant but with opposite signs. Note that profits are standardized and risk measures are normalized. Thus the estimated coefficients for profits show the change in risk in number of standard deviations for a 1-standard deviation change in profit. For example, in table 1 the estimated coefficient for profit_{t-1} for trader 1 in the delta equation is 0.0828, which means that if profit in $t-1$ increases (decreases) by 1 standard deviation the trader will increase (decrease) his delta by 0.0828 standard deviations in t .

Table 1. Estimated coefficients for delta and vega equations

Trader	Delta equation			Vega equation		
	constant	delta_{t-1}	profit_{t-1}	constant	vega_{t-1}	profit_{t-1}
1	0.4356 *	-0.1777 *	0.0828 **	0.1147 *	0.6226 *	-0.0087
2	0.6528 *	-0.0374	0.0042	0.3644 *	0.2873 *	-0.0531 **
3	0.4064 *	0.1425 **	0.1064 **	0.4509 *	0.3043 **	-0.0543
4	0.0793 *	0.5218 *	0.0508 **	0.1453 *	0.6022 *	0.1491 *
5	0.4940 *	0.1690 *	0.0956 *	0.1242 *	0.7195 *	-0.0378 *
6	0.7832 *	-0.0228	-0.0723	0.4190 *	0.2609 *	0.1934 *
7	0.1579 *	0.4338 *	0.1564 *	0.0885 *	0.3863 *	-0.0020
8	0.1286 *	0.5439 *	-0.1411 **	0.2617 *	0.5078 *	-0.1125 **
9	0.6750 *	0.0224	-0.1372 **	0.6077 *	0.1439	0.0604
10	0.1745 *	0.3936 *	0.0125 *	0.1870 *	0.6659 *	-0.0482
11	0.5062 *	0.0449	-0.1230 **	0.1497 *	0.6811 *	0.0277
12	0.6334 *	0.0696 **	-0.0636	0.4362 *	0.0098	-0.0559 **

* statistically significant at 1%, ** statistically significant at 5%, *** statistically significant at 10%

Estimated coefficients for profit_{t-1} in both equations in table 1 suggest that the magnitude of house-money effect and loss aversion differ substantially across traders. For example, trader 4 increases (reduces) his delta by 0.0508 after a 1-standard deviation increase (decrease) in profits. Trader 7 shows the same type of behavior in terms of vega, but his change in vega is much larger (0.1934). Similarly, trader 12 reduces (increases) his vega by 0.0559 after an increase in profits. Traders 8 and 9 do the same with their deltas, but in a much larger magnitude (0.1411 and 0.1372, respectively).

Behavior inferred from trading records indicates great heterogeneity across traders. Next, we compare these findings with the utility functions elicited from the computer experiments. First we focus on the risk attitudes implied by the elicited utility functions. The results of the experiments suggest that 10 traders exhibit utility functions consistent with loss aversion

(concave for gains and convex for losses), 1 trader exhibits utility function consistent with house-money effect (convex for gains and concave for losses), and 1 trader shows risk aversion for the whole range (concave for gains and losses). Behavior inferred from the regression model based on trading records is consistent with behavior inferred from utility elicitation for only 4 out of 12 traders (table 2).

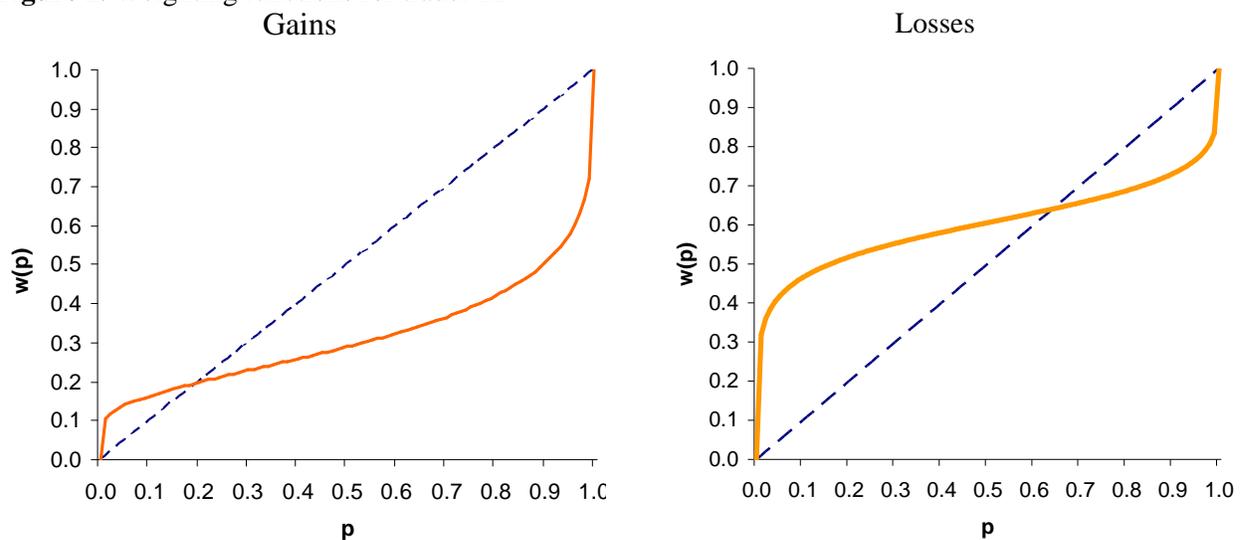
Table 2: Characteristics of traders, profits and behavior

Trader	trading records (*)	utility function (*)	weighting function		Can weighting function help explain observed behavior?
			gains	losses	
1	HM	risk aversion	less risk-taking	more risk-taking	only for losses
2	LA	LA	less risk-taking	less risk-taking	yes
3	HM	LA	more risk-taking	more risk-taking	only for gains
4	HM	LA	more risk-taking	more risk-taking	only for gains
5	inconclusive	LA	less risk-taking	less risk-taking	–
6	HM	LA	more risk-taking	less risk-taking	yes
7	HM	LA	less risk-taking	more risk-taking	no
8	LA	LA	more risk-taking	less risk-taking	yes
9	LA	LA	less risk-taking	more risk-taking	yes
10	HM	LA	less risk-taking	less risk-taking	only for losses
11	LA	LA	less risk-taking	more risk-taking	yes
12	LA	HM	less risk-taking	more risk-taking	yes

(*) HM = house-money effect (risk seeking for gains, risk aversion for losses), LA = loss aversion (risk aversion for gains, risk seeking for losses)

A partial explanation for this apparent inconsistency is the weighting function. The effect of probability weighting on behavior can offset the risk attitude implied by the utility function, which would explain why trading records for some traders show a behavior that is distinct from their risk attitudes. Consider trader 12, trading records suggest a loss-averse individual (risk aversion for gains and risk seeking for losses), but his elicited utility function suggests the opposite behavior since it is convex for gains (risk seeking) and concave for losses (risk aversion). The findings can only be consistent if the elicited weighting function indicates that this trader tends to underweight probabilities for gains (making him less willing to take risks) and overweight probabilities for losses (making him more willing to take risks). Figure 2 depicts the weighting functions for trader 12 in the gain and loss domains, which indeed shows a high degree of probability underweighting for gains and probability overweighting for losses. In effect the risk-seeking attitude for gains implied by the utility function is offset by the high degree of probability underweighting, and trader 12 behaves as a risk-averse individual for gains. In addition, his weighting function for losses indicates large probability overweighting which makes him more willing to take risks when losing, and consistent with his trading records.

Figure 2. Weighting functions for trader 12

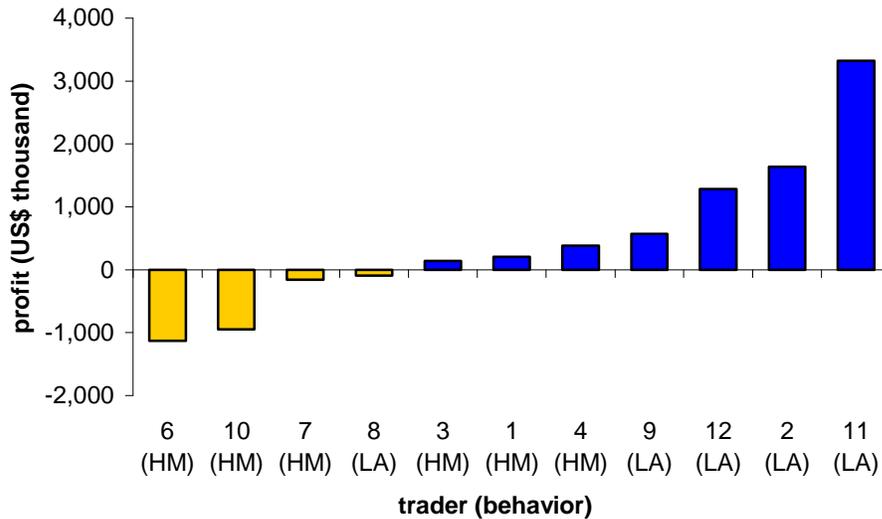


Similar patterns are found for other traders, but not in all cases (table 2, last column). Nevertheless, it is clear that when weighting functions are considered together with utility functions the experimental results are more consistent and able to explain to a greater degree individual behavior inferred from trading records.

Finally, there seems to be no clear relation between markets (corn, soybeans, and soybean oil), trading platform (pit or electronic), and behavior as can be seen in table 2. However, traders whose trading records show evidence of loss aversion appear to be more profitable than their colleagues whose trading records show evidence of house-money effect. The cumulative profit of 4 out of 5 loss-averse traders is positive, while only 3 out of 6 house-money traders make money. Furthermore, gains of loss-averse traders (2, 9, 11, 12) are larger than gains of house-money traders (1, 3, 4), while losses of the loss-averse trader 8 is smaller than the losses of house-money traders 6, 7 and 10. These comparisons can be seen more clearly in figure 3, which essentially shows that traders with larger gains exhibit loss aversion while traders with larger losses exhibit a house-money effect. In effect, loss-averse traders lose relatively less among losing traders and gain relatively more among winning traders.

Table 3: Characteristics of traders, profits, and behavior

Trader	Market	Trading platform	Cumulative profit (US\$ thousand)	Behavior from trading records
1	corn	pit/electronic	207	HM effect
2	corn	pit/electronic	1,637	LA
3	soybeans	pit	142	HM effect
4	corn	pit/electronic	384	HM effect
5	soybean oil	pit	1,225	inconclusive
6	corn	pit	-1,129	HM effect
7	corn/soybeans	pit	-159	HM effect
8	corn	pit	-93	LA
9	soybeans	pit	569	LA
10	corn	pit / electronic	-950	HM effect
11	soybean oil	pit	3,324	LA
12	corn/soybeans	pit	1,282	LA

Figure 3: Traders' behavior and profits

CONCLUSION AND DISCUSSION

This paper investigates the dynamics of sequential decision-making in agricultural futures and options markets. Analysis of trading records of 12 traders suggests that there is great heterogeneity in individual trading behavior. There is evidence of a house-money effect for 6 traders and loss aversion for 5 traders, while results are inconclusive for 1 trader. The magnitude of these effects also varies substantially, i.e. there can be large differences in the amount of risk taken among the same type of traders. Estimated coefficients of how prior profits affect current risk-taking range from 0.0125 to 0.1934 among house-money traders, and from -0.0378 to -0.1411 among loss-averse traders. These numbers suggest that there are house-money traders who would take about 15 times more (less) risk than others after gains (losses), while there are loss-averse traders who would take about 4 times less (more) risk than others after gains (losses).

Individual behavior inferred from utility functions elicited in the experiment is not consistent with behavior inferred from trading records for most traders, suggesting that risk attitudes by themselves cannot explain behavior observed in trading records. But when weighting functions are considered together with utility functions then behavior is more consistent with the results obtained from the trading records. The heterogeneity in trading behavior found in our sample and the importance of the weighting function in determining behavior call into question the results of the aggregate analyses reported in previous studies. In particular, assuming traders possess similar expectations about price changes to develop a measure of risk may be inappropriate and yield misleading results about dynamic behavior.

Discrepancies between experimental findings and trading records can also be explained by the distinct nature of experiments and real-world choices in terms of dynamic decision making. While the experiment was designed to mimic the actual decision environment of futures and options traders, it relies on a prospect theory framework. Prospect theory was developed for one-shot gambles and thus it does not directly incorporate dynamic decision making allowing past results to affect later decisions. This doesn't invalidate the relevance of experiments to the analysis of dynamic decision making as suggested by our results which identify the importance of probability weighting in explaining trading behavior. Since the idea that prior profits affect current decisions in a dynamic context can be consistent with a prospect theory framework (Ackert et al., 2006), a challenge remains to develop encompassing experimental designs that can be readily applied to understand actual trader dynamic behavior.

In contrast to previous studies (Heisler, 1994; Locke and Mann, 2005; Frisno et al., 2008), there appears to be evidence that loss-averse traders make more (lose less) money than house-money traders among the winners (losers). Even though both types of traders gain or lose money, it seems that loss-averse traders are relatively more successful than house-money traders. While the exact reason for this is difficult to determine, loss-averse traders may be more willing to consolidate gains and be less likely to use gains in risk-seeking market activities.

Finally the importance of probability weighting is highly consistent with recent work by Blavatsky and Pogrebna (2005), Langer and Weber (2005), and Davies and Satchell (2005) that also suggest behavior can change considerably in its presence. Using a risk measure that does not require assumptions about probability weighting, we find mixed results in terms of house-money effect and loss aversion, and individual behavior that is consistent with probability weighting and risk attitude for most traders. Behavior and its determinants need to be explored using these measures to gain deeper insights into how traders respond. Such investigations would be in the spirit of Blavatsky and Pogrebna (2005) and Langer and Weber (2005), who find that behavior can change dramatically when probability weighting is considered in decision-making models, and also consistent with Barberis and Thaler's (2003) call for a more integrated assessment of behavioral phenomena.

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