Behavioral Biases in Grain Marketing: Evidence from Market Advisory Service Recommendations

by

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Abstract

This study evaluates whether advisory service trading recommendations in corn and soybean markets exhibit evidence of the representativeness bias and loss realization aversion. The representativeness bias implies a naïve extrapolation of past price trends, loss realization aversion refers to the tendency to liquidate winning positions and keep losing ones. Results do not provide evidence of advisory programs extrapolating past price movements. Instead, they are consistent with the belief in a trend reversing mechanism. Also, for advisory programs as a group, there is no relationship between the time that futures positions remain open and whether the positions represent gains or losses. Some individual advisors act as they put limit on losses, using some kind of stop-loss orders, when positions are closed after a maximum acceptable loss is reached.

Agricultural commodity marketing – Behavioral finance – Market advisory services

Market advisory services are firms whose primary activity is the analysis of commodity markets and the development of trading recommendations for market participants. These firms advertise themselves as being able to develop price enhancement marketing strategies for farmers by selecting the appropriate timing and type of transactions to market the crops. For a subscription fee, advisory services provide market information and specific recommendations on marketing transactions via email or web pages at least daily, with some offering multiple updates each day. Market advisory services are popular with US farmers. Several surveys, including Patrick, Musser and Eckman; Schroeder et al. and Penning et al., report that farmers consider professional market advisory services, as an important source of marketing information and advice.

Several studies have evaluated the performance of market advisory services. In these studies, the value of advisory services is measured based on the difference between the price obtained when following advisory service marketing recommendations and external benchmarks, such as the average marketing year cash price. The Agricultural Market Advisory Services (AgMAS) project was initiated at the University of Illinois in 1994 with the goal of providing a complete and rigorous evaluation of advisory services' performance in crop marketing. The performance of at least 23 advisory programs has been tracked for each crop year between 1995 and 2004. In the most recent evaluations, Irwin et al. and Irwin, Good and Martines-Filho indicate that, there is a positive performance for the advisory services when compared to the average price offered by the market, being the price differences of small magnitude.

Previous research on agricultural market advisory services focuses on the effectiveness of marketing recommendations in increasing prices received by farmers without emphasizing on the process employed to develop these marketing recommendations. The objective of the current study is to expand previous research through a deeper analysis of the trading recommendations of agricultural market advisory services.

In recent years, economists have become increasingly concerned with the effects of imperfect rationality on trading behavior (e.g., Lo; Daniel, Hirshleifer and Teoh, Barberis and Thaler). Psychologists have documented extensive evidence of systematic deviations from rationality in the ways that people form beliefs and preferences (e.g., Camerer; Kahneman and Riepe). It is now common in the financial literature to use psychological insights about human behavior to better understand trading behavior and prices in markets.

Brorsen and Anderson (2001) indicated that behavioral theory can be useful in understanding farmers' marketing decisions and should be considered by marketing extension economists when giving advice to them. According to these authors, marketing behaviors that may be related to psychological biases include overestimating one's ability to predict prices, decisions based on a few past price observations, and storing grain too long at a loss. Research studies have found some evidence of behavioral biases in farmers' selling decisions and suggest that farmers should incorporate “disciplined” strategies in marketing plans to reduce the effect of these biases (Brorsen and Anderson, 2005; Cunningham, Brorsen and Anderson). Mechanical marketing strategies are one example, where selling quantities and timing are decided in advance and are fairly stable from one year to the next.

In the current study concepts from behavioral finance are employed to analyze the recommendations of market advisory programs. In particular, this study analyzes whether there is evidence of certain behavioral biases in the strategies recommended by market advisors. It would seem reasonable to expect market experts to have less of a tendency towards behavioral biases. However, previous research indicates that market professionals may be subject to the same types of irrational behavior as individual investors (e.g., Lakonishok, Shleifer and Vishny; Locke and Mann; Haigh and List).

Only one previous study has indirectly investigated behavioral biases on the part of agricultural market advisory services. Cabrini, Irwin and Good examined the recommendations of advisory services for evidence of an overconfidence bias, which results from advisors overestimating their ability to forecast price movements. A positive relationship between the degree of activeness in marketing recommendations and pricing performance was found in the study, suggesting that more active programs are based on superior information and/or analytical skills, rather than on overconfidence.

Two other important behavioral biases have been widely studied in the finance literature in the last years: representativeness bias and loss realization aversion. Extensive research work has been done in the theoretical modeling of the relationship between these philological biases and trading behavior. Additionally, several empirical studies analyzed these behavioral biases based on experimental and actual market transactions data.

The representativeness bias is a commonly observed behavior that refers to the tendency to believe that small samples are more informative about some population characteristics than actually is the case (Tversky and Kahneman, 1971). There is evidence that people assign excessive weight to recent or salient information, even when it concerns only a small sample (Tversky and Kahneman, 1974). This behavioral bias predicts, for instance, that investors may extrapolate past price trends naïvely. Loss realization aversion is related to the tendency to hold losing positions too long. This behavior is related to prospect theory (Kahneman and Tversky) and implies that individuals are risk-averse over gains and risk-seeking over losses and have greater sensitivity to losses than gains. Prospect theory predicts that investors will have a tendency to liquidate winning positions and keep losing ones (Shefrin and Statman).

The purpose of this study is to investigate the process that advisory programs employ to develop marketing recommendations. In particular this study evaluates whether advisory service recommendations in corn and soybean markets exhibit evidence of the representativeness bias and loss realization aversion. Representativeness bias is measured by the relationship between trading recommendations and recent price history. Loss realization aversion is evaluated by comparing the holding time of gaining vs. losing positions in futures markets. The analysis is based on the recommended transactions of corn and soybeans advisory programs tracked by the AgMAS Project at the University of Illinois.

Data

The sample for this study consists of advisory programs evaluated by the AgMAS project for the 1995 through 2004 corn and soybean crops. The term "advisory program" is used because several advisory services have more than one distinct marketing program. When it was first launched, AgMAS monitored and evaluated a sample of 25 advisory programs, including the most popular among Midwest farmers. Additions and deletions to this original sample occurred for a variety of reasons, resulting in 23 to 27 programs each crop year, with a total of 41 programs considered in at least one crop year. A list of the included advisory programs and years they were evaluated by AgMAS is presented in table 1. AgMAS subscribes to the services that are followed and records their marketing recommendations on a real-time basis. This process assures that all recommendations, along with the exact time when they were delivered to farmers, are recorded by the project. The richness of this data set provides a unique opportunity to explore the different aspects of marketing programs recommended by advisory services.

Representativeness Bias

The rational method of forming expectations about future price movements is often described as a Bayesian updating process. This implies that individuals have some prior beliefs and, as new information becomes available, they update the prior beliefs with the new data following Bayes rule. However, psychologists documented systematic biases in this updating process, leading to predictable errors in people's forecasts. The r*epresentativeness heuristic* bias is a commonly observed behavior that refers to the tendency to believe that small samples are more informative about some population characteristics than they actually are (Tversky and Kahneman, 1971). There is evidence that people assign excessive weight to recent or salient information, even when it concerns only a small sample (Tversky and Kahneman, 1974). The representativeness bias leads, for instance, to a clustering illusion with people perceiving random clusters as reflecting some pattern. This behavioral bias predicts that investors may extrapolate past price trends naïvely. For example, successive upward price movements that are highly probable in a random walk process are interpreted as a positive trend that is expected to continue in the future.

Lakonishok, Shleifer and Vishny studied trading behavior of institutional investors and they found that there is a tendency to buy past winners and sell past losers for small stocks.

Marketing decisions may also suffer from representativeness bias. For instance, some trading decisions could be based on naïve extrapolation of recent price history. Brorsen and Anderson (2005) found empirical evidence that wheat farmers tend to hold the grain after price increases and sell after price decreases. McNew and Musser employ a game setting to investigate preharvest selling decisions of six grain marketing clubs in Maryland and found a tendency to sell less when the recent price history showed a positive trend. However, the relationship between sales and trend is significant only for two of the six clubs examined.

To consider whether trading recommendations of advisory programs are related to recent past prices movements, different methods of measuring price trends will be considered, including lagged price changes and trend-following technical trading systems. The procedures and results for each approach are presented below.

Relationship between Recommended Transactions and Lagged Futures Returns

The simplest way to model the relationship between trading recommendations and recent price history is with a linear regression model. Several studies have used this approach for testing the relationship between past price history and trading decisions in futures markets (e.g., Irwin and Yoshimaru; Sanders, Boris and Manfredo). The following regression model was estimated:

(1)
$$\Delta I_{it} = \alpha + \sum_{j=1}^{n} \beta_j r_{t-j} + \varepsilon_{it}$$

where ΔI_{it} is change in the net amount priced, as percentage of total crop production, for program *i* on day *t*. All positions in cash, forward, futures, and options markets recommended by a program are combined into an index (I_{it}) of the cumulative percentage of a crop priced for each day in the marketing window. The percentage of the crop sold under cash, forward contract or futures positions is added to compute the total percentage priced. Likewise, the percentage of the crop owned under long futures positions is subtracted. Option delta is used to convert an option position into an equivalent position in the underlying futures market in terms of price sensitivity. A complete explanation on the index computation can be found in Colino et al. (2006a, 2006b). The change in the index ΔI_{it} takes positive values when transactions that represent sales of grain are recommended, negatives values when transaction that represent purchases of grain are recommended and equals 0 for days without new trading recommendations. The explanatory variable, r_{t-j} , is the continuously-compounded futures return j days in the past, expressed as percentage. Futures returns are computed using futures prices expiring at harvest for the preharvest months and nearby futures for the postharvest months.[1] The number of lags is defined based on AIC values. Negative and significant values for the slope coefficients would indicate that advisory programs sell more after price decreases and therefore are consistent with recommendations being based on extrapolation of past price trends. The net trend effect is measured by the sum of the slope coefficients. [2]

Table 2 presents the estimation results for model (1) in corn and soybean markets. Note that the results are similar for both crops. The estimated coefficient for the first lag is negative and the rest of the coefficients are positive, with most of them being statistically significant and small in magnitude. A negative coefficient for the first lag indicates that advisory programs are more likely to recommend higher crop sales following a day with price decrease. The rest of the coefficients indicate the opposite effect, with sales of crops being higher after price increases. The sum of the estimated coefficients is positive and significant for both crops, which indicates that advisors tend to recommended more crop sales after a price increase in the preceding week. However, note that effect is of small magnitude. For instance in corn, an increase in past returns of 1% is associated with an increase of 0.05% in crop sales. [3]

Relationship between Recommended Transactions and Trend Indicators

An alternative approach to trend definition is to use trend-following systems from technical analysis. This seems a reasonable approach since advisory programs commonly mention technical indicators in their market analysis reports and marketing recommendations. In the current study three systems are considered, *Simple Moving Average with Percentage Price Band, Dual Moving Average Crossover* and *Outside Price Channel*. These systems were selected because they are the most popular and simple trend-following systems employed in technical trading (Park and Irwin).

The Simple Moving Average with Percentage Price Band (MAB) is based on the price moving average for the last *n* days and a band surrounding this value, with the band being defined as a proportion of the moving average. A current price above and outside the band indicates a positive trend. A current price below and outside the band indicates a negative trend. Prices within the band are related to non-trending conditions. Equations (2) to (4) show moving average and band limits computations:

(2) $$MA_t = \frac{\sum_{j=1}^{n} P_{t-j}^{c}}{n}$$ Moving average

(3) $$MA_t + b\ MA_t$$ Upper band limit

(4) $$MA_t - b\ MA_t$$ Lower band limit

where P^c_{t-j} is the closing futures price *j* days in the past. This system is similar to the one employed by McNew and Musser to analyze farmers' preharvest pricing behavior.

For *Dual Moving Average Crossover (DMC)* two moving averages are compared, a shorter moving average (SMA_t) and a longer moving average (LMA_t):

(5) $$SMA_t = \frac{\sum_{j=1}^{s} P^c_{t-j}}{s}$$ *Shorter moving average*

(6) $$LMA_t = \frac{\sum_{j=1}^{l} P^c_{t-j}}{l}$$ *Longer moving average*

where $s < l$. The system indicates an upward trend if $SMA_t > LMA_t$ and a downward trend if $SMA_t < LMA_t$.

Outside Price Channel (OPC) compares the current price with the price range observed in the previous *n* days. Two price levels are defined, the *highest high* which is the highest of the daily maximum futures prices observed in the past *n* days. And the *lowest low*, which is the lowest of the daily minimum futures prices observed in the past *n* days.

(7) $$HH_t = \max(P^h_{t-1}, P^h_{t-2} ..., P^h_{t-n})$$ *Highest high*

(8) $$LL_t = \min(P^l_{t-1}, P^l_{t-2} ..., P^l_{t-n})$$ *Lowest low*

A current closing price higher than HH_t indicates an upward trend and a closing price lower than LL_t, a downward trend. A closing price in between LL_t and HH_t indicates a non-trending situation.

In each of the three systems it is necessary to assign values for the parameters. In the current study the parameters are set equal to the average of the values that generated maximum trading profits for the years 1978 through 1993, as reported by Park and Irwin. In the corn market the parameters are n =36 and $b=0.03$ for *SMA*; $s=13$ and $l=53$ for *DMAC* and $n=31$ for *OPC*. In the soybean market the parameters are n =38 and $b=0.03$ for *SMA*; $s=15$ and $l=45$ for *DMAC* and $n=22$ for *OPC*. For each day in crop years 1995 through 2004 a trend indicator under each of the three systems is computed. Then, the number of days with each possible combination of trading recommendation and trend signal is recorded. Therefore, for each system, data consists of absolute frequencies of days with:

- Upward trend signal and sell recommendation
- Downward trend signal and sell recommendation
- No trend signal and sell recommendation
- Upward trend signal and purchase recommendation
- Downward trend signal and purchase recommendation
- No trend signal and purchase recommendation
- Upward trend signal and no trading recommendation
- Downward trend signal and no trading recommendation
- No trend signal and no trading recommendation.

The trend signal is based on the value of the technical indicator on the previous date. A sell recommendation corresponds to $\Delta I_{it} > 0$, a purchase recommendation to $\Delta I_{it} < 0$ and a no trading recommendation to $\Delta I_{it} = 0$, with ΔI_{it} defined as in the previous paragraphs.

A χ^2 tests for independency is performed to test the null hypothesis of no relationship between trading recommendations and trend indicators. Expected frequencies under the null hypothesis that trades and trends indicators are independence are computed and compared to observed ones. The Pearson-χ^2 test statistic is computed as:

(9)
$$\chi_v^2 = \sum_{i=1}^{l}\sum_{j=1}^{k}\frac{(o_{ij}-e_{ij})^2}{e_{ij}},$$

where i refers to the trend signal, *i={upward trend, downward trend, no trend}*[4], and j refers to the trade recommendation, *j={net sell recommendation, net buy recommendation, no trade recommendation}*, o_{ij} and e_{ij} are observed and expected frequencies of days for each combination of events.

Figures 1 and 2 present some descriptive results of relative frequencies of days with sell and purchase recommendations. White bars represent the percentage of days with purchase recommendations $(\Delta I_{it} < 0)$, and gray bars percentage of days with sell recommendations $(\Delta I_{it} > 0)$. If there were not a relationship between trading recommendations and past price movements, the bars with the same color would have similar height across trend indicators. Note that this is not the case, instead there is a tendency of higher proportion of days with sell recommendations for upward trend. For example, panel A in figure 1 indicates that there were sell recommendations in approximately 2% of the days with downward trend or no trend, instead there is a 3% of days with sell recommendations on upward trend days. The formal testing for differences in frequencies is presented below.

Tables 3 and 4 present the results of the analysis of the relationship between trading recommendations and trend signals. The tables contain the contingency tables with the frequency of days with sell, buy and no trade recommendations for days with upward, downward and no trend signal. These values combine the information of all advisory programs in the sample. For each combination of events the tables present the observed and expected frequency.

Expected frequencies are the number of days in which each combination of events would occur if the trading recommendations were independent of the trend signals. Note, for example, that for SMA in the corn market, the observed frequency of sell recommendations and upward trend signal is 50% higher than expected (971 vs. 651), and the number of days with buy recommendation and downward trend signal is 14 % higher than expected (284 vs. 248). In the other tables the relationship between observed and expected frequencies are similar. In all cases the frequency of sell recommendation and upward trend signal is greater than expected, and in most cases the frequency of buy recommendation and downward trend signal is also higher than expected. In all cases the Pearson χ^2 test-statistic and the related p-values listed below each contingency table indicate that trading recommendations are not independent of trend indicators.[5]The results from testing the relationship between trading recommendations and trend signals are not consistent with advisory programs naively extrapolating past price movements.

Overall, the two procedures used to measure the relationship between past price movement and trade recommendations provide the same information. Results indicate that advisory programs tend to deliver sell recommendations after price increases and buy recommendations after price decreases. This result is not consistent with advisory programs naively extrapolating past price movements. Instead, the relationship between trading recommendations and lagged returns are consistent with the belief that an increase (decrease) in price is followed by a decrease (increase) in price, under this view selling after an increase in price would be a profitable strategy. This kind of behavior has been called *contrarian* by other others and has been documented for the financial markets (e.g., Dhar and Kumar).

Loss Realization Aversion

Expected utility theory (Von Neumann and Morgenstern) is often employed to study decision making under uncertainty. However, there is wide evidence that in many circumstances this theory fails to predict people's choices. Kahneman and Tversky documented systemic deviations from expected utility theory in the way people order alternatives. Based on this evidence, the researchers developed *prospect theory* as an alternative model to explain the structure of people's preferences. Prospect theory suggests that people behave as if they maximize an "S-shaped" value function, which is defined with respect to gains and losses (Figure 3). The value function is concave for gains and convex for losses and steeper for losses than for gains. This shape implies that people evaluate alternatives as gains/losses with respect to a reference point. It also implies that individuals are risk averse over gains and risk seeking over losses and have greater sensitivity to losses that gains. This kind of behavior is known as *loss aversion*.

Shefrin and Statman related the shape of the prospect theory valuation function with the tendency of investors to liquidate winning positions and keep losing ones. Consider, for example, the case of someone who opens a sell (short) position in the futures market in the first period. In the next period price goes up and the trader loses $100. After this initial price movement the individual faces the decision of closing the position and realizing the $100 loss, or keeping the position open for the next period. Suppose that he/she believes that there is a 50/50 % probability of prices going up or down in the following period, implying an equal chance of a total loss of the $200 and breaking even. The convex shape of the valuation function for losses implies that the choice will be to stay one more period in the market. On the contrary, if the first result of the position was a $100 win, for the second period, the individual would consider the concave part of the valuation function and the best choice would be to liquidate the position. Shefrin and Statman called this behavior the *disposition effect.*

A related concept that contributes to explain the delay in selling losing positions is *mental accounting*. Shefrin and Statman suggested that when a stock is purchased a new mental account is opened with the asset purchasing price as the reference point. Decision makers are reluctant to close a mental account at a loss. Professional investors, aware of this psychological bias, use certain rules to mandate realization of losses. An example of this rule is: “never let a loss be greater than 10%”.

Several studies in the finance literature have searched for evidence of loss aversion in trading decisions. Odean found evidence that individual investors sell winners more readily than losers. He suggests that behavior is consistent with prospect theory and also with investors having the mistaken belief that losses will mean revert. Locke and Mann found that professional traders, who are expected to be more disciplined in trading decisions, also exhibit loss realization aversion. The authors examine the behavior of futures traders operating for their personal accounts in the Chicago Mercantile Exchange. Their results indicate that, as a group, professional futures traders hold losses significantly longer than gains, differences being more important for futures on agricultural commodities than financial futures. Moreover, for traders with the lowest performance the disposition effect was more important.

In the agricultural marketing literature, Brorsen and Anderson (2001) and Cunningham, Brorsen and Anderson suggested that loss aversion may explain farmers storing grain at a loss after they passed the economically optimal selling time. The current study evaluates whether there is evidence of loss realization aversion in market advisory service recommendations. In particular, it is consider whether the timing for closing recommended positions in futures markets can be related to loss realization aversion.

The analysis is based on the recommended positions in derivatives. Cash positions are not considered in this case, since the interest is in the timing of closing the positions, and cash transactions cannot be cancelled by making the opposite trade. For simplicity, only the futures position on the contract expiring after harvest of each year will be considered. This is the December futures contract for corn and the November futures contract for soybean. These are the contracts most commonly used in the marketing programs. For each advisory program in each crop year, the time that each position in December corn futures and November soybeans futures remain open is divided into gaining and losing periods. A gaining period consists of consecutive gains for the position and a losing period consist of consecutive losses, with gains and losses measured with respect to the position's opening price. The length of each period is recorded, along with the information of whether or not the position is closed at the end of the period. Some gaining and losing periods end, not because the futures position is closed, but because a loss occur after a gaining period, a gain occur after a losing period, or the position reaches the expiration date. In this cases this lengths times are recorded as "censored". A censored time of 10 days indicates that the position was still open on the 10th day from the opening time, while an observed time of 10 days indicates that the position was closed on the 10th day.

Similar to the approach used by Locke and Mann, when a recommendation increases the size of an existing futures position the opening price is updated to reflect a weighted average of the previous opening price and the new opening price, with the weights determined by the size of the transactions. Also, when a position is closed in two or more different dates, the closing times are record as observe times and the day count keeps increases until the position is fully liquidated. An example of holding times computations is presented in table 5 for a hypothetical position in corn December futures for the 2002 crop year.

The data of censored and observed holding times is used to estimate survival functions for gaining and losing positions. A survival function, *S(t)*, measures the probability that a futures position will remain open for more than *t* days. For example, *S(30)=0.25* indicates that there is a 25% of probability that a position will be open 30 or more days. Survival functions for gaining vs. losing positions are compared using the log-rank test. A statistically significant difference between the survival functions with longer holding times for losing positions would be consistence with the existence of loss realization aversion in trading recommendations of market advisory programs.

The estimated survival curves for gaining vs. losing positions are presented in figures 4 and 5 for corn and soybeans futures transactions, respectively. Note by comparing the two curves in each figure, that the distributions of holding time for gaining positions and losing positions are similar. For example in corn futures, the probability of surviving more than 50 days is approximately 45% for both curves. For larger times the curves are more different with a probably greater than zero of surviving more than 200 days only for gaining positions. However, the differences between the survival curves are not significant. The p-values from the Log-rank test for equality between the survival functions are 0.34 and 0.3 for corn and soybeans, respectively. These results indicate that gains or losses generated by an open position do not appear to affect the decision to terminate it.

Survival analysis results for individual programs (not presented) indicate that only in three programs for corn (no. 8, 35 and 39) and soybeans (no. 8, 18 and 37) the survival functions of gaining vs. losing positions are statistically different. For these 6 programs the holding time tends to be shorter for loosing positions. Overall the survival analysis results provide no evidence that advisory programs tend to hold longer losing positions in futures markets.

Summary and Conclusions

In this study, concepts from behavioral finance are employed to study the process that market advisory services employ to develop marketing recommendations. The analysis is based on the recommended transactions of advisory programs tracked by the AgMAS Project at the University of Illinois between 1995 and 2004. Specifically, the purpose of this study is to evaluate whether advisory service recommendations in corn and soybean markets exhibit evidence of the representativeness bias and loss realization aversion.

The representativeness bias implies a naïve extrapolation of past price trends. The relationship between recent price history and trading recommendations is analyzed using lagged futures returns and trend indicators from technical trading systems. Results indicate that advisory programs tend to deliver sell recommendations after price increases and buy recommendations after price decreases. This result does not provide evidence of advisory programs naively extrapolating past price movements. Instead, the relationship between trading recommendations and past price trends is consistent with the belief in a trend reversing mechanism. This kind of behavior has been documented for the financial markets by other authors (e.g., Dhar and Kumar). The magnitude on the effect of trends on trading recommendations is of very small magnitude suggesting that there is not a strong influence of recent price history of trading recommendations.

Loss realization aversion is investigated by comparing the holding time of gaining vs. losing positions in futures markets. For this analysis, December corn futures and November soybeans futures transactions are considered. Results provide no evidence of market advisors holding longer losing positions, and therefore are not consistent with loss realization aversion. For advisory programs as a group, there is no relationship between the time that futures positions remain open and whether the positions represent gains or losses. A few programs tend to liquidate earlier losing positions. This result may indicate that these advisors put limit on losses, using some kind of stop-loss orders, when positions are closed after a maximum acceptable loss is reached.

This research is the first to apply behavioral finance concepts to study the trading recommendation of agricultural market advisory services. Overall, results show that this group of professional traders does not have a strong tendency towards the behavioral biases analyzed. An interesting extension of this research would be to carry the same analysis with marketing transaction of farmers who do not follow the recommendations of professional market advisors. It is possible that some farmers could have a stronger tendency to these behavioral biases. In this case the access to the required data is surely the major challenge.

Endnotes

[1] Returns are recorded as missing for days when there is a change in the contract expiration month.

[2] Note that the independent variable in the regression model differs from the one employed in the cited studies. In these studies it takes positive values for long futures transactions (purchase transactions).

[3] The same regression was estimated for individual programs (results not presented). In the corn market, the sum of the five coefficients is positive and significant for approximately half of the programs and only one program (no.20) has negative and significant sum of coefficient. For one third of the soybeans programs the sum of the five coefficients is positive and significant, and it is negative and significant for only one program (no. 3). These results indicate that for half of the programs in corn and for most programs in soybeans there is no evidence of a relationship between the trading recommendations and recent past price history, only one program in each market shows evidence consistent with advisors naïvely extrapolating past price movements.

[4] i={upward trend, downward trend} for DMAC since under this indicator there is always a trend signal, upward or downward.

[5] The relationship between trading and trend indicators was also analyzed for individual programs (results not presented). For one third to half of the programs the null hypothesis of independency between trading recommendations and trend signal is reject (α=0.1), depending on the trend-following system employed. In most cases the relationship between observed and expected frequencies indicates a tendency to sell more with upward trends indicators. However,

for two of the programs selling is more likely in days with downward trend, under DMAC and OPC trend-following systems.

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