Smart Money?

The Forecasting Ability of CFTC Large Traders

by

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Practitioner's Abstract

The forecasting ability of the Commodity Futures Trading Commission's Commitment's of Traders data set is investigated. Bivariate Granger causality tests show very little evidence that traders' positions are useful in forecasting (leading) market returns. However, there is substantial evidence that traders respond to price changes. In particular, non-commercial traders display a tendency for trend-following. The other trader classifications display mixed styles, perhaps indicating that those trader categories capture a variety of traders. The results generally do not support the use of the Commitment's of Traders data in predicting market movements.

Key Words: Commitment's of Traders, futures markets, forecasting

Introduction

The Commodity Futures Trading Commission's (CFTC) Commitment of Traders (COT) report highlights the aggregate futures positions held by reporting (large) traders, both commercial (hedgers) and non-commercial (speculators). Commodity futures traders often view these data as akin to insider information about the positions of "smart money" traders and tout its usefulness in predicting price movements, where "indicators derived from the participant activity can provide insight into the future direction of price" (Upperman, p. 1). This contrasts with the CFTC's use of the reports as a component of the market monitoring and Large Trader Reporting System (CFTC).

Several academic studies have investigated the ability of large traders to predict or forecast returns in futures markets. For example, in an early look at this topic, Kahn uses the COT report to mimic the positions of reporting non-commercial traders. He finds that following their positions (upon release of the COT reports) does not generate statistically significant profits. More recently, Wang found that over intervals from one to twelve weeks, that non-commercial traders' positions forecast price continuations and commercial traders forecast price reversals. In the energy markets, Buchanan, Hodges, and Theis, find that non-commercial speculative positions provide information on the magnitude and direction of weekly price changes in the natural gas futures market. In contrast, Sanders, Boris, and Manfredo fail to find any evidence that reporting traders' positions, either commercial or non-commercial, are useful in predicting weekly energy futures returns. Most recently, Bryant, Bessler, and Haigh use causal inference algorithm's to test for relationships between traders' positions from the COT reports and futures prices. The author's results "call into question the usefulness of the COT data in formulating successful speculative strategies" (p. 1054). While these studies are important, recent shifts in market participation warrant further investigation.

In recent years, academic studies have shown that commodity futures portfolios can generate returns comparable to equities (Gorton and Rouwenhorst). As a result, the financial industry has developed products that allow institutions to "invest" in commodities through long-only index funds. The rapid growth in these non-traditional speculators has led traders to claim that the excessive speculation is creating "price distortions" in traditional agricultural commodity markets (Morrison, 2006). Indeed, Domanski and Heath argue that the "financialisation" of commodity markets warrants additional study on the strategies, motivation, and the potential market impact of non-traditional traders. Along these lines, the CFTC recently reviewed the COT reports and have added an “index trader” category to the COT classifications for agricultural commodities (CFTC). Clearly, the markets are changing, and it is important that researchers, regulators, and market participants understand the relationship (if any) between trader positions and price behavior

The goal of this research is to thoroughly address the predictive value of trader positions in agricultural futures markets. Specifically, Granger causality will be used to directly test for the impact of traders’ positions on futures returns using weekly data from 1992 through 2006. A number of different position measures will be used to explore the sensitivity of the results to these “indicators.” Trading styles are also revealed by examining the causality from returns to positions, revealing if CFTC traders are trend followers or adhere to value or contrarian type strategies.

The research results are of interest to academics and traders alike. Academic researchers gain a more thorough understanding of this important data. Also, the research will help to answer some crucial questions about trader behavior and the potential impact of speculation on agricultural futures prices. Finally, traders and other market participants will benefit from a rigorous analysis of the COT data. Analysts may find that the COT data provides little insight as to future price direction. Or, alternatively, they may want to start following the “smart money.”

COT Data

The COT report provides a breakdown of each Tuesday’s open interest for markets in which 20 or more traders hold positions equal to or above the reporting levels established by the CFTC. The weekly reports for *Futures-Only Commitments of Traders* and for *Futures-and-Options-Combined Commitments of Traders* are released every Friday at 3:30 p.m. Eastern Standard Time.

Reports are available in both a short and long format. The short report shows open interest separately by reportable and non-reportable positions. For reportable positions, additional data are provided for commercial and non-commercial holdings, spreading, changes from the previous report, percentage of open interest by category, and number of traders. The long report, in addition to the information in the short report, also groups the data by crop year, where appropriate, and shows the concentration of positions held by the largest four and eight traders.

In early 2007, as a response to complaints by traditional traders about index traders, the CFTC released supplemental reports which also break out the positions of index traders for twelve agricultural markets. The release of this report offers historical data starting in 2006, and it largely confirms the presupposition that index traders are generally long-only traders. As an example, in the corn futures market, index traders are 96% long and hold roughly 12% of the open interest. In Chicago Board of Trade wheat futures, index traders are reported to remain 95% long and maintain 21% of the market’s open interest. The traders in the index category were found to have come from both the commercial and non-commercial categories. As expected, index traders seldom alter positions other than to roll contract months, resulting in virtually no variation in their directional position. The index trader data is insightful in regards to market composition, and it undoubtedly will warrant alternative paths of inquiry. However, for the focus of this research, the negligible variation in these “long-only” traders’ positions makes it highly unlikely that they contain any predictive power. Likewise, the strategies and motivations for this group of traders are clear.

Therefore, here, we focus on the traditional CFTC classifications: commercials, non-commercials, and non-reporting traders.

Using the information in the short report, non-commercial open interest is divided into long, short, and spreading; whereas, commercial and non-reporting open interest is simply divided into long or short. The following relation explains how the market's total open interest (TOI) is disaggregated:

$$(1) \qquad \underbrace{[NCL + NCS + 2(NCSP)] + [CL + CS]}_{\text{Reporting}} + \underbrace{[NRL + NRS]}_{\text{Non-Reporting}} = 2(TOI)$$

where, NCL, NCS, and NCSP are non-commercial long, short, and spreading positions, respectively. CL (CS) represents commercial long (short) positions, and NRL (NRS) are long (short) positions held by non-reporting traders. Reporting and non-reporting positions must sum to the market's total open interest (TOI), and the number of longs must equal the number of short positions.

Data on trader positions are collected for each Tuesday from 1995 through 2006, resulting in 616 observations. The *COT* data reflects traders' positions as of Tuesday's close; although, for much of the sample it is not released until Friday. A matching set of futures returns, $R_t = \ln(p_t/p_{t-1})$, are calculated for nearby futures using Tuesday-to-Tuesday closing prices. We make no assumptions about how or why traders' positions might change over the course of a week, and the data are organized such that the collected prices are coincidental with the reported positions.

Position Indicators

Prior research results have varied, potentially due to alternative measures of position size. For example, Sanders, Boris and Manfredo utilize the a measure of speculative pressure proposed by De Roon, Nijman, and Veld and fail to find any market impact caused by trader groups. In contrast, Wang utilizes a "sentiment index" that normalizes positions by there three year range. Using this index, Wang finds a market impact of in some agricultural futures. The disparity of results suggests that multiple position indicators should be utilized to understand the robustness of the results.

The first position indicator utilized is the "percent net long" (PNL), which measures the net position of the average trader in a CFTC classification (De Roon, Nijman, and Veld). The PNL is calculated as the long minus the short positions divided by their sum. For instance, the percent net long for the reporting non-commercials is defined as follows:

$$(2) \qquad \text{Non-Commercial}\, PNL_t = \frac{NCL_t - NCS_t}{NCL_t + NCS_t}.$$

The PNL for each CFTC classification represents the net position held by the group normalized by their total size.

The second position measure is Wang's "sentiment index", $SI_{i,t}$. Wang defines the net long position for each trader category, $S_{i,t}$, as the total long positions minus the total short positions for that category at time t. Then, Wang defines his sentiment index by normalizing the net long position by its range over the prior three years,

(3) $$\mathrm{SI}_{i,t} = \frac{S_{i,t} - Min(S_{i,t})}{Max(S_{i,t}) - Min(S_{i,t})}.$$

Where, the minimum and maximum functions are applied to the prior three years. Wang's sentiment index is essentially an oscillator bound in the range (0,1). A value of 0 indicates that the net long position is at a three year low, while a value of 1 occurs when the net long position or trader sentiment is at a three year high.

The use of multiple position measures is important to make the empirical results comparable to the literature and more robust. In the following section, we demonstrate how these position measures are used to uncover statistical lead-lag relationships within the data using Granger causality.

Method

Hamilton suggests the direct or bivariate Granger test for examining the lead-lag or "causal" relationship between two series. Granger causality is a technique for determining whether one time series is useful in forecasting another. It consists of running a vector autoregression (VAR) and then testing the resulting coefficients. A VAR with two time series variable, x_t and y_t, consists of two equations: in one, the dependent variable is y_t; in the other the dependent variable is x_t. The regressors in both equations are lagged values of both variables. More generally a VAR with k time series variables consists of k equations, one for each of the variables, where the regressors in all equations are lagged values of all the variables. The coefficients of the VAR are estimated by estimating each of the equations using OLS. Under the VAR assumptions the OLS estimators are consistent and have a joint normal distribution in large samples, and statistical inference proceeds in the usual manner.

In our case the two time series variables we use are futures returns and trader positions (PNL or SI). The following models are estimated,

(4) $$R_t = \alpha_t + \sum_{i=1}^{m} \gamma_i R_{t-i} + \sum_{j=1}^{n} \beta_j PNL_{t-j} + \varepsilon_t \text{ , and}$$

(5) $$PNL_t = \phi_t + \sum_{i=1}^{n} \lambda_i PNL_{t-i} + \sum_{j=1}^{m} \theta_j R_{t-j} + \omega_t$$

Each model is estimated for lag lengths of 1 to 12, and the lag structure of the most efficient model is selected by minimizing the AIC criteria. The models are estimated with OLS. If the residuals demonstrate serial correlation (Breusch-Godfrey Lagrange multiplier test), the additional lags of the dependent variable are added until the null of no serial correlation cannot be rejected. We test for heterskedasticity using White's test (1980), and White's robust errors where used to correct the standard errors.

In equation (4), the null hypothesis of interest is that traders' positions (PNL) cannot be used to predict (do not lead) market returns:, $H_0 : \beta_j = 0$ for all j. A rejection of this null hypothesis would provide evidence trader positions are indeed useful for forecasting market returns. In order to gauge the aggregate impact of trader positions, we also test the null hypothesis that $\sum_{j=1}^{n} \beta_j = 0$, which will reveal the cumulative impact of traders positions on returns (if any). Finally, the null hypothesis if full rationality (efficiency) in futures returns ($\gamma_i = \beta_j = 0 \forall i, j$) and autocorrelation in returns ($\gamma_i = 0 \forall i$).

In equation (5) there are two null hypothesis of interest. First, do returns lead traders' positions, $\theta_j = 0$ for all j? Second, what is the cumulative impact of past returns on traders' positions ($\sum_{j=1}^{n} \Theta_j = 0$). If we reject that $\theta_j = 0$ and find that $\sum_{j=1}^{n} \Theta_j > 0$, then the trader group may be classified as trend followers or "positive feedback" traders because they increase their long position after prices increase and vice versa. Conversely, traders who buck the trend may be called "negative feedback" traders or contrarians. In equation (5), contrarians are characterized by finding that $\theta_j \neq 0$ and $\sum_{j=1}^{n} \Theta_j < 0$. These traders tend buy after price declines and sell after price rallies, essentially a counter-trend strategy. The tests outlined in equations (4) and (5) will provide important insight in regards to the usefulness of the COT data in predicting price movements and the trading "style" of each trader group.

Results

Trends in Positions

The data are first examined visually to reveal simple trends and basic characteristics. In this section, we concentrate on a major feed grain, corn, and a major livestock market, live cattle. The trends in these futures markets are generally representative of the agricultural markets included in the study. Figure 1 shows the total open interest (futures plus delta-adjusted options) for corn (panel A) and live cattle (panel B). Total open interest for corn was relatively steady between 500 and 700 thousand contract through mid-2003. Then, open interest increased steadily to over 2 million contracts in late 2006. Over the same period, live cattle open interest experienced a doubling from 300 thousand to 600 thousand contracts. Many market participants attribute this increase to greater overall speculative activity, including long-only index funds (O'Hara). However, as shown in Figure 2, the COT trader classifications are unable to confirm (or deny) this conjecture. Indeed, over the same time period, the commercial corn positions (panel A) were relatively flat at 45%-50% of total open interest. But, there was marked increase in non-commercial activity from roughly 30% of open interest to more than 35% of open positions. However, this increase came mostly at the expense of non-reporting speculators, whose open interest declined from nearly 25% to below 15%. Similar trends are shown for live cattle (panel B), where commercial positions are relatively stable and the non-commercial position size increases at the expense of the non-reporting group. Since non-reporting traders are not classified as commercial or non-commercials, we do not know if there was a relative loss of commercial or speculative traders. Still, it is clear from Figures 1 and 2 that the markets seem to have undergone some structural changes since 2003, which gives rise to this investigation.

In this research, two position measures—percent net long (PNL) and the sentiment index (SI)—are utilized to summarize the net position held by each trader category. To illustrate these measures through time, the PNL and SI for non-commercial corn positions are plotted in Figure 3. In Figure 3, it is clear that the PNL and SI are highly correlated in both corn (panel A) and live cattle (panel B) with a simple correlation coefficients in excess of 0.90. Because of the high correlation across measures, it is unlikely that the empirical methods will generate dramatically different results across alternative position measures.

Traders often cite the COT positions as a cause of price moves or a reason to expect a “sell-off” or “rebound” in prices. Indeed, many market analysts make weekly assessments of trader positions as part of their market commentary (Upperman). In Figure 4, a simple visual analysis does indeed reveal an apparent relationship between corn price levels and the PNL for non-commercial corn traders. For instance, in panel A, a high corn price (325 cents per bushel) in early 2004 coincided with non-commercial traders being over 40% net long. However, the visual evidence can be misleading. A high contemporaneous correlation (0.62) between non-commercial PNL and corn price levels clearly does not imply causality from positions to prices. In the following section, the data are subjected to a more rigorous causal test for predictive ability.

Do Positions Lead Returns?

Equation (4) is estimated to test if trader positions are indeed useful in forecasting returns. In particular, a rejection of $\beta_j = 0\ \forall$j would provide some evidence that the importance placed on the COT data by the trading industry is well-founded. The p-values for this and the other null hypothesis of interest are presented in Tables 1, 2, and 3 for the non-commercial, commercial, and non-reporting trader groups, respectively.

In Table 1, the null hypothesis that non-commercial positions (PNL) lead or forecast market returns is rejected at the 5% level only in soybeans (p-value =0.046). In five of the model specifications, lagged values of the positions enter the equation at just a single lag. In those where there are more than a single lag, the null hypothesis ($\beta_j = 0\ \forall$j) is still not rejected, and the cumulative position impact ($\sum_{j=1}^{n}\beta_j$) is also not statistically different from zero. Collectively, there is little evidence that non-commercial positions are systematically useful in predicting returns. Interestingly, however, full rationality in futures returns ($\gamma_i = \beta_j = 0 \forall i, j$) is rejected at the 5% level in two markets mostly to a low-order autocorrelation in returns ($\gamma_i = 0 \forall i$), which is rejected at the 5% level in three markets.

The null hypothesis that commercial trader positions do not lead futures returns is rejected in CBOT wheat, KCBT wheat, and lean hogs. So, in three of the ten markets, there is some evidence that commercial traders’ positions are useful in forecasting returns. In both of the wheat markets, we reject $\sum_{j=1}^{n}\beta_j = 0$ and find that the cumulative directional impact is positive, suggesting that commercials increase long positions prior to price increases. In lean hogs, the aggregate impact is not statistically different from zero, suggesting an unusual directional impact with some lagged β coefficients positive and others negative. While this evidence is not overwhelming, there is certainly more evidence of forecasting ability among commercial traders than among non-commercials. Again, it is worth noting that full rationality in futures returns ($\gamma_i = \beta_j = 0 \forall i, j$) is rejected at the 5% level in six markets primarily due to a low-order autocorrelation in returns ($\gamma_i = 0 \forall i$), which is rejected at the 5% level in four markets.

In Table 3, we see that the null hypothesis that non-reporting traders' positions do not lead returns is not rejected at the 5% level for any market. There is no substantive evidence that non-reporting traders' positions are useful for forecasting returns. This finding may not be surprising given the likely mixed motives of non-reporting traders, who may be speculators or hedgers. The results in Table 3 again show evidence of low order autocorrelation in returns.

Collectively, the results in Tables 1, 2, and 3 suggest that there is little systematic causality from traders' positions to returns within the agricultural futures markets examined. The possible exception being from commercial traders positions in the CBOT and KCBT wheat markets. However, in these cases, the direction of the causality is positive, which is counter to the results documented by Wang. The empirical results do point to one potentially important finding: weekly futures returns tend to show some low-order positive autocorrelation. This result is consistent with other research (Boris, Sanders, and Manfredo; Sanders, Irwin, and Leuthold), and it suggests that a failure to model lagged returns when investigating the COT data may result in misspecification errors.

It is important to verify that the results in Tables 1, 2, and 3 are robust to alternative position measures. So, equation (4) is also estimated using the sentiment index (SI) of Wang as well as just the change in the net trader position for each category. The p-values for just the null hypothesis of no causality from positions to returns ($\beta_j = 0 \; \forall$j) are presented in Tables 4, 5, and 6.

Table 4 shows the p-values for the causality tests using non-commercial traders. The results using the PNL are shown first (same as shown in Table 1) followed by the change in net position and the sentiment index (equation 2). There is a single rejection of the null hypothesis (soybeans) using the PNL, zero rejections using the change in net position, and one rejection (lean hogs) using the SI. While the markets that show rejections seem to be somewhat sensitive to the position indicator, the lack of systematic causality is evident across the measures.

Results for commercial traders using alternative position measures are shown in Table 5. Using the PNL, the null hypothesis is rejected in CBOT wheat, KCBT wheat, and lean hogs (5% level). In contrast, using the change in net position as the indicator, the null is rejected in the KCBT wheat and corn (5% level). The sentiment index (SI) provides statistically significant forecasts of returns just in the CBOT wheat. So, no market shows predictability across all measures; but, the CBOT wheat and KCBT wheat reject the null hypothesis with two of the three measures. In each of these cases the signs on the lagged position coefficients are positive suggesting that commercial traders increase (decrease) long positions prior to price increases (decreases). For non-reporting traders (Table 6), the results are consistent across measures. The null hypothesis of no causality is only rejected in one market (feeder cattle) with a single position measure (SI). There is no evidence that the non-reporting traders' positions are useful for forecasting returns, regardless of the position measure employed.

The evidence that traders' positions lead futures returns is limited. Indeed, there is no systematic evidence that non-reporting traders' positions are useful for predicting market returns. Likewise, for non-commercials, the null hypothesis of no causality is rejected only sporadically across markets and position measures. There is some evidence that commercial positions in CBOT and KCBT wheat may provide some forecasting ability for returns. In these two markets, the null hypothesis is rejected for two of the three position measures. Still, even with these specific rejections, there is no pervasive evidence that extends across all markets.

Do Returns Lead Positions?

It is important to understand the dynamics of traders' positions. For instance, behavior finance theories suggest that positive feedback traders may be market de-stabilizing (De Long, et al). To reveal potential trading "styles" among trader groups, equation (5) is estimated with the focus on the null that returns do not lead positions ($\theta_j = 0 \;\; \forall$j) and whether or not the cumulative directional impact is positive ($\sum_{j=1}^{n}\Theta_j > 0$) or negative ($\sum_{j=1}^{n}\Theta_j < 0$). A positive directional impact is indicative of trend followers or "positive feedback" traders because they increase their long position after prices increase and vice versa. A negative directional impact suggests "negative feedback" traders or contrarian strategies.

The results from estimating equation (5) are presented in Table 7 for the non-commercial classification. The null hypothesis that returns do not cause positions is rejected at the 5% across all markets. There is a systematic and pervasive tendency for returns to lead positions. Moreover, the aggregate directional impact is statistically different from zero in nine out of ten markets at the 5% level with six of those nine markets clearly displaying positive feedback trading on the part of non-commercial traders. These results are consistent with the findings of other researchers (e.g., Sanders, Irwin, and Leuthold), and they suggest that the non-commercial traders may be utilizing trend-following systems.

The results for commercial traders (Table 8) show that the null hypothesis ($\theta_j = 0 \;\; \forall$j) is rejected in all ten markets. The cumulative directional impact is positive ($\sum_{j=1}^{n}\Theta_j$) is statistically different from zero at the 5% level in six of ten markets, of which half display a negative cumulative impact or "value" strategies. In total, seven of the ten directional indicators are negative, indicating that short hedgers are scale-up sellers and long hedgers are scale-down buyers. However, the directional evidence is not overwhelming toward either style. This may stem from a heterogeneous group of traders captured in the commercial category.

Perhaps not surprisingly, the results for non-reporting traders are also mixed. The null hypothesis that returns do no lead positions is again rejected in all markets. However, the cumulative impact is different from zero in six out of ten markets with four of those showing a negative feedback style.

In total, the above results build a strong case that returns lead positions. While the general trading style of non-commercials can be classified as one of positive feedback strategies, the results of for the commercial and non-reporting categories are more mixed with no clearly dominant style within each group. These results may reflect that both the commercial and non-reporting categories are capturing a diverse group of traders, where the composition may change across markets (Ederington and Lee).

Conclusions

The goal of this research is to explicitly examine the usefulness of COT data in predicting futures market returns. In light of the evolving nature of the speculative participants in futures markets, and the industry's "fascination" with the positions held by funds (non-commercials), it is important to directly address the usefulness of this data in a forecasting framework. Here, we use a standard bivariate Granger causality approach to investigate the lead-lag dynamics between traders' positions and market returns.

The empirical results suggest two primary findings. First, traders' positions do not show a systematic and pervasive tendency to lead returns. In particular, there is practically no ability to forecast market returns using either non-commercial (funds) or non-reporting (small speculators) positions. There is some weak evidence that commercial (hedgers) positions lead returns in a few specific markets (i.e., CBOT and KCBT wheat); however, this is not a pervasive theme across markets. The results are relatively consistent across alternative position measures.

Second, the results clearly demonstrate that positions follow returns. In particular, non-commercial traders increase long positions after prices increase: they are trend followers. The directional findings for commercial traders and non-reporting traders are more mixed, with some markets showing trend-following styles and other showing contrarians or value strategies. The mixed directional evidence may reflect a hodgepodge of speculators and hedgers captured in these categories.

The results of this work have some very practical ramifications for market participants and academic researchers. First, academic researchers should make note of the strong case for trading styles documented in this work, in particular the trend-following displayed by non-commercial traders. This suggests that there may be groups of traders who systematically employ simplified trading or hedging rules. Based on a number of behavior finance theories, the existence of these noise traders can have implications for market behavior even though it was not captured by the methods specific to this study (De Long, et al).

For practitioners, the usefulness of the COT data in forecasting returns is suspect. In particular, non-commercial or fund positions provide virtually no forecasting information for market returns in agricultural futures markets. Indeed, non-commercial positions are basically a linear extrapolation of past price changes, reflecting the trend-following strategies of this group. If the COT data provide any forecasting information, it is likely found in the commercial category and in isolated markets.

Overall, the evidence for predictive power is rather weak. The presented results are consistent with those of Dale and Zyren who state that "noncommercial traders follow price trends: they don't set them" (p. 23). Still, active traders and market analysts frequently rely on the COT data as it is widely used in discussing market activity. So, there is a seeming paradox between the predictive power of the COT data as presented in this research and its perceived (or real) usefulness to those in the industry. Perhaps the COT data simply provide market commentators with a convenient talking point or justification for otherwise difficult-to-explain market movements. Alternatively, the COT data may indeed provide a glimpse of the "smart money" in a fashion not easily captured by standard empirics.

References

Bryant, H., D.A. Bessler, and M.S. Haigh. “Causality in Futures Markets.” *Journal of Futures Markets*. 26(2006):1039-1057.

Buchanan, W.K, Hodges, P., and J. Theis. “Which way the Natural Gas Price: An Attempt to Predict the Direction of Natural Gas Spot Price Movements Using Trader Positions.” *Energy Economics*. 23(2001):279-293.

Chatrath, A., Y. Liang, and F. Song. “Commitment of Traders, Basis Behavior, and the Issue of Risk Premia in Futures Markets.” *Journal of Futures Markets*. 17(1997): 707-731.

Commodity Futures Trading Commission. “Comprehensive Review of the Commitments of Traders Reporting Program.” Federal Register. 71(2006): number 119.

Dale, C. and J. Zyren. “Noncommercial Trading in the Energy Futures Market.” *Petroleum Marketing Monthly*, Energy Information Administration, U.S. Department of Energy, May, 1996.

De Long, J.B., A. Shleifer, L.H. Summers, and R.J. Waldmann. "Positive Feedback Investment Strategies and Destabilizing Rational Speculation." *Journal of Finance*. 45 (1990):379-395.

Domanski, D., and A. Heath. “Financial Investors and Commodity Markets.” Bank for International Settlements Quarterly Review, March (2007):53-67.

Ederington, L. and J.H. Lee. “Who Trades Futures and How: Evidence From the Heating Oil Market.” *Journal of Business*. 75(2002):353-373.

Gorton, G., and K.G. Rouwenhorst. “Facts and Fantasies About Commodity Futures.” *Financial Analysts Journal*. 62(2006):47-68.

Hartzmark, M. “Luck and Forecast Ability: Determinants of Trader Performance in Futures Markets.” *Journal of Business*. 64(1991): 49-74.

Haigh, M.S., J. Hranaiova, and J.A. Overdahl. “Price Dynamics, Price Discovery and Large Futures Trader Interactions in the Energy Complex.” U.S. Commodity Futures Trading Commission, Working Paper, April, 2005 (http://www.cftc.gov/files/opa/press05/opacftc-managed-money-trader-study.pdf)

Hieronymus. T.A. *Economics of Futures Trading for Commercial and Personal Profit*. New York: Commodity Research Bureau, 1971.

Leuthold, R.M., P. Garcia, and R. Lu. “The Returns and Forecasting Ability of Large Traders in the Frozen Pork Bellies Futures Market.” *Journal of Business*. 67(1994):459-73.

Morrison, K. “Commodities Lure Funds Investors.” *Financial Times*. December 28, 2004, www.ft.com. Accessed on October 19, 2006.

O’Hara, N. “Mutual Funds Tap into Commodities.” *The Magazine of the Futures Industry*. May/June (2006): 19-22.

Sanders, D.R., K. Boris, and M. Manfredo. “Hedgers, Funds, and Small Speculators in the Energy Futures Markets: An Analysis of the CFTC’s Commitments of Traders Reports.” *Energy Economics*. 26(2004):425-445.

Sanders, D.R., S.H. Irwin, and R.M. Leuthold. “The Theory of Contrary Opinion: A Test Using Sentiment Indices in Futures Markets.” *Journal of Agribusiness*. 21(2003): 39-64.

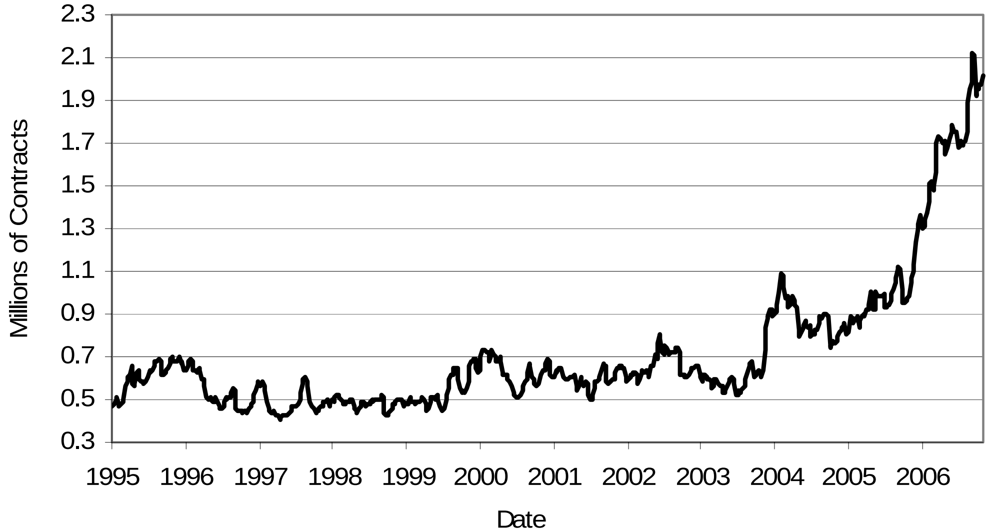
Upperman, F. *Commitments of Traders: Strategies for Tracking the Market and Trading Profitably*. John Wiley & Sons, New Jersey, 2006.

Wang, C., “The Behavior and Performance of Major Types of Futures Traders,.” *Journal of Futures Markets*, 23(2003):1-31.

Working, H. “Speculation on Hedging Markets.” *Food Research Institute Studies*. 1(1960): 185-220.

Figure 1. Combined Futures and Options Open Interest, 1995-2006

Panel A: Corn



Panel B: Live Cattle

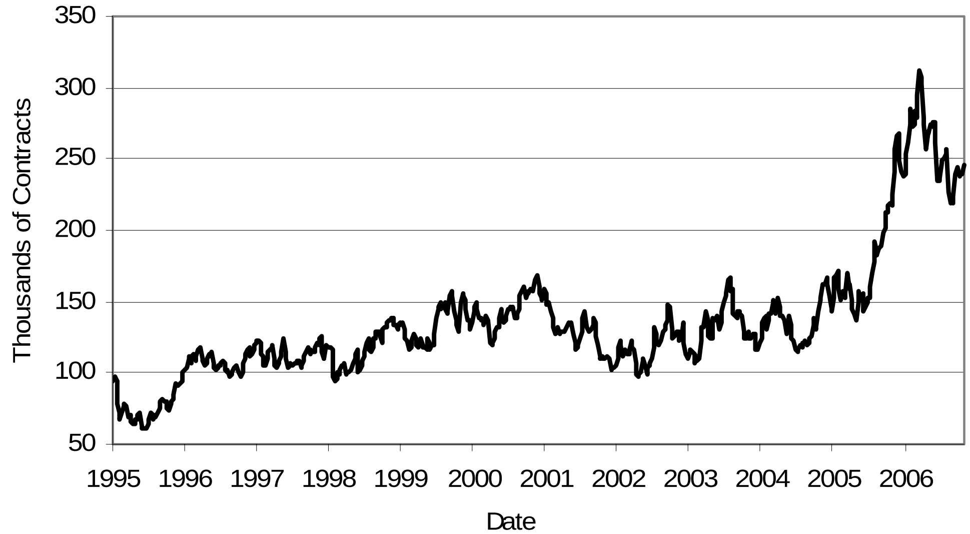
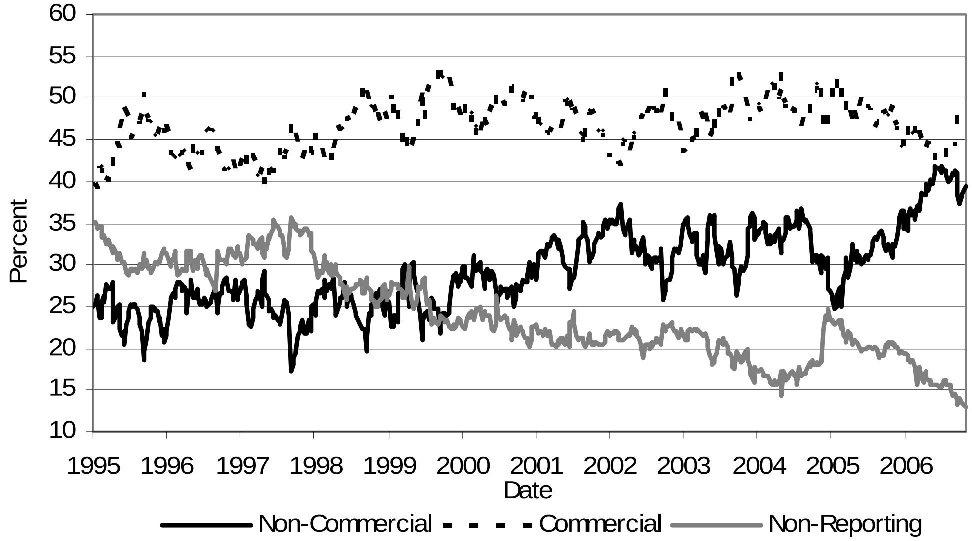


Figure 2. Percent of Open Interest by Trader Category, 1995-2006

Panel A: Corn



Panel B: Live Cattle

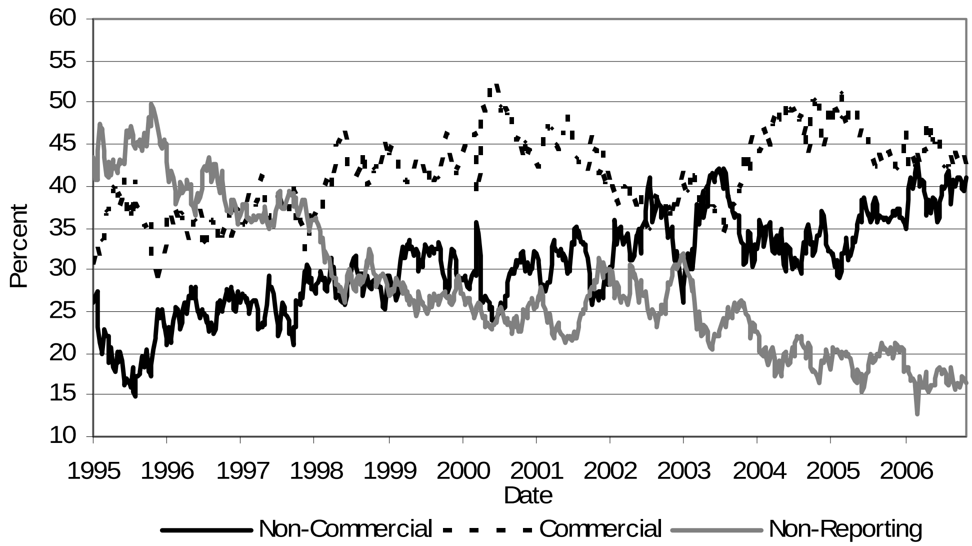
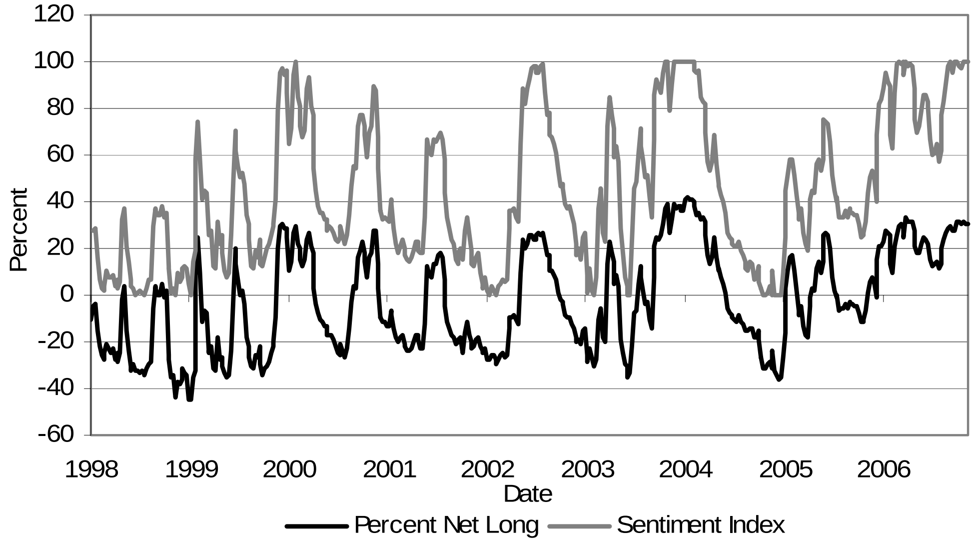


Figure 3. Non-Commercial Position Measures, 1998-2006.

Panel A: Corn



Panel B: Live Cattle

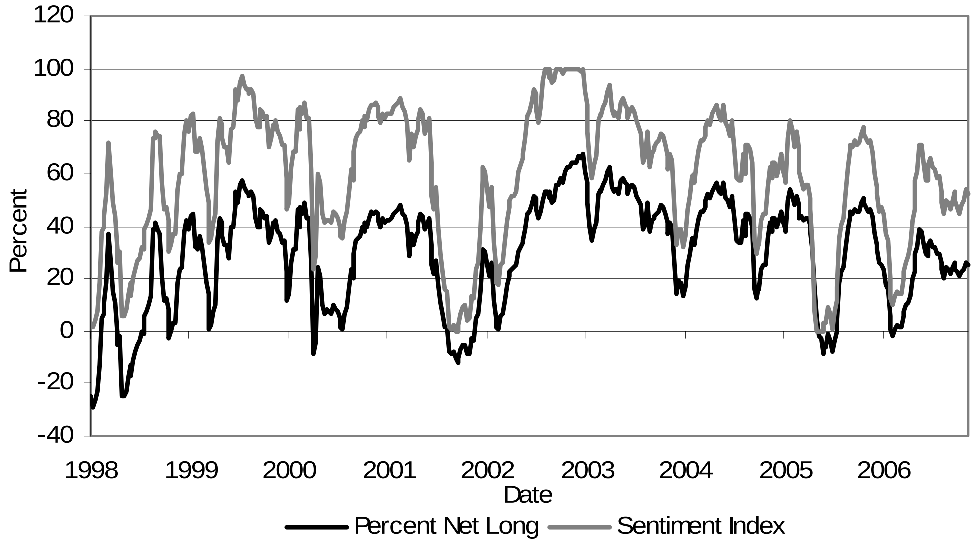
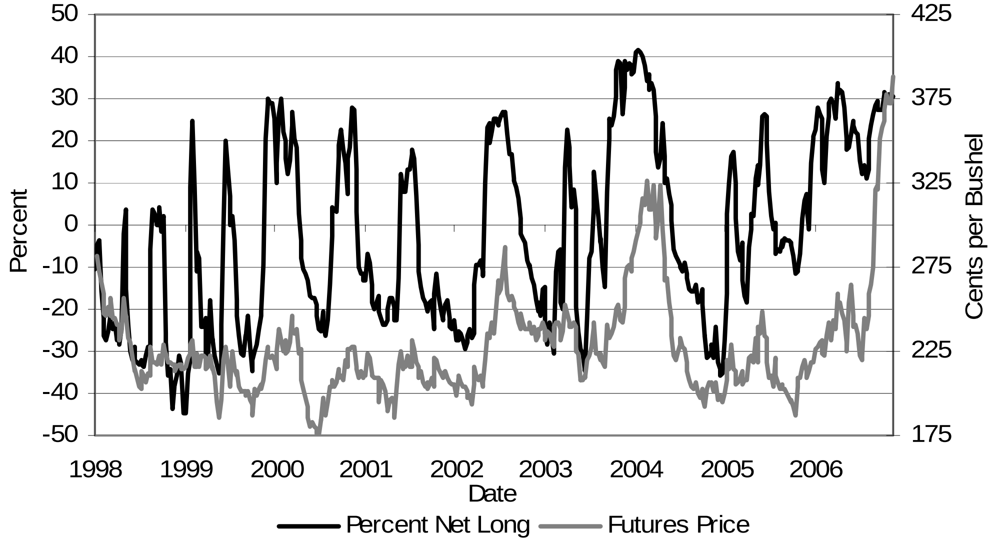


Figure 4. Non-Commercial Percent Net Long and Futures Prices, 1998-2006.

Panel A: Corn



Panel B: Live Cattle

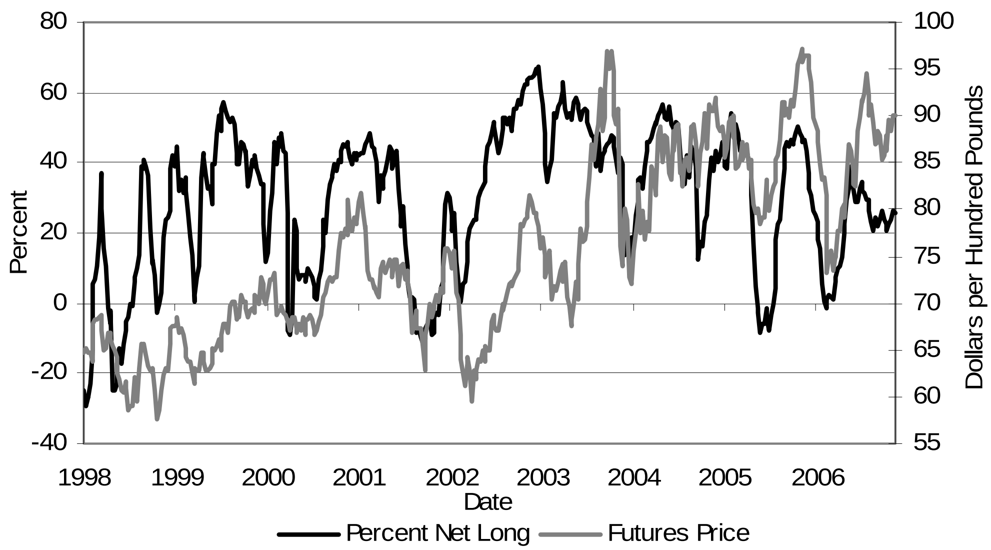


Table 1. Granger Causality, Non-Commercials, $R_t = \alpha_t + \sum_{i=1}^{m} \gamma_i R_{t-i} + \sum_{j=1}^{n} \beta_j PNL_{t-j} + \varepsilon_t$.

Market	n,m	Hypothesis Tests and P-values				Direction
		β_j=0, $\forall$j	$\sum \beta_j$=0	γ_i =0, $\forall$i	γ_i=β_j=0, $\forall$i,j	$\sum \beta_j$
Wheat CBOT	1,2	0.186	0.648	0.034	0.156	0.113
Corn	1,4	0.813	0.813	0.062	0.108	0.223
Feeder Cattle	1,2	0.144	0.144	0.026	0.042	-0.180
Wheat KCBOT	6,1	0.235	0.353	0.278	0.313	0.050
Lean Hogs	1,6	0.440	0.440	0.126	0.160	-0.058
Live Cattle	1,11	0.901	0.901	0.000	0.000	-0.037
Wheat MGE	1,1	0.149	0.149	0.891	0.342	0.006
Soybean Meal	1,1	0.929	0.929	0.661	0.907	0.022
Soybean Oil	1,1	0.300	0.300	0.379	0.554	0.047
Soybeans	1,1	0.046	0.046	0.882	0.069	-0.008

Table 2. Granger Causality, Commercials, $R_t = \alpha_t + \sum_{i=1}^{m} \gamma_i R_{t-i} + \sum_{j=1}^{n} \beta_j PNL_{t-j} + \varepsilon_t$.

Market	m,n	Hypothesis Tests and P-values				Direction
		β_j=0, $\forall$j	$\sum \beta_j$=0	γ_i =0, $\forall$i	γ_i=β_j=0, $\forall$i,j	$\sum \beta_j$
Wheat CBOT	1,2	0.007	0.041	0.066	0.020	0.115
Corn	1,4	0.213	0.213	0.009	0.017	0.318
Feeder Cattle	1,5	0.095	0.095	0.009	0.009	0.131
Wheat KCBOT	6,4	0.050	0.030	0.005	0.005	0.251
Lean Hogs	7,5	0.051	0.953	0.085	0.024	-0.029
Live Cattle	1,11	0.688	0.688	0.000	0.000	-0.089
Wheat MGEX	1,1	0.628	0.628	0.522	0.792	0.030
Soybean Meal	1,1	0.715	0.715	0.422	0.703	0.044
Soybean Oil	1,1	0.239	0.239	0.321	0.486	0.059
Soybeans	1,1	0.831	0.831	0.605	0.824	0.025

Table 3. Granger Causality, Non-Reporting, $R_t = \alpha_t + \sum_{i=1}^{m} \gamma_i R_{t-i} + \sum_{j=1}^{n} \beta_j PNL_{t-j} + \varepsilon_t$.

		Hypothesis Tests and P-values				Direction
Market	m,n	$\beta_j=0, \forall j$	$\sum \beta_j=0$	$\gamma_i=0, \forall i$	$\gamma_i=\beta_j=0, \forall i,j$	$\sum \beta_j$
Wheat CBOT	1,5	0.548	0.548	0.038	0.066	0.043
Corn	1,4	0.339	0.339	0.024	0.040	0.171
Feeder Cattle	1,5	0.250	0.250	0.015	0.014	0.054
Wheat KCBOT	1,4	0.684	0.684	0.035	0.064	0.052
Lean Hogs	1,5	0.083	0.083	0.108	0.047	0.048
Live Cattle	1,11	0.337	0.337	0.000	0.000	-0.081
Wheat MGEX	1,1	0.763	0.763	0.617	0.860	0.021
Soybean Meal	1,1	0.953	0.953	0.665	0.907	0.021
Soybean Oil	1,1	0.605	0.605	0.929	0.839	-0.004
Soybeans	1,1	0.780	0.780	0.528	0.672	0.029

Table 4. Granger Causality, Non-Commercials, $R_t = \alpha_t + \sum_{i=1}^{m} \gamma_i R_{t-i} + \sum_{j=1}^{n} \beta_j Position_{t-j} + \varepsilon_t$.

	P-values for $\beta_j=0, \forall j$		
Market	PNL	Δ Net Position	SI
Wheat CBOT	0.186	0.251	0.311
Corn	0.813	0.178	0.747
Feeder Cattle	0.144	0.725	0.482
Wheat KCBOT	0.235	0.055	0.200
Lean Hogs	0.440	0.203	0.011
Live Cattle	0.901	0.823	0.120
Wheat MGEX	0.149	0.176	0.933
Soybean Meal	0.929	0.323	0.285
Soybean Oil	0.300	0.879	0.303
Soybeans	0.046	0.243	0.276

Table 5. Granger Causality, Commercials, $R_t = \alpha_t + \sum_{i=1}^{m} \gamma_i R_{t-i} + \sum_{j=1}^{n} \beta_j Position_{t-j} + \varepsilon_t$.

	P-values for β_j=0, $\forall$j		
Market	PNL	Δ Net Position	SI
Wheat CBOT	0.007	0.147	0.004
Corn	0.213	0.052	0.736
Feeder Cattle	0.095	0.271	0.524
Wheat KCBOT	0.050	0.018	0.457
Lean Hogs	0.051	0.096	0.524
Live Cattle	0.688	0.876	0.680
Wheat MGEX	0.628	0.163	0.423
Soybean Meal	0.715	0.256	0.858
Soybean Oil	0.239	0.530	0.337
Soybeans	0.831	0.577	0.430

Table 6. Granger Causality, Non-Reporting, $R_t = \alpha_t + \sum_{i=1}^{m} \gamma_i R_{t-i} + \sum_{j=1}^{n} \beta_j Position_{t-j} + \varepsilon_t$.

	P-values for β_j=0, $\forall$j		
Market	PNL	Δ Net Position	SI
Wheat CBOT	0.548	0.646	0.369
Corn	0.339	0.203	0.225
Feeder Cattle	0.250	0.555	0.022
Wheat KCBOT	0.684	0.783	0.462
Lean Hogs	0.083	0.503	0.013
Live Cattle	0.337	0.575	0.480
Wheat MGEX	0.763	0.806	0.190
Soybean Meal	0.953	0.415	0.762
Soybean Oil	0.605	0.555	0.276
Soybeans	0.780	0.366	0.899

Table 7. Granger Causality, Non-Commercials, $PNL_t = \phi_t + \sum_{i=1}^{n} \lambda_i PNL_{t-i} + \sum_{j=1}^{m} \theta_j R_{t-j} + \omega_t$

		Hypothesis Tests and P-values		Direction
Market	n,m	$\theta_j=0, \forall j$	$\sum \theta_j=0$	$\sum \theta_j$
Wheat CBOT	1,6	0.000	0.000	-84.6
Corn	5,2	0.000	0.000	70.6
Feeder Cattle	8,1	0.000	0.000	-77.6
Wheat KCBOT	2,1	0.000	0.000	94.7
Lean Hogs	12,2	0.000	0.000	24.6
Live Cattle	2,12	0.000	0.031	139.4
Wheat MGEX	1,8	0.000	0.142	159.4
Soybean Meal	2,9	0.000	0.001	135.3
Soybean Oil	10,2	0.000	0.000	-122.6
Soybeans	11,1	0.000	0.000	58.3

Table 8. Granger Causality, Commercials, $PNL_t = \phi_t + \sum_{i=1}^{n} \lambda_i PNL_{t-i} + \sum_{j=1}^{m} \theta_j R_{t-j} + \omega_t$

		Hypothesis Tests and P-values		Direction
Market	n,m	$\theta_j=0, \forall j$	$\sum \theta_j=0$	$\sum \theta_j$
Wheat CBOT	7,1	0.000	0.000	36.1
Corn	2,4	0.000	0.079	-18.6
Feeder Cattle	5,1	0.000	0.027	27.7
Wheat KCBOT	2,1	0.000	0.000	-24.7
Lean Hogs	13,2	0.000	0.000	-28.1
Live Cattle	8,3	0.000	0.000	-62.7
Wheat MGEX	7,3	0.000	0.150	-21.9
Soybean Meal	1,10	0.000	0.109	-29.4
Soybean Oil	10,1	0.000	0.000	42.5
Soybeans	11,1	0.000	0.222	-8.8

Table 9. Granger Causality, Non-Reporting, $PNL_t = \phi_t + \sum_{i=1}^{n} \lambda_i PNL_{t-i} + \sum_{j=1}^{m} \theta_j R_{t-j} + \omega_t$

		Hypothesis Tests and P-values		Direction
Market	n,m	θ_j=0, $\forall$j	$\sum \theta_j$=0	$\sum \theta_j$
Wheat CBOT	5,2	0.000	0.469	4.7
Corn	1,2	0.000	0.001	-10.8
Feeder Cattle	2,1	0.000	0.000	28.1
Wheat KCBOT	3,1	0.000	0.067	9.4
Lean Hogs	1,6	0.000	0.655	6.2
Live Cattle	3,1	0.000	0.039	-13.7
Wheat MGEX	3,1	0.000	0.851	1.3
Soybean Meal	3,1	0.000	0.000	21.1
Soybean Oil	5,4	0.000	0.000	-116.0
Soybeans	1,2	0.000	0.014	-13.5