Noise Trader Demand in Futures Markets

Dwight R. Sanders, Scott H. Irwin, and Raymond M. Leuthold

Dwight R. Sanders
Senior Commodity Analyst
The Pillsbury Company

Scott H. Irwin
Department of Agricultural Economics
The Ohio State University

Raymond M. Leuthold
Department of Agricultural and Consumer Economics
University of Illinois at Urbana Champaign

OFOR Paper Number 96-02
June 1996

I. INTRODUCTION

Black defines "noise" as noninformation (e.g., chart formations, technical signals, and investing fads) and "noise trading" as trading on noise as if it were information. The impact and motivations of noise traders have long been debated. Some renowned economists (i.e., Friedman) dismiss these traders as fodder for rational arbitrageurs, while others (i.e., Keynes) assert their impact on long-term market expectations. Traditional arguments rely on simple logic or casual observation; but, recently a rigorous theoretical literature has developed that examines the impact of noise traders on asset price behavior (e.g., De Long, Shleifer, Summers, and Waldmann, 1989,1990a, 1990b, 1991). These models suggest that noise traders can impact market prices and social welfare; furthermore, they can profitably exist within the economy. However, the theoretical specification of noise trader demand is crucial to the models' predictions and subsequent empirical tests (Cutler, Poterba, and Summers, 1989). To date, little work has been done on rigorously describing and quantifying noise trader demand (e.g., Solt and Statman; De Bondt). The purpose of this research is to empirically examine the nature of noise trader demand in commodity futures markets.

Noise traders take market positions based on nonfundamental information.[1] The theoretical demand structure of noise traders has been specified in numerous forms. For

[1]A particular type of noise trader is a positive feedback trader. Positive feedback traders buy after price increases; whereas, negative feedback traders sell. A feedback trader has a short-memory if demand is a function of very recent market returns. A feedback trader with a long-memory would utilize a longer history of returns in forming expectations. Clearly, long-memory is a relative term. In this paper, it refers to a trader using more than the most recent period's return in forming expectations.

instance, Cutler, Poterba, and Summers (1989) specify noise trader demand as a function of past prices. That is, uninformed traders are purely trend-followers with extrapolative expectations. On the other hand, De Long, Shleifer, Summers, and Waldmann (DSSW, 1990a) specify noise trader demand as a function of a random variable, sentiment. In this particular model, noise trader demand is driven by fads, social trends, and whims that stroke market sentiment. The demand function assumed in these models can alter their results. For instance, in Cutler *et al*.'s (1989) model positive feedback traders can create negative short-run autocorrelation in returns or long-run mean reversion depending on the exact demand specification. Clearly, a realistic demand specification is vital for the correct interpretation and empirical testing of noise trader models. The following research seeks to provide empirical insights as to an appropriate characterization of this demand.

Noise traders are often categorized as retail or small speculators. There has been some attempt to characterize the speculative demand or decision-making process of these investors; however, this research has focused almost exclusively on equity markets. For instance, Solt and Statman examine the sentiment of retail stock investors as captured in the Bearish Sentiment Index compiled by Investor's Intelligence. This gauge of market sentiment is constructed by surveying market newsletters as to their outlook. Solt and Statman find that this market sentiment index contains no useful information for forecasting market returns. Furthermore, the aggregate sentiment among newsletters is positively correlated with past market returns. Similarly, De Bondt finds that the individual speculators surveyed by the American Association of Individual Investors demonstrate trend-following tendencies. That is, they are most bullish immediately following price increases. Collectively, this work suggests that the retail stock market speculator displays extrapolative expectations.

The following research expands previous work by examining a comprehensive set of futures markets and explicitly examining the demand structure of noise traders: Is noise trader demand driven by past prices, i.e., extrapolative expectations, or is it a function of unobservable social variables? To confront this issue, the research relies on two measures of investor sentiment: Consensus' Index of Bullish Market Opinion and Market Vane's Bullish Consensus Index. The sentiment indices essentially gauge the degree of bullishness (or bearishness) among retail futures speculators. Assuming that retail speculators do not have private fundamental information, then their sentiment and, hence, the indices serve as a proxy for noise trader demand. Using these data along with returns from a large cross-section of futures markets, the demand structure of noise traders is directly addressed.

II. MEASURING NOISE TRADER SENTIMENT

Two investment services firms, Consensus Incorporated and the Market Vane Corporation, compile sentiment indices for futures markets. Each uses a slightly different methodology, but the general idea is the same. Market advisory services, newsletters, electronic bulletin boards, and hotlines are surveyed as to whether they are bullish or bearish on particular commodities. The number of services that are bullish is then expressed as a percent of the total surveyed. The indices are referred to as bullish sentiment.

CONSENSUS' Index of Bullish Market Opinion

The methodology Consensus uses to compile its bullish sentiment index is quite simple. Consensus publishes a weekly market paper, *CONSENSUS: National Futures and Financial Weekly*, that contains a sampling of investment newsletters. From the sample of letters that Consensus receives, it compiles a sentiment index with a simple count of the number of bullish newsletters as a proportion all newsletters expressing an opinion. Consensus only considers those opinions which have been committed to publication. The Consensus bullish sentiment index at time t ($CBSI_t$) is expressed as:

$$CBSI_t = \frac{number\ \ of\ \ bullish\ \ newsletters}{number\ \ of\ \ newsletters\ \ expressing\ \ an\ \ opinion}\ .$$

For instance, if Consensus receives 100 newsletters that comment on the frozen pork bellies market and 25 of those think that belly prices are going to increase, then the CBSI is 0.25 or 25 percent.[2] The CBSI is compiled each Friday, reflecting the opinions expressed in newsletters that were published during the week. It is released early the following week by recorded telephone message and published in the following Friday's edition of *CONSENSUS*.

Market Vane's Bullish Consensus Index

The Market Vane Corporation takes a slightly different and more detailed approach to calculating a sentiment index. It receives market recommendations from brokerage firms and market advisors *via* newsletters, hotlines, and electronic transmission. Each market opinion (for

[2]Consensus, Inc. indicates that some interpretation is required for newsletters that do not explicitly make buy or sell recommendations.

a commodity) is weighted on a scale (B) from zero to eight with 0 and 8 being fully bearish and bullish, respectively. Next, each market letter is weighted according to its perceived influence or following. For newsletters, hotlines, and electronic bulletins this weight (W) is proportional to the subscriber base, and for brokerage firms it is proportional to the number of brokers at the firm.[3] The Market Vane bullish sentiment index ($MVBSI_t$) at time t is:

$$MVBSI_t = \frac{\sum_{j=1}^{N} B_j W_j}{8\sum_{j=1}^{N} W_j}$$

where, B_j is the degree of bullishness on a scale from 0 to 8 for advisor j, W_j is the influence weight assigned to the advisor, and there are a total of N advisors commenting on the market. The index is compiled each Tuesday, reflecting the opinions received since the prior Tuesday. The index is released on the same Tuesday *via* wire and facsimile.

Noise Traders and Information Sources

As a maintained hypothesis, it is assumed that the indices compiled by Consensus and Market Vane reflect the sentiment of noise traders--not rational or informed market participants. That is, the market views subsumed within the indices are those of small retail speculators who are acting on noninformation: technical trading rules, extrapolation, or old news that is already

[3]Market Vane, Inc., does not go into great detail as to the exact weighting scheme, method of calculation, or the determination of weights for particular advisory services.

incorporated into the market price. This maintained hypothesis is supported by reviewing the decision-making rules of small traders and sampling their information sources.

In a 1965 survey of amateur futures speculators, Smidt attempted to classify their trading styles and decision-making criteria. Smidt found that more than one-half of the 349 traders surveyed relied exclusively (or moderately) on price charts to render trading decisions. Only four percent of those surveyed considered themselves information specialists who obtain and use information before it is widely available to other traders. Finally, most amateur speculators surveyed preferred to trade commodities about which they had personal knowledge or advice.

Surveys by the Chicago Board of Trade and *Barron's* suggest that small speculators do not behave in an entirely rational manner (see also Brennan; Nagy and Obenberger). Draper summarizes the surveys' findings. The surveys suggest that the average futures trader is highly educated, and they trade for the leverage and excitement. Furthermore, their important sources of information include: articles/publications, broker and newsletter recommendations, advisory services, and their own analysis. Consistent with these findings, Canoles' 1990 survey of 115 retail futures traders in Alabama reveals that speculators enjoy the drama and suspense of carrying open positions. Their favorite sources of information are professional trading advisory services and general financial publications. Collectively, these results suggest that retail speculators generally do not bring new information to bear on the markets, and they garnish much of their information from focused media sources such as those surveyed by Consensus, Inc. and the Market Vane Corporation.

Market advisors, brokers, and newsletters provide decision-making information for retail futures speculators; but, are they providing real information, or simply relaying old news and technical comments? Excerpts from an issue of *CONSENSUS* provide insight as to the information contained within advisors' recommendations and market newsletters.

Many market advisors rely on technical indicators and simply pass along this information to their retail subscribers.[4]

> The (soybean) market is in a sideways pattern between 563 and 547. If the 547 support is taken out, then the market could decline to 530....Charts suggest the market has confirmed the sideways pattern and thus we feel comfortable selling and did so today (Biedermann, Allendale, Inc.).
>
> The major uptrending channel line is at 102-00 today. The strong close puts the market in a strong position once again. The old main top at 102-29 was taken out. This means that 101-08 is the new main bottom. Now that the (T-Bond) market has closed inside of the uptrending channel the upside potential is 103-17. Long-term swing chart is still projecting a rally to 103-26 by February 24th (James A. Hyerczyk, Hyerczyk Technical Comments).

Each issue of *CONSENSUS* is filled with this type of technical commentary for nearly every futures market. Although much more rare than technical analysis, some newsletters are fundamental in nature, relaying government reports, seasonal tendencies, and pertinent cash market conditions.

---

[4]The following quotes are taken from *CONSENSUS: National Futures and Financial Weekly*, Consensus, Inc, Volume XXV, Number 7, February 17, 1995.

> The USDA left the 1994-95 ending stocks of soybeans unchanged at 510 M.B. which suggests that the market will not be as sensitive to weather as corn or possibly wheat....Seasonally, the market tends to bottom in late February and work higher into March and May (Strickler, Bradford & Co., Inc.).

> Cash cattle prices reached $75.00/cwt. this week as tight market-ready supplies and solidarity among feedlot operators forced packers to bid prices upward....Extremely current marketings enabled them (feedlots) to drive hard bargains with packers and force prices higher. This bodes well for the cash market for the next six to eight weeks (Vaught, A.G. Edwards & Sons, Inc.).

Although they often contain detailed interpretations of relevant supply and demand factors, the fundamental analysis tends to reiterate public information.

The noninformational nature of the market newsletters, coupled with the evidence that retail investors rely on this advice in making decisions, supports the maintained hypothesis: the sentiment indices are valid proxies for noise trader demand. To the extent that market opinion is correlated across advisors, noise traders will act in concert (Shleifer and Summers).

III. DATA, METHODOLOGY, and RESULTS

Futures Data and Markets

Weekly futures returns are calculated for the closest to expiration contract where the maturity month has not been entered. Two different time series of futures returns are created to match-up with the sentiment data. First, nearby contract returns are calculated Friday-to-Friday using closing prices. This data series corresponds to that of the weekly Consensus sentiment data. Second, to match the weekly Market Vane sentiment data, futures returns are calculated from Tuesday-to-Tuesday using closing prices. Returns (R_t) are calculated as the log-relative change in closing prices, $\ln(p_t / p_{t-1})$. Weekly data from May 1983 to September 1994 are available for analysis (591 observations).

A cross-section of twenty-eight futures markets is examined to strengthen the studies' general conclusions and to avoid erroneous implications based on the nuances of a particular market. Markets are chosen based on the availability of the futures and sentiment data. To facilitate the presentation of results and for relevant comparisons, related markets are designated into commodity groups. Group classification is based on common production/consumption patterns and expectations concerning the correlation of returns and sentiment among the markets. The five commodity groups include: grain (corn, wheat, soybeans, soybean meal, and soybean oil); livestock (live cattle, feeder cattle, live hogs, and frozen pork bellies); food/fiber (coffee, sugar, cocoa, orange juice, cotton, and lumber); financial (Deutsche mark, British pound, Swiss franc, Canadian dollar, Japanese yen, Treasury bills, and Treasury bonds); and metal/energy (gold, silver, platinum, heating oil, crude oil, and gasoline). A complete listing of markets and contracts is presented in Table 1.[5]

Summary Statistics

The general characteristics of the sentiment indices are explored with simple summary statistics presented in Tables 2 and 3. The mean sentiment level (% bullish) tends to be fairly neutral at around 50 for the MVBSI (Table 3); however, the CBSI (Table 2) have means that are

[5] In the following discussion and tables, the commodities are referred to by their ticker symbols given in Table 1.

notably less than a neutral 50. In fact, the mean CBSI is statistically less than 50 at the 1% level (two-tailed t-test) for all the markets except LC and SB. The range of the mean CBSI is from a low of 38.5 for HU to a high of 51.6 for LC. In comparison, the MVBSI means are in a rather narrow range from 47.1 for PB to a high of 55.3 for SB. Although some of the markets have a mean MVBSI that is statistically different than 50, they are in general much closer to and more evenly distributed around 50 than the CBSI means.[6]

For both sets of indices, sentiment is quite volatile with large standard deviations and extremes of above 90 and below 10. Again, the CBSI are notably more volatile and extreme (especially at lower levels) than the MVBSI. The disparities between the Market Vane and Consensus data sets are likely due to differences in sampling size and procedures. The extreme values of sentiment along with its volatility suggest that the advisors that make-up the indices are reacting to correlated market signals. As an illustration of the sentiment behavior over time, the CBSI for coffee is plotted in Figure 1.

The sentiment data also display a high level of correlation both across the two indices and across markets. As shown in the final column of Table 3, the simple correlations between the CBSI and MVBSI range from 0.596 for FC to 0.799 for GC. This suggests that the two indices capture the sentiment of an alike group of traders that share decision-making criteria.[7] Similarly, the cross-market correlations are strong within commodity groups. Table 4 presents the simple

---

[6]Of the twenty-eight markets, thirteen mean MVBSI are statistically greater than 50 at the 1% level, and one, PB, is statistically less than 50 at the 1% level.

[7]The degree of overlap among the sources surveyed by Consensus and Market Vane is not known. Certainly any overlap will create correlation between the two indices; however, given their different selection criterion it is unlikely that this accounts for the correlation.

correlation coefficients among related markets. Note, the correlation of sentiment within commodity groups is relatively strong. For instance, the correlation between C and S for the CBSI is 0.631, and it is 0.782 between JY and DM for the MVBSI. These type of correlations are indicative of systematic noise trader demand that covaries across traders and markets (see DSSW, 1990a).

Noise Trader Demand and Extrapolative Expectations

Solt and Statman as well as De Bondt document that retail stock market speculators exhibit extrapolative expectations--becoming more bullish after recent market increases. They demonstrate this with simple OLS regressions of sentiment on past stock market returns. Here, that methodology is refined, and the specific form of extrapolative expectations is tested.

A general method of exploring the linear linkages between and sentiment and price is within the "Granger causality" framework.[8] Hamilton suggests the following direct or bivariate Granger test:

$$\rho_t = c_0 + \sum_{i=1}^{p} a_i \rho_{t-i} + \sum_{j=1}^{q} b_j R_{t-j} + e_t \ , \tag{1}$$

where, ρ_t and R_t represent noise trader sentiment and futures returns, respectively, and e_t is a white noise error term.

Causality from returns to sentiment in equation (1) is tested under the null of $b_j = 0 \ \forall \ j$. Specifically, equation (1) is estimated with OLS, and the null hypothesis that R_t does not lead ρ_t

[8]To avoid the philosophical connotations associated with strict cause-and-effect, the terms "lead" and "lag" are used in reference to the stated hypothesis.

(i.e., $b_j = 0 \ \forall j$) is tested with a Chi-squared test (Hamilton, p. 305).[9, 10] The aggregate sign of causality (positive or negative) is addressed by summing the impact of lagged returns, $\sum b_j$, and testing if it equals zero using a two-tailed t-test. If $\sum b_j > 0$, then the noise traders are also positive feedback traders or trend-followers. That is, their demand is an increasing function of past prices.

Choosing the appropriate lag lengths (p,q) is of practical significance in performing the causality test (see Thorton and Batten; Jones). As suggested by Beveridge and Oickle, the order of an autoregressive system may best be determined by searching all possible lags for the combination that minimizes a model selection criterion. For example, in (1) the model is estimated by varying the own-lag length of ρ_t from $p=1,2,...p^{max}$, and the lag length of R_t from $q=1,2,...,q^{max}$ such that a total of (p^{max} x q^{max}) regressions are estimated. The p,q lag length combination that minimizes Akaike's information criteria (AIC) is chosen as the final model specification. This purely objective procedure has the advantage of not placing the artificial restriction that p=q. Additionally, it eliminates the uncertainty in multivariate cases of deciding

---

[9]Note, misspecification of equation (1) due to cointegration and an omitted error-correction term is not a problem with these data as sentiment is clearly stationary I(0) in levels.

[10]The causality test assumes that the two series, ρ_t and R_t, are covariance stationary, and e_t is an i.i.d. white noise error. This assumption is tested using White's general test for heteroskedasticity in the error term. If e_t is heteroskedastic, then the model is re-estimated using White's heteroskedastic consistent covariance estimator, and the appropriate test for the parameter restrictions is a Wald Chi-squared test (Greene, p. 392). A Lagrange multiplier test is used to verify that the residuals are serially uncorrelated. If, after choosing the optimal lag length, the residuals demonstrate autocorrelation, then additional lags of the dependent variable are added as explanatory variables (i.e., p is increased in equation 1) until the autocorrelation is eliminated.

the order in which to enter additional variables into a model. For equation (1), all possible lag-length combinations are estimated with $p^{max} = q^{max} = 8$, and p,q is chosen to minimize AIC.

The estimation results for each market are presented in Tables 5 and 6 for the CBSI and MVBSI, respectively. The results indicate that noise traders are predominately positive feedback traders, i.e., returns lead sentiment and the cumulative impact is positive. In each market examined, the null hypothesis that returns do not lead sentiment is rejected at the 0.01 level. The additive effect of lagged returns is statistically positive (1% level) for every market except PL in the Market Vane data set. Past returns and sentiment levels explain a fairly large portion of the variation in sentiment with the adjusted R-squared ranging from 0.53 to 0.78 in the CBSI models and 0.37 to 0.69 in the MVBSI models. These results are consistent with prior work on sentiment (Solt and Statman; De Bondt) and conjectures that noise traders are often trend-followers.

Close examination of Tables 5 and 6 reveal that the degree of trend-following differs somewhat across commodities and the data sets. For a more general characterization of noise trader demand, the causality test in (1) is estimated by pooling the time series data across the designated commodity groups. The pooled cross-sectional time series models are estimated using the GLS procedure of Kmenta (pp. 616-635) correcting for cross-sectional correlation and heteroskedasticity. The lag-lengths for the pooled regressions are specified by choosing the maximum p and the maximum q from among the individual market specifications within each group. For instance in the CBSI grain group the maximum p is 2 (S and BO) and the maximum q is 2 (C, S, SM, BO); therefore, the pooled grain model's lag structure is 2,2. This specification procedure may over-specify lag structures at the expense of statistical power, but it assures that the model does not suffer from an under-specification bias.

The estimated pooled models are presented in Tables 7 and 8 for the Consensus and Market Vane data, respectively. For each pooled regression, the null hypothesis that returns do not lead sentiment (i.e., $b_j = 0 \ \forall j$) is tested with a Wald Chi-squared test, and the cumulative impact of lagged returns is again tested with a two-tailed t-test (i.e., $\sum b_j = 0$). Concentrating on the CBSI results in Table 7, certain characteristics of sentiment are evident. First, across groups, sentiment follows a fairly strong positive autoregressive process with first-order coefficients around 0.65. Second, statistically significant positive extrapolation is demonstrated at one and two week lags for all the groups, i.e., positive feedback traders have relatively long memories. For instance, in grains, a one percent weekly return results in sentiment increasing by 1.26 percent the following week and 0.376 percent the week after that. For all the groups, the null that returns do not lead sentiment can be rejected at the 1% level, and the cumulative impact of lagged returns is significantly positive (1% level). These results hold for the MVBSI models in Table 8 as well, where again the null hypothesis are rejected for each commodity group.

To illustrate the behavior of sentiment when driven by extrapolative expectations, the impulse response function for a one standard deviation shock to returns is calculated (see Harvey, p. 234).[11] Figures 2 and 3 show the impulse response functions for the pooled CBSI and MVBSI models, respectively. Looking at the CBSI results (Figure 2), a standard deviation shock in

---

[11] Implicitly, it is assumed that sentiment is endogenous and impacted by an exogenous shock to returns.

weekly returns causes the greatest initial increase in food/fiber market sentiment.[12] Notably, the impact on metal/energy and financial market sentiment does not reach a peak until two weeks after the initial shock. All of the response functions decline rather smoothly and at similar rates, except for the livestock group where extrapolative effects are less pronounced.[13] The impulse response functions for the MVBSI (Figure 3) display a greater disparity of demand response among the groups. Consistent with the CBSI data, the MVBSI data show that the food/fiber group is most prone to trend-following. The strength of extrapolative expectations in this group may arise from a relatively high proportion of uninformed traders or a scarcity of public fundamental information. In total, the pooled models strongly suggest that the noise traders subsumed within the sentiment indices are long-memory positive feedback traders.

IV. SUMMARY AND CONCLUSIONS

The presented analysis uses commercial market sentiment indices to explore noise trader demand in futures markets. It is maintained that the market sentiment indices adequately measure the demand of retail speculators. Furthermore, these small speculators rely on nonfundamental information in forming their expectations; thus, they are noise traders. The role of extrapolative expectations in noise trader demand is investigated within a Granger causality framework. The results suggest that noise trader demand (i.e., sentiment) is an increasing

---

[12]The standard deviation of weekly returns (in parenthesis) for each group is as follows: grain (0.029), livestock (0.029), food/fiber (0.042), financial (0.013), and metal/energy (0.036).

[13]The impulse response functions decline toward their long-run or total multiplier which is zero, as is the case for any stationary series.

function of past returns. Furthermore, noise traders have relatively long memories. That is, sentiment is influenced by returns over at least the previous two weeks. The sentiment indices exhibit other characteristics of theoretical noise trader demand. Sentiment is very volatile with many extreme observations, and it covaries across related markets. These characteristics are consistent with systematic noise trader risk that can impact markets (see DSSW, 1990a).

Collectively, the findings suggest that the traders composing the indices are long-memory positive feedback traders. Clearly, these traders respond to similar pseudo market signals (i.e., past returns), and as a result sentiment moves in unison and takes large swings to extreme values. These empirical findings have direct implications for the interpretation and testing of theoretical models. For instance, Cutler *et al.*'s (1989) model generates returns that are positively correlated if noise traders are short-memory negative feedback traders. The evidence presented here would shun that scenario in favor of the results for long-memory positive feedback traders. For this type of noise trader, their model generates short-run positive autocorrelation and long-run negative autocorrelation in returns (i.e., mean-reversion). Perhaps not surprisingly, these are the anomalous characteristics of asset returns that are considered stylized facts (see Cutler, Poterba, and Summers, 1991).

Bibliography

Beveridge, S. and C. Oickle. "A Comparison of Box-Jenkins and Objective Methods for Determining the Order of a Non-seasonal ARMA Model." *Journal of Forecasting*. 13(1994):419-434.

Black, F. "Noise." *Journal of Finance*. 41(1986):529-543.

Brennan, M.J. "The Individual Investor." *Journal of Financial Research*. 18(1995):59-74.

Canoles, B.W. "An Analysis of the Profiles, Motivations, and Modes of Habitual Commodity Speculators." Ph.D. Dissertation, Department of Agricultural Economics, University of Illinois, 1994.

CONSENSUS: National Futures and Financial Weekly, Consensus, Inc., Kansas City, Missouri. Volume XXV, Number 7, February 17, 1995.

Cutler, D.M., J.M. Poterba, and L.H. Summers. "Speculative Dynamics and the Role of Feedback Traders." *American Economic Review*. 80(1989):63-68.

Cutler, D.M., J.M. Poterba, and L.H. Summers. "Speculative Dynamics." *Review of Economic Studies*. 58(1991):529-546.

De Bondt, W.F.M. "Betting on Trends: Intuitive Forecasts of Financial Risk and Return." *International Journal of Forecasting*. 9(1993):355-371.

De Long, J.B., A. Shleifer, L.H. Summers, and R.J. Waldmann. "Noise Trader Risk in Financial Markets." *Journal of Political Economy*. 98(1990a):703-738.

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(1990b):379-395.

De Long, J.B., A. Shleifer, L.H. Summers, and R.J. Waldmann. "The Size and Incidence of the Losses from Noise Trading." *Journal of Finance*. 44(1989):681-696.

De Long, J.B., A. Shleifer, L.H. Summers, and R.J. Waldmann. "The Survival of Noise Traders in Financial Markets." *Journal of Business*. 64(1991):1-19.

Draper, D.W. "The Small Public Trader in Futures Markets." in *Futures Markets: Regulatory Issues*. Ed. Anne E. Peck. Washington, D.C.: American Enterprise Institute for Public Policy Research, 1985.

Friedman, M. "The Case for Flexible Exchange Rates." in *Essays in Positive Economics*. University of Chicago Press, Chicago, 1953, pp. 157-203..

Greene, W.H. *Econometric Analysis*. MacMillan, New York, 1993.

Hamilton, J.D. *Time Series Analysis*. Princeton University Press, New Jersey, 1994.

Harvey, A.C. *The Econometric Analysis of Time Series*. Second edition. MIT Press, Cambridge, Massachusetts, 1991.

Jones, J. "A Comparison of Lag-Length Selection Techniques in Tests of Granger Causality Between Money Growth and Inflation: Evidence for the U.S., 1959-86." *Applied Economics*. 24(1989):809-822.

Keynes, J.M. *The General Theory of Employment Interest and Money*. New York: Harcourt, Brace, and Co., 1936.

Kmenta, J. *Elements of Econometrics*. Second edition. Macmillan Publishing Company, New York, 1986.

Market Vane's Bullish Consensus. Hadady Corporation, Pasadena, California. Volume 29, Issue 6, 1994.

Nagy, R.A. and R.W. Obenberger. "Factors Influencing Individual Investor Behavior." *FinancialAnalysts Journal*. July/August 1994:63-68.

Shleifer, A. and L.H. Summers. "The Noise Trader Approach to Finance." *Journal of Economic Perspectives*. 4(1990):19-33.

Smidt, S. "Amateur Speculators." *Cornell Studies in Policy Administration*. Cornell University, 1965.

Solt, M.E. and M. Statman. "How Useful is the Sentiment Index." *Financial Analyst Journal*. September(1988):45-55.

Thorton, D. and D. Batten. "Lag-Length Selection and Tests of Granger Causality Between Money and Income." *Journal of Banking And Finance*. 17(1985)164-178.

Table 1. Markets and Contract Months.

Market(ticker symbol)	Contract Months
Grain	
Corn(C)*	March, May, July, Sept., Dec.
Wheat(W)	March, May, July, Sept., Dec.
Soybeans(S)	Jan., March, May, July, Aug., Sept., Nov.
Soybean Meal(SM)	Jan., March, May, July, Aug., Sept., Oct., Dec.
Soybean Oil(BO)	Jan., March, May, July, Aug., Sept., Oct., Dec.,
Livestock	
Live Cattle(LC)	Feb., April, June, Aug., Oct., Dec.
Feeder Cattle(FC)	Jan., March, April, May, Aug., Sept., Oct., Nov.
Live Hogs(LH)	Feb., April, June, July, Aug., Oct., Dec.,
Pork Bellies(PB)	Feb., March, May, July, Aug.
Food/Fiber	
Coffee(KC)	March, May, July, Sept., Dec.
Sugar(SB)	March, May, July, Oct.
Cocoa(CC)	March, May, July, Sept., Dec.
Orange Juice(JO)	March, May, July, Sept., Nov.
Cotton(CT)	March, May, July, Oct., Dec.
Lumber(LB)	Jan., March, May, July, Sept., Nov.
Financial	
Deutsche mark(DM)	March, June, Sept., Dec.
British pound(BP)	March, June, Sept., Dec.
Swiss franc(SF)	March, June, Sept., Dec.
Canadian dollar(CD)	March, June, Sept., Dec.
Japanese yen(JY)	March, June, Sept., Dec.
Treasury bills(TB)	March, June, Sept., Dec.
Treasury bonds(US)	March, June, Sept., Dec.
Metal/Energy	
Gold(GC)	Feb., March, April, June, Aug., Oct., Dec.
Silver(SI)	March, May, July, Sept., Dec.
Platinum(PL)	Jan., April, July, Oct.
Heating Oil(HO)	Jan.-Dec.
Crude Oil(CL)	Jan.-Dec.
Gasoline(HU)	Jan.-Dec.

*Ticker symbols are presented in parenthesis and used throughout the remainder of the tables when referring to the various markets.

Table 2. Summary Statistics, Consensus Data: May 1983 - September 1994.

Market	Mean	St. Dev.	Min.	Max.
C*	45.701	19.916	5	92
W	46.413	20.193	3	91
S	46.783	17.882	12	90
SM	42.501	20.012	5	95
BO	43.992	21.861	5	96
LC	51.584	15.547	15	87
FC	46.998	19.617	6	95
LH	44.332	15.696	13	88
PB	39.716	17.913	4	88
KC	43.992	20.906	5	96
SB	51.279	22.112	5	94
CC	41.755	20.455	4	94
JO	40.294	22.731	6	94
CT	45.981	21.331	7	96
LB	42.181	21.033	5	94
DM	46.876	21.822	4	89
SF	45.205	21.739	3	94
JY	42.701	20.821	3	91
BP	42.870	22.017	0	96
CD	41.591	19.899	0	92
TB	46.619	20.917	5	93
US	44.406	17.525	9	86
GC	43.570	20.630	3	96
SI	43.531	19.254	4	95
PL	44.450	21.641	6	95
HO	39.679	20.469	4	87
CL	40.401	18.471	3	86
HU	38.551	20.674	5	93

*All of the markets have 591 weekly observations, except CL and HU which begin in April 1985 and have 494 observations.

Table 3. Summary Statistics, Market Vane Data: May 1983 - September 1994.

Market	Mean	St. Dev.	Min.	Max.	Correlation** Coefficient
C*	53.286	16.343	12	89	0.763
W	52.797	14.715	16	88	0.703
S	52.673	15.429	16	93	0.740
SM	51.321	15.767	12	89	0.718
BO	52.983	15.838	11	89	0.716
LC	52.975	14.680	16	90	0.750
FC	51.418	17.225	5	95	0.596
LH	49.318	15.065	15	87	0.720
PB	47.146	15.018	15	91	0.653
KC	52.526	17.270	11	93	0.721
SB	55.299	16.758	15	91	0.749
CC	49.550	17.481	11	91	0.725
JO	51.602	19.316	5	93	0.716
CT	50.613	16.071	9	88	0.722
LB	50.355	16.503	5	93	0.632
DM	53.044	15.692	15	96	0.770
SF	52.958	15.508	14	96	0.745
JY	52.526	15.186	14	95	0.712
BP	51.051	16.283	13	95	0.745
CD	50.689	15.628	10	97	0.659
TB	51.585	14.711	11	94	0.612
US	50.555	13.085	13	90	0.676
GC	52.673	13.572	16	85	0.799
SI	52.854	13.382	12	92	0.745
PL	52.029	16.263	10	97	0.726
HO	50.871	16.102	10	90	0.673
CL	48.876	16.737	8	95	0.616
HU	49.645	16.384	9	89	0.636

*The Market Vane summary statistics are calculated with 591 weekly observations.
**The final column is the simple correlation coefficient between the Market Vane and Consensus indices. They are calculated with 591 weekly observations, except for HU and HO which have 494 observations. All the correlations are statistically different from zero at the 1% level.

Table 4. Correlation Matrices, Sentiment Across Markets: May 1983 - September 1994.

The upper (lower) off-diagonal entries are correlations for Consensus (Market Vane) data.

Simple Correlation Coefficients

Panel A: Grain

	C*	W	S	SM	BO
C		0.472	0.631	0.481	0.549
W	0.525		0.387	0.335	0.352
S	0.716	0.534		0.692	0.693
SM	0.593	0.458	0.714		0.332
BO	0.617	0.449	0.744	0.415	

Panel B: Livestock

	LC	FC	LH	PB
LC		0.673	0.470	0.268
FC	0.792		0.315	0.180
LH	0.605	0.491		0.654
PB	0.447	0.373	0.764	

Panel C: Food/Fiber

	KC	SB	CC	JO	CT	LB
KC		0.005	0.249	0.023	0.102	0.049
SB	-0.015		0.062	0.037	0.073	0.069
CC	0.334	0.061		0.006	0.046	-0.017
JO	0.057	0.101	0.153		-0.072	-0.021
CT	0.076	0.144	0.156	0.138		0.217
LB	-0.012	0.215	0.004	0.067	0.242	

Table 4 (continued). Correlation Matrices, Sentiment Across Markets: May 1983 - September 1994.

Simple Correlation Coefficients

Panel D: Financial

	DM	SF	JY	BP	CD	TB	US
DM		0.916	0.613	0.774	0.299	0.168	0.259
SF	0.946		0.605	0.789	0.288	0.135	0.186
JY	0.782	0.800		0.591	0.286	0.181	0.126
BP	0.757	0.771	0.624		0.331	0.134	0.152
CD	0.190	0.196	0.139	0.280		0.046	0.191
TB	0.134	0.152	0.106	0.026	0.052		0.627
US	0.107	0.098	0.081	0.012	0.099	0.778	

Panel E: Metal/Energy

	GC	SI	PL	HO	CL	HU
GC		0.700	0.611	0.101	0.087	-0.081
SI	0.813		0.653	0.059	0.032	0.024
PL	0.676	0.693		0.086	0.122	0.068
HO	0.206	0.246	0.215		0.762	0.634
CL	0.287	0.310	0.302	0.877		0.751
HU	0.146	0.227	0.183	0.784	0.805	

[*]The correlations are calculated over 591 observations, except for those using the Consensus CL and HU data which begin April 5, 1985 and have 494 observations. The standard error of the estimated correlations is $(1/n-3)^{½}$, so with n=591 the standard error is 0.04123 and anycorrelation coefficient greater than 0.0809 (0.106) is statistically different from zero at the 5% (1%) level using a two-tailed t-test.

Table 5. Granger Causality Test, Returns Lead Sentiment, Consensus Data.

$$\rho_t = c_0 + \sum_{i=1}^{p} a_i \rho_{t-i} + \sum_{j=1}^{q} b_j R_{t-j} + e_t$$

The model is estimated with OLS, and the Wald Chi-squared statistic tests the null, H_0: $b_j=0 \ \forall$ j. The cumulative impact of returns is calculated, $\sum b_j$ j=1,2,..,q., and tested against the null, H_0: $\sum b_j=0$, with a t-test.

Market	p,q	$\chi^2_{(q)}$	p-value	$\sum b_j$	t-stat.	p-value	adj. R^2
C*	1,2	39.56	0.000	152.6	4.94	0.000	0.761
W	1,1	63.83	0.000	140.7	7.98	0.000	0.741
S	2,2	23.70	0.000	135.3	4.17	0.000	0.701
SM	1,2	42.64	0.000	172.9	5.45	0.000	0.658
BO	2,2	45.70	0.000	178.5	6.29	0.000	0.653
LC	1,6	73.92	0.000	424.3	5.67	0.000	0.608
FC	4,1	43.17	0.000	266.1	6.57	0.000	0.531
LH	2.2	89.65	0.000	183.8	3.96	0.000	0.675
PB	2,3	54.17	0.000	79.3	3.96	0.000	0.630
KC	3,3	92.76	0.000	211.7	7.65	0.000	0.652
SB	3,2	60.91	0.000	90.2	6.75	0.000	0.782
CC	2,2	81.92	0.000	175.2	7.64	0.000	0.631
JO	5,2	37.82	0.000	175.6	5.71	0.000	0.693
CT	5,2	68.17	0.000	215.8	6.75	0.000	0.715
LB	1,2	63.92	0.000	155.6	6.52	0.000	0.608
DM	2,2	97.44	0.000	379.8	7.23	0.000	0.759
SF	2,3	100.5	0.000	460.7	7.42	0.000	0.769
JY	1,5	73.15	0.000	685.8	6.47	0.000	0.745
BP	4,3	81.07	0.000	466.3	6.52	0.000	0.759
CD	3,2	59.12	0.000	917.5	6.84	0.000	0.688
TB	4,1	66.43	0.000	2194	8.15	0.000	0.679
US	4,2	106.3	0.000	388.3	8.22	0.000	0.727
GC	2,2	71.74	0.000	282.5	7.59	0.000	0.795
SI	4,6	98.77	0.000	201.8	4.71	0.000	0.709
PL	2,2	73.41	0.000	213.4	7.91	0.000	0.703
HO	1,1	51.06	0.000	89.4	7.14	0.000	0.645
CL	4,1	40.55	0.000	65.5	6.36	0.000	0.683
HU	4,2	30.15	0.000	119.2	5.03	0.000	0.587

*All models are estimated over 536 weekly observations, except for those involving CL and HU which are estimated over 438 observations.

Table 6. Granger Causality Test, Returns Lead Sentiment, Market Vane Data.

$$\rho_t = c_0 + \sum_{i=1}^{p} a_i \rho_{t-i} + \sum_{j=1}^{q} b_j R_{t-j} + e_t$$

The model is estimated with OLS, and the Wald Chi-squared statistic tests the null, H_0: $b_j=0 \; \forall \; j$. The cumulative impact of returns is calculated, $\sum b_j$ $j=1,2,..,q.$, and tested against the null, H_0: $\sum b_j=0$, with a t-test.

Market	p,q	$\chi^2_{(q)}$	p-value	$\sum b_j$	t-stat.	p-value	adj. R^2
C*	3,2	22.16	0.000	123.7	4.16	0.000	0.576
W	3,2	52.52	0.000	201.2	6.92	0.000	0.513
S	1,6	39.74	0.000	186.4	3.80	0.000	0.549
SM	2,2	54.78	0.000	145.9	5.82	0.000	0.572
BO	3,3	65.84	0.000	171.9	6.03	0.000	0.591
LC	6,1	54.99	0.000	192.5	7.41	0.000	0.551
FC	6,2	33.29	0.000	305.8	4.90	0.000	0.376
LH	1,2	46.71	0.000	150.9	5.56	0.000	0.549
PB	1,2	39.41	0.000	88.5	5.18	0.000	0.463
KC	5,2	54.91	0.000	145.2	7.17	0.000	0.577
SB	2,3	54.18	0.000	54.7	3.18	0.002	0.598
CC	5,1	47.18	0.000	102.1	6.86	0.000	0.529
JO	2,2	64.21	0.000	172.2	7.44	0.000	0.629
CT	2,1	32.91	0.000	94.8	5.73	0.000	0.644
LB	2,3	63.56	0.000	178.1	6.37	0.000	0.575
DM	1,1	54.60	0.000	181.4	7.38	0.000	0.699
SF	1,1	46.50	0.000	166.3	6.81	0.000	0.645
JY	1,3	33.25	0.000	311.5	4.86	0.000	0.635
BP	2,1	41.83	0.000	164.3	6.46	0.000	0.693
CD	2,1	41.10	0.000	501.5	6.41	0.000	0.597
TB	6,2	28.37	0.000	1651	4.82	0.000	0.610
US	5,4	37.60	0.000	243.3	3.42	0.001	0.601
GC	1,1	17.84	0.000	71.85	4.22	0.000	0.637
SI	4,5	33.19	0.000	94.1	3.01	0.002	0.538
PL	4,6	44.33	0.000	74.17	1.58	0.115	0.618
HO	1,4	25.38	0.000	140.8	4.63	0.000	0.533
CL	5,1	20.87	0.000	54.6	4.56	0.000	0.591
HU	1,4	38.33	0.000	169.5	5.63	0.000	0.466

*All models are estimated over 558 weekly observations, except for those involving CL and HU which are estimated over 539 and 457 observations, respectively.

Table 7. Pooled Causality Test, Returns Lead Sentiment, Consensus Data.

Independent Variables	Grain	Livestock	Food/Fiber	Financial	Metal/Energy
intercept	11.09	12.03	10.45	10.33	10.02
	(16.9)*	(12.3)	(17.0)	(16.6)	(13.7)
ρ_{t-1}	0.664	0.617	0.645	0.692	0.685
	(31.2)	(26.1)	(33.2)	(39.2)	(32.7)
ρ_{t-2}	0.091	0.049	0.028	0.021	0.026
	(4.57)	(1.78)	(1.21)	(0.96)	(1.02)
ρ_{t-3}		0.022	0.044	-0.003	0.029
		(0.80)	(1.94)	(-0.15)	(1.15)
ρ_{t-4}		0.053	0.011	0.052	0.022
		(2.32)	(0.49)	(3.11)	(1.07)
ρ_{t-5}			0.026		
			(1.54)		
R_{t-1}	126.5	95.9	104.0	233.8	94.1
	(14.6)	(11.6)	(18.8)	(17.5)	(13.8)
R_{t-2}	37.6	25.9	32.9	79.6	29.5
	(4.44)	(3.03)	(5.64)	(5.67)	(4.15)
R_{t-3}		4.09	5.22	28.4	4.64
		(0.47)	(0.90)	(2.01)	(0.65)
R_{t-4}		-5.76		28.5	-1.95
		(-0.78)	(2.11)	(-0.28)	
R_{t-5}		-7.65		-5.93	9.54
		(-0.94)	(-0.44)	(1.38)	
R_{t-6}		-4.67			-3.37
		(-0.58)		(-0.50)	
$\sum b_j$	164.1	107.8	142.2	364.6	132.4
	(12.8)	(4.86)	(13.2)	(10.7)	(7.24)
$\chi^2_{(q)}$	221.6**	143.9	368.7	364.6	202.7
Buse R^2	0.667	0.545	0.683	0.671	0.653

*T-statistics in parenthesis test if the coefficient equals zero, with degrees of freedom equal to N*K-(p+q+1), where N=536 (438 for metal/energy) and K=number of markets in the group.

**All the $\chi^2_{(q)}$ statistics reject that the coefficients on lagged returns are zero at the 1% level.

Table 8. Pooled Causality Test, Returns Lead Sentiment, Market Vane Data.

Independent Variables	Grains	Livestock	Food/Fiber	Financial	Metal/Energy
intercept	20.58 (17.9)[*]	19.80 (15.3)	15.77 (18.7)	13.84 (17.5)	14.62 (13.7)
ρ_{t-1}	0.518 (25.1)	0.511 (22.1)	0.552 (27.6)	0.622 (36.1)	0.567 (27.5)
ρ_{t-2}	0.024 (1.05)	0.018 (0.73)	0.090 (3.96)	0.046 (2.28)	0.032 (1.36)
ρ_{t-3}	0.063 (3.09)	0.017 (0.69)	0.044 (1.99)	0.063 (3.16)	0.054 (2.32)
ρ_{t-4}		0.044 (1.81)	-0.025 (-1.19)	-0.033 (-1.68)	0.061 (2.60)
ρ_{t-5}		-0.016 (-0.68) (2.05)	0.034 (1.21)	0.023 (0.30)	0.006
ρ_{t-6}		0.037 (1.81)		0.009 (0.57)	
R_{t-1}	116.5 (15.5)	76.5 (9.95)	83.9 (16.1)	133.3 (12.6)	55.8 (9.52)
R_{t-2}	44.5 (5.65)	33.2 (4.24)	24.6 (4.49)	33.8 (3.14)	32.2 (5.36)
R_{t-3}	15.74 (2.04)		1.91 (0.35)	-3.19 (-0.29)	4.93 (0.82)
R_{t-4}	0.67 (0.08)			1.01 (0.09)	4.10 (0.68)
R_{t-5}	-3.85 (-0.52)				-11.4 (-1.94)
R_{t-6}	3.35 (0.47)				-6.34 (-1.09)
$\sum b_j$	177.1 (8.35)	109.8 (9.74)	110.5 (10.7)	165.0 (7.27)	79.3 (4.98)
$\chi^2_{(p)}$	258.8[**]	112.9	264.1	164.8	111.3
Buse R^2	0.501	0.389	0.581	0.556	0.518

[*]T-statistics in parenthesis test if the coefficient equals zero, with degrees of freedom equal to N*K-(p+q+1), where N=558 (457 for metal/energy) and K=number of markets in the group.
[**]All the $\chi^2_{(q)}$ statistics reject that the coefficients on lagged returns are zero at the 1% level.

Figure 1. Consensus Index of Bullish Market Opinion, Coffee: Weekly, May 1983 - September 1994.

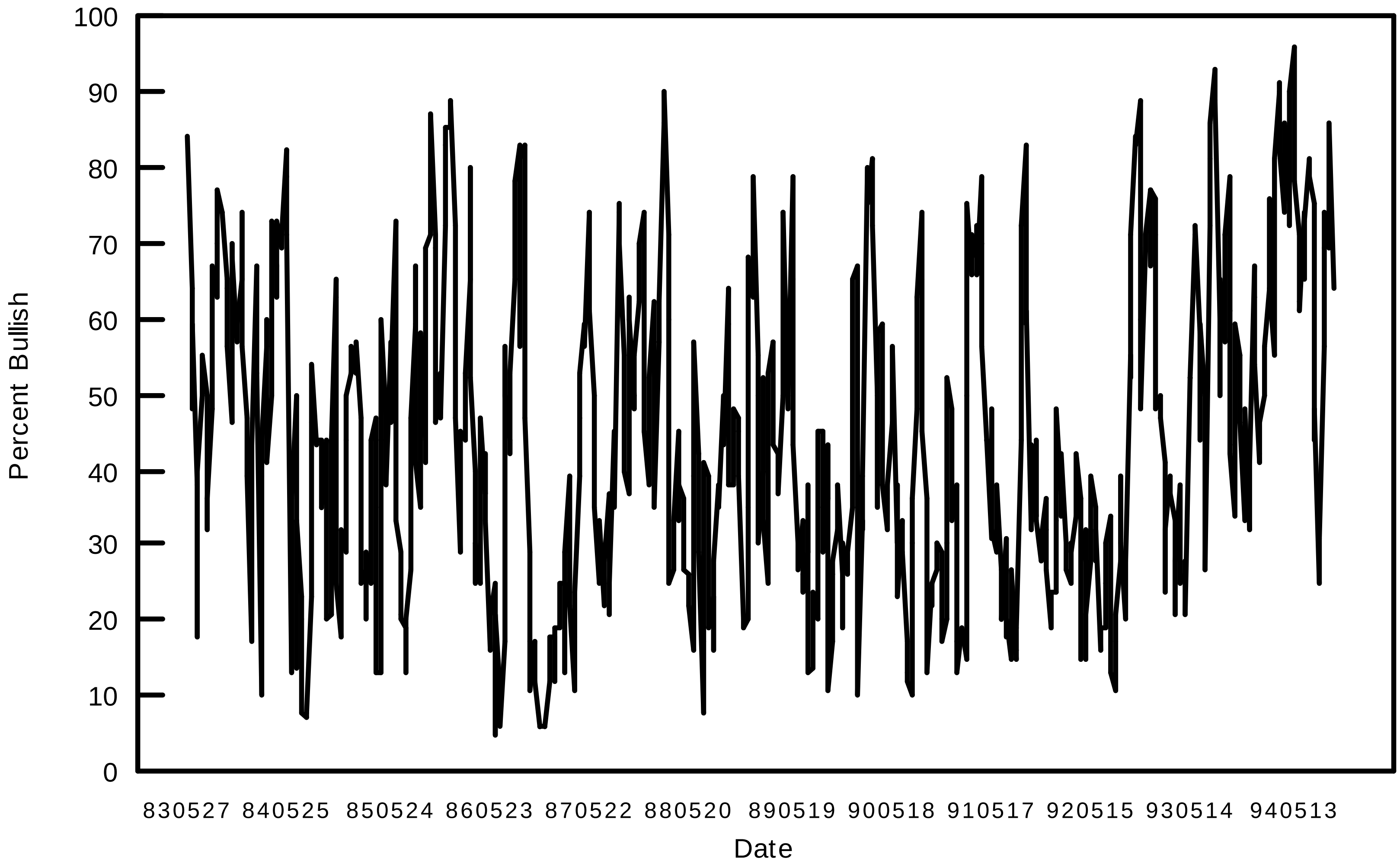

Figure 2. Extrapolative Expectations, Impulse Response Function, Consensus Data.

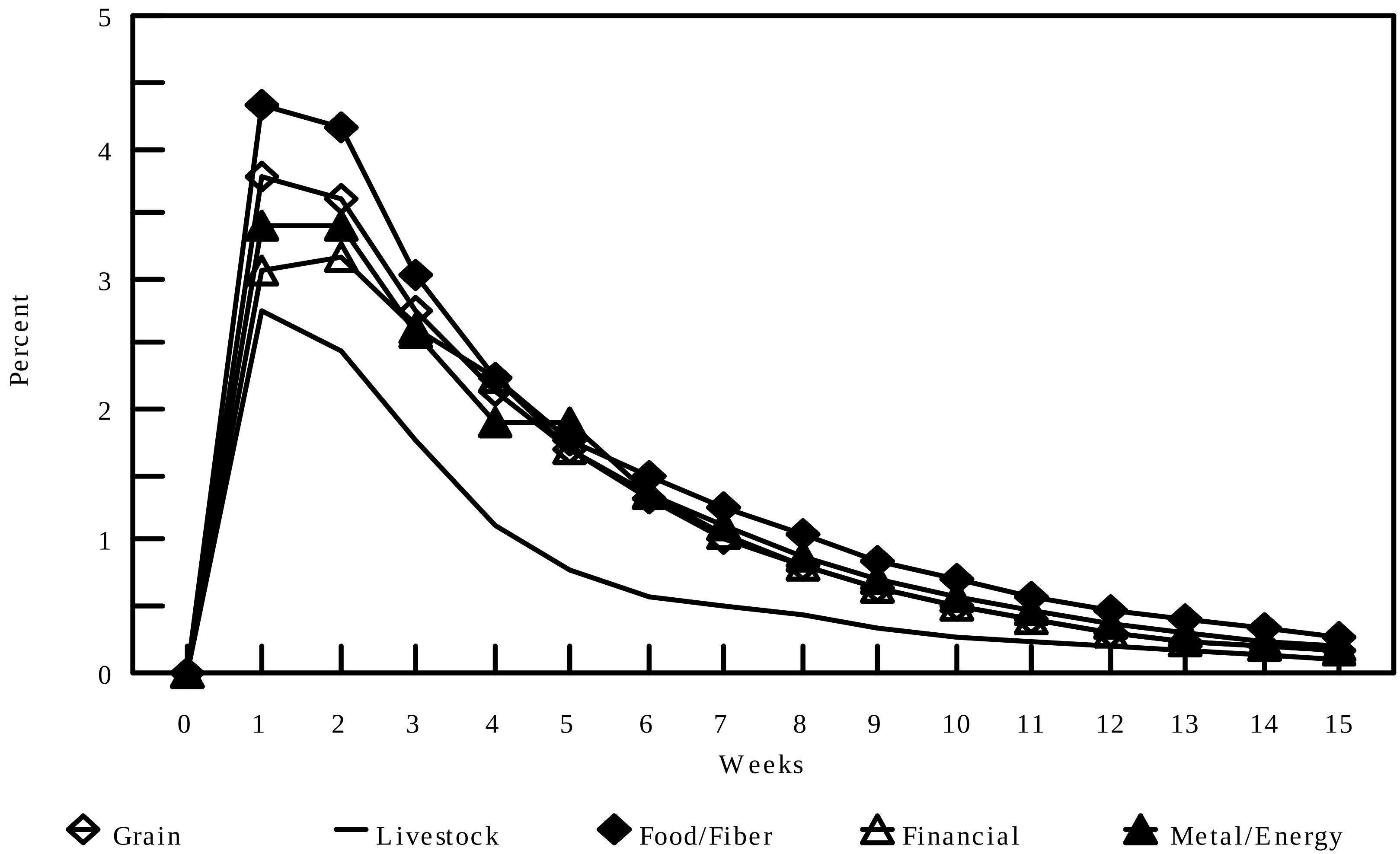

Figure 3. Extrapolative Expectations, Impulse Response Function, Market Vane Data.