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by

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This paper investigates the dynamics of sequential decision-making in agricultural futures and options markets using a quantile regression framework. Analysis of trading records of 12 traders suggests that there is great heterogeneity in individual trading behavior. Traders respond differently to prior profits depending on how much risk their portfolios are carrying. In general, no significant response is found at average and below-average levels of risk, but response can become large and significant at above-average levels of risk. These results are consistent with studies which argued that behavior may be uneven under different circumstances, and calls into question the adoption of conditional mean framework to investigate trading behavior. Focusing the analysis on the effect of prior profits on the conditional mean of the risk distribution can yield misleading results about dynamic behavior.

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

INTRODUCTION

Despite the importance of understanding dynamic decision in financial markets, only recently has research begun to emerge. A main framework used to investigate decision making has been prospect theory, which is characterized by loss aversion where individuals' preferences are risk averse over gains and risk seeking over losses. While prospect theory's relies on one-shot gambles as opposed to a sequential decision-making (Thaler and Johnson, 1990; Ackert et al., 2006), there is evidence that traders take more risks after losses than after gains (Jordan and Diltz, 2004; Coval and Schumway, 2005). An alternative explanation for sequential decision making is the house-money effect proposed by Thaler and Johnson (1990), who present evidence that people take more risk after gains and less risk after losses.

Only two studies have explored the presence of the house-money effect and loss aversion in futures and options markets using actual trading records of professional futures traders. Coval and Shumway (2005) find that traders' behavior is consistent with loss aversion (more risk after losses and less risk after gains). In contrast, Frino et al. (2008) who conduct a similar study find evidence of a house-money effect with traders taking more risk after gains and less risk after losses. Both studies investigate trading behavior using a regression framework with current risk being a function of prior gains or losses. Estimated coefficients show how prior gains or losses affect the conditional mean of the distribution of risk. However, this procedure provides only limited information as it assumes that the effects are constant across different risk levels.

Empirical studies show that behavior is not homogenous for different levels of risk and return (Rabin, 2003). There is evidence that decisions are made in terms of gains and losses with respect to a reference point, behavior differs over gains and losses, and probabilities are evaluated non-linearly and with respect to reference points. This combination can lead to a fourfold pattern of risk, i.e. risk aversion for gains of high probability and losses of low probability, and risk seeking for gains of low probability and losses of high probability (Tversky and Kahneman, 1992). Finally, it is relevant to explore behavior over the whole distribution of risk because market outcomes are often driven by behavior at the margin, not at the mean (Haigh and List, 2005).

The purpose of this paper is to address the issues raised, conducting an analysis of sequential decision-making in futures and options markets using quantile regression. A selected group of 12 agricultural futures and options traders is used in the study. Their proprietary data consist on time series of daily gains and losses in dollars for the portfolios of each individual trader, along with daily values for several risk measures (delta, gamma, vega, and theta) from January 2006 through November 2007. Data analysis indicate that the distribution of risk measures exhibit fat tails and skewness, which suggest that inference based on the conditional mean may not capture properly the effect of prior gains and losses on their entire distributions.

Quantile regressions is used to model the relationship between current risk-taking and prior profits not only with respect to the mean of the conditional distribution of risk, but also relative to situations in which traders take very large or very small amounts of risk. For instance, Barnes and Hughes (2002) use quantile regression to test the capital asset pricing model. Consistent with previous studies, their results show that beta oscillates around zero and is statistically insignificant around the mean of the distribution. However, they also find that beta is strongly significant in the tails of the distribution and its importance in explaining cross section returns varies across firms.

This study offers innovative contributions as it explores the behavior of futures and options traders using quantile regression. The investigation of how prior gains and losses affect current risk taking over the distribution of risk can help shed light on individual heterogeneity in behavior as opposed to the standard assumption of a representative agent. The dataset used is unique and provides insights to understand the dynamics of decision-making in futures and options markets.

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 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.

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

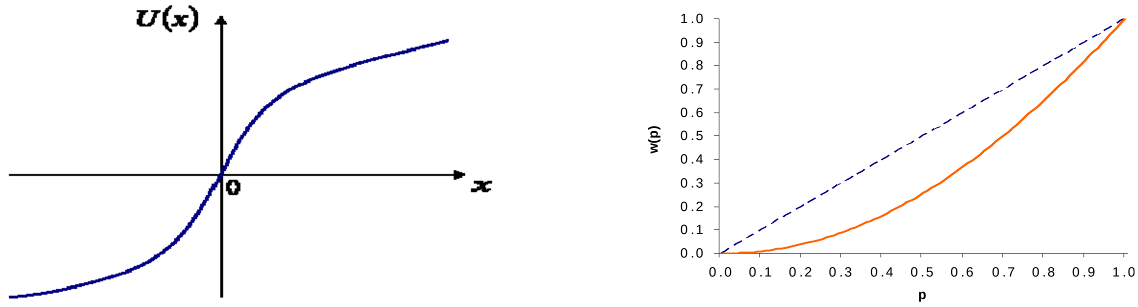
.

The utility function measures value in terms of 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).[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.

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

Figure 1: Utility and weighting functions

Utility function Weighting function



A second component of prospect theory is a probability weighting function, which was developed from observation 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.[2] 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 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 used 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 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 utility 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 utility function.

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'

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

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, while previous losses make losing in the subsequent period more painful. They argue that this occurs because integration of subsequent outcomes is not necessarily sequential or automatic.

PREVIOUS STUDIES

The effect of gains and losses on risk-taking behavior has been investigated in several studies. Evidence that investors are more likely to take risks when losing and less likely to take risks when gaining is found using both laboratory experiments (Weber and Camerer, 1998; Haigh and List, 2005; Weber and Zuchel, 2005) and actual transaction data (Shefrin and Stataman, 1985; Heisler, 1994; Odean, 1998; Frino et al., 2004; Jordan and Diltz, 2004; Locke and Mann, 2005). Early work focuses on the disposition effect, which emerges when traders hold losing positions too long and liquidate winning positions too soon. The disposition effect was initially attributed to loss aversion, i.e. traders dislike losing so much that they would be willing to take more risks to avoid the prospect of further losses, but it also can be caused by biases in return expectations, time-varying risk aversion, regret theory, and escalation of commitment (Zuchel, 2001). The opposite behavior – risk seeking after gains and risk aversion after losses – is known as house-money effect and is also found in several studies (Thaler and Johnson, 1990; Massa and Simonov, 2005; Ackert et al., 2006).

Recent work adopts a more direct measure of risk which can be used to evaluate whether traders take more or less risk after gains and losses. In the context of professional trading only two studies develop a risk measure to examine dynamic decision making in terms of both loss aversion and house-money effect. Coval and Shumway (2005) investigate the intra-day behavior of futures pit day-traders in the T-Bond market at the Chicago Board of Trade during 1998 and find that behavior is consistent with loss aversion, a willingness to take more risk after losses and less risk after gains. Their results indicate that when morning profit increases by one standard deviation the average trader assumes an afternoon risk which is about 1% of a standard deviation smaller than normal. Frino 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, Frino et al. (2008) find evidence of a house-money effect, with traders taking more risk after gains and less risk after losses. Their findings indicate that when morning profit increases by one standard deviation the average trader assumes an afternoon risk which is about 5% of a standard deviation larger than normal.

Coval and Shumway (2005) and Frino et al. (2008) use conditional mean regression models to investigate how prior gains and losses affect current risk-taking, i.e. they only look into behavior at average levels of risk. This approach can be misleading and unable to properly capture the effect of prior gains and losses if the distribution of risk exhibits skewness and excess kurtosis. A quantile regression approach allows us to model how traders respond to prior gains and losses when their positions exhibit above or below average levels of risk, which suggests that their behavior can be over- or underestimated by the conditional mean approach. In addition to issues related to the statistical relevance of the conditional mean approach, Haigh and List (2005) argue that it is relevant to explore behavior over the entire distribution of risk because market outcomes are often driven by behavior at the margin, not at the mean.

A recent study illustrates the relevance of quantile regression framework. Barnes and Hughes (2002) adopt this approach to test the capital asset pricing model (CAPM). They point out that quantile regression allows exploring why conditional mean approaches have yielded ambiguous results regarding the impact of beta on returns and investigating the relationship between returns and beta for firms that under- or overperform relative to the mean of the conditional distribution. Their results show that beta oscillates around zero and is statistically insignificant around the mean of the distribution, which is consistent with previous studies, but they also find that beta is strongly significant in the tails of the distribution. Their results indicate that the coefficient on beta has opposite signs at opposite tails of the distribution of conditional returns, and it is zero around the mean of the distribution. Thus conditional mean regressions tend to find that the coefficient on beta cannot be statistically distinguishable from zero, while quantile regressions can find statistically significant coefficients at the both tails of the distribution.

DATA

Dynamic decision making is investigated in a sample of 12 traders. They are all 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 market experience. 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 options only. 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. Returns are used to used to pay transaction and overhead costs; the remainder is profit.

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 (delta, gamma, vega, and theta) are also available. Computer software calculates the risk measures for the portfolio of each trader at the end of each trading day using the formula developed by Barone-Adesi and Whaley (1987).

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. When these measures are zero, the value of an 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 implies that their aggregate position has no risk. 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 incorporate options with higher delta, gammas, vegas and thetas in their portfolios.

RESEARCH METHOD

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 Frino 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 traders' probability weighting functions are equal and correspond to objective reality.[3] However, empirical evidence suggests that probability weighting is an important determinant of individual behavior in financial settings (Fox et al., 1996; Blavatskyy and Pogrebna, 2005; Langer and Weber, 2005; Mattos et al., 2008) .

We investigate whether traders' behavior using two risk measures—delta and vega—derived from the trader's portfolio. They represent the risk of changes in the underlying price and underlying volatility, and are selected because they were identified by our traders as the most important measures. Since our sample is composed of relatively long-term traders (as opposed to day traders used in previous studies) who carry open positions for several days, we adopt a weekly time horizon in our empirical analysis and use risk measures on Friday and cumulative profits over a Monday-to-Friday period. Most traders in our sample have 99 weekly observations for risk measures and profits between January 3, 2006 and November 23, 2007. However two traders have slightly less observations because they started trading a few weeks later in 2006.

To account for severe outliers in the series, all variables are winsorized. Upper and lower bounds (mean plus and minus two standard deviations) are created for each variable. If a data point is above the upper bound it is set to the upper bound value, and if it is below the lower

[3] Coval and Shumway (2005) and Frino 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 their different risk measures.

bound it is set to the lower bound value. So outliers are not eliminated from the sample, but set to either the upper or lower bound.

Deltas and vegas can be positive or negative but the relevant variables here are their absolute values (a delta of 10 and –10 represent the same amount of risk). Thus deltas and vegas are expressed in absolute values. Equations (2) and (3) are estimated for each trader based on their specific risk measures and profits for 20 quantiles ranging from the 5^{th} to the 95^{th}. In order to discuss and explore the presence of loss aversion or house-money effect we will rely on the set of estimated β_P^D and β_P^V coefficients which indicate the effect of prior profits on delta and vega. If $\beta_P^D > 0$ or $\beta_P^V > 0$ in equations (2) and (3) traders tend to take more risk after gains (profit>0) and less risk after losses (profit<0), which is consistent with the idea of loss aversion from standard prospect theory. On the other hand, if $\beta_P^D < 0$ or $\beta_P^V < 0$ it means that traders tend to take less risk after gains and more risk after losses, which is consistent with a house-money effect.

$$\left|delta_t\right| = \alpha_D + \beta_D \left|delta_{t-1}\right| + \beta_P^D\, profit_{t-1} + \varepsilon_t^D \tag{2}$$

$$\left|vega_t\right| = \alpha_V + \beta_V \left|vega_{t-1}\right| + \beta_P^V\, profit_{t-1} + \varepsilon_t^V \tag{3}$$

The statistical significance of coefficients β_P^D and β_P^V is assessed through Wald tests. Standard errors for the parameter estimates are calculated using the design matrix bootstrap procedure with 500 replications. Buchinsky (1995) tests several estimators and finds that the design matrix bootstrap procedure yields the best results. This procedure allows for autocorrelation and heteroscedasticity and was also adopted by Barnes and Hughes (2002) and Meligkotsidou et al. (2009).

To assess the extent to which prior profits affect current risk taking, we calculate risk/profit elasticities for each trader as indicated in equations (4) and (5). Elasticities are calculated for each quantile and show the percent change in portfolio risk as $profit_{t-1}$ changes by 1%.

$$\varepsilon_P^D = \frac{\partial\left|delta_t\right|}{\partial profit_{t-1}} \frac{profit_{t-1}}{\left|delta_t\right|} \tag{4}$$

$$\varepsilon_P^V = \frac{\partial\left|vega_t\right|}{\partial profit_{t-1}} \frac{profit_{t-1}}{\left|vega_t\right|} \tag{5}$$

RESULTS

All variables are tested for the presence of unit roots using Dickey-Fuller and Phillips-Perron tests. The null hypothesis of unit root can be rejected in both tests for all traders, with the exception of $|vega_t|$ for traders 1 (both tests) and 6 and 10 (only in Dickey-Fuller test). In the few cases that the null hypothesis cannot be rejected regressions are run in differences.

Results from the quantile estimation of equations (2) and (3) are heterogeneous in terms of behavior. Table 1 classifies traders based on the sign of statistically significant estimated coefficients β_p^D and β_p^V of the lagged profit term (if the estimated coefficient is not statistically significant it is classified as zero in Table 1). There is evidence of a house-money effect (a willingness to take more risk after gains and less risk after losses, $\beta_p^D > 0$ or $\beta_p^V > 0$) for five traders (2, 4, 5, 7, 9), and evidence of loss aversion (less risk after gains and more risk after losses, $\beta_p^D < 0$ and $\beta_p^V < 0$) for four traders (3, 8, 10, 12). Traders 1, 6, and 11 show both $\beta_p^D = 0$ and $\beta_p^V = 0$, which indicates that lagged profits have no effect on current risk taking.

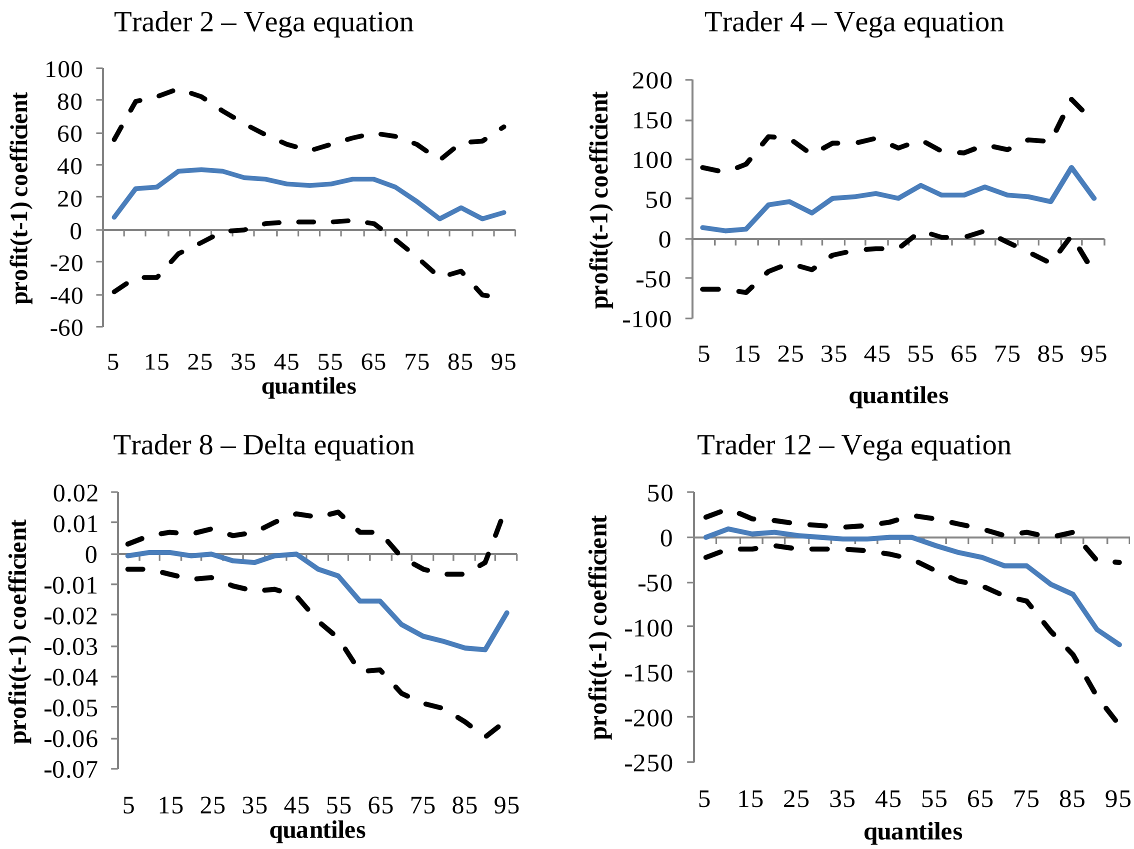
Table 1: Classification of traders based on sign of β_p^D and β_p^V

Vega equation	Delta equation $\beta_p^D < 0$	$\beta_p^D = 0$	$\beta_p^D > 0$
$\beta_p^V < 0$	-	3, 10, 12	-
$\beta_p^V = 0$	8	1, 6, 11	-
$\beta_p^V > 0$	-	2, 4, 7, 9	5

Estimated coefficients are considered to be positive or negative if they are statistically significant at 10% in at least one quantile.

Most of the statistical significance of β_p^D and β_p^V is found above the 50th quantile; previous profits affect current risk taking mainly when traders are carrying a relatively high level of risk in their portfolios. Examples are shown in Figure 2, which presents the quantile estimation of β_p^V for traders 2, 4, and 12 and β_p^D for trader 8. The coefficients for traders 2 and 4 tend to be statistically significant close to the 50th quantile, while for traders 8 and 12 statistical significance emerges only at higher quantiles. A similar pattern of emergence at higher quantiles is observed for traders 3, 5, 7, 9, and 10 whose results are not presented for brevity.

Figure 2: Quantile estimation of profit$_{t-1}$ coefficients

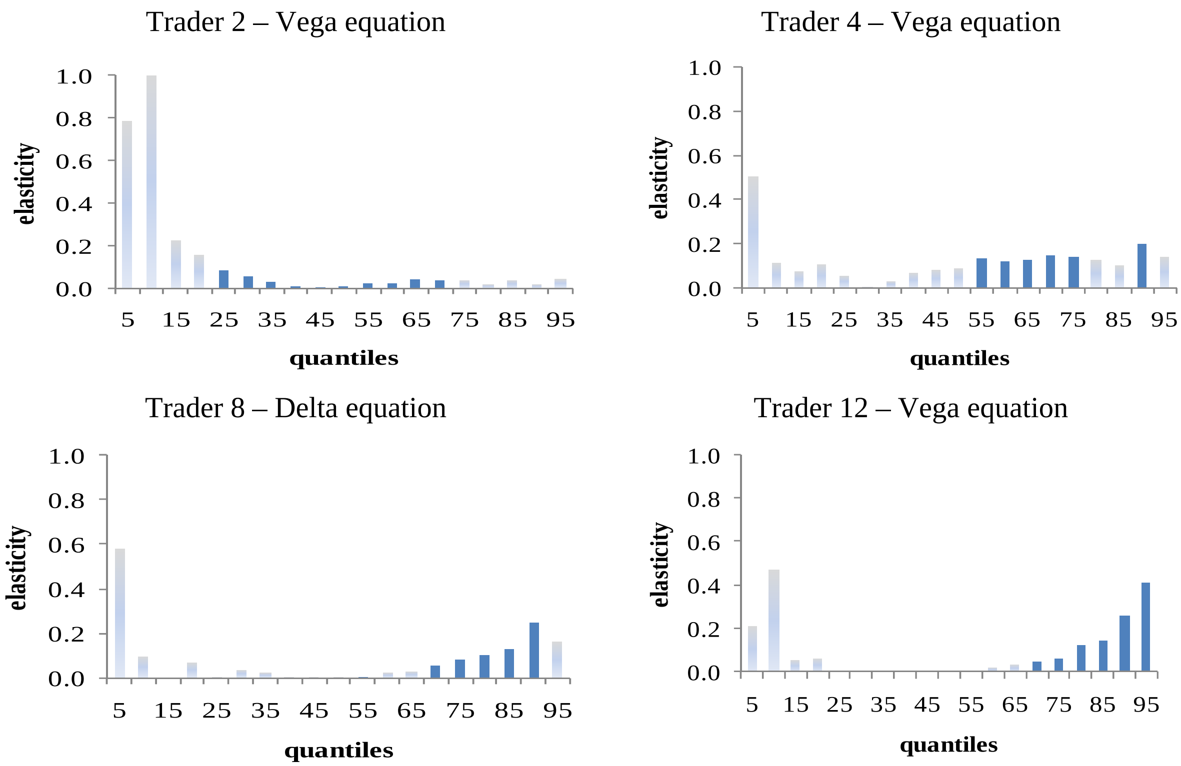


Continuous line: point estimates, dotted line: confidence interval

Risk/profit elasticities are calculated to gain insight on the extent to which prior profits affect current risk. Figure 3 presents these elasticities in absolute values for traders 2, 4, 8, and 12, the same traders whose estimated coefficients are shown in Figure 2.[4] Elasticities are calculated for each quantile; dark bars identify those calculated using statistically significant coefficient values. Elasticities show the percent change in portfolio risk as profit$_{t-1}$ changes by 1%. For instance, when the vega of trader 12's portfolio is in the 95th quantile and his profit last week changes by 1% he will change his portfolio's vega by 0.4% this week (Figure 3).

[4] Elasticities are presented in absolute values in Figure 3 as the focus here is on the magnitude of the effect of prior profits. The direction of this effect was previously discussed in Table 1 and Figure 2.

Figure 3: Risk/profit elasticities for each quantile (absolute values)



Dark bars indicate the quantile at which the coefficient on $profit_{t-1}$ is statistically significant.

Two points emerge from the calculated elasticities. First, they are small around the 50th quantile and larger in the tails. Second, they are statistically significant mostly at higher quantiles, or above average risk. These two points suggest that elasticities become statistically distinguishable from zero for risk levels around the 50th quantile, but tend to become larger as risk levels increase. In general this pattern implies that traders are not responsive to prior profits when they are trading at relatively low risk levels, and become increasingly responsive to prior profits as they take more risk. However, overall the calculated elasticities indicate that risk is inelastic with respect to prior profits (i.e. a change in last period's profit leads to a proportionally smaller change in risk in the current period).

CONCLUSION AND DISCUSSION

The study investigates the dynamics of sequential decision-making in commodity futures and options markets using a quantile regression framework. Analysis of trading records of twelve traders suggests that there is much heterogeneity in individual trading behavior. We found five traders who exhibited house-money behavior, four traders who exhibited loss aversion, and three traders for which prior profits did not affect their risk behavior. Traders also respond differently to prior profits based on the extent of risk their portfolios are carrying. In general, risk response to the previous profits is inelastic and no significant response to prior profits is found at average and below-average portfolio risk. However, risk response becomes large and significant at above-average levels of risk.

With regards to dynamic decision making, our findings identify the difficulty in determining whether traders in a market exhibit loss aversion or house money behavior. Assuming all traders have the same probability weighting function that corresponds to objective reality, Coval and Shumway (2005) and Frino et al. (2008) are able to classify their traders as loss averse and house money, respectively. Here, when using risk measures developed from their portfolios, we find behavior across traders differs greatly with respect to loss aversion and house money effect. Part of this heterogeneity may result from market differences, but many of the agricultural markets traded here experienced similar changes in levels and volatility. Further, examination of the risk-responses and characteristics of the markets demonstrated no systematic relationships. In our view, this suggests that care must be taken in empirical work to allow for differences in probability weighting across traders which have been shown to influence dramatically assessment of behavior in other research.

The heterogeneity in trading behavior across quantiles also calls into question basing an assessment of the dynamic risk-response on procedures that focus only on a conditional mean approach. In particular, focusing on the effect of prior profits at the conditional mean of the risk distribution may yield misleading results about dynamic behavior. In our analysis, coefficients on prior profits can rarely be distinguishable from zero around the 50^{th} quantile of the distribution of risk, suggesting that a conditional mean approach would indicate that traders do not respond to prior profits. However, risk responsiveness increases substantially at above-average levels of risk. This behavior would not be captured by the conditional mean approach.

Our results call for research on trading behavior focusing on the tails of distribution of risk, which may help understand market behavior in extreme situations. It is also relevant for managers who train and monitor groups of traders as further research can help them appreciate how traders react to different market conditions. Finally, a better understanding of our results and individual behavior in general also calls for further research into how reference points change over time. We define a constant reference point at zero, i.e. any profit above (below) zero is seen as a gain (loss). But some studies (Kahneman and Tversky, 1979; Weber and Camerer, 1998; Arkes et al., 2008) argue that different traders have different reference point (which may not be zero) or even that the reference point can change over time.

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