Noise Traders, Market Sentiment, and Futures Price Behavior

by

Dwight R. Sanders, Scott H. Irwin, and Raymond M. Leuthold[1]

May 1997

[1]Dwight R. Sanders is Manager, Commodities Analysis with Darden Restaurants. Scott H. Irwin is Francis B. McCormick Professor of Agricultural Marketing and Policy in the Department of Agricultural Economics at The Ohio State University. Raymond M. Leuthold is the Thomas A. Hieronymus Professor in the Department of Agricultural and Consumer Economics at the University of Illinois at Urbana-Champaign.

Noise Traders, Market Sentiment, and Futures Price Behavior

Abstract

The noise trader sentiment model of De Long, Shleifer, Summers, and Waldmann (1990a) is applied to futures markets. The theoretical results predict that overly optimistic (pessimistic) noise traders result in market prices that are greater (less) than fundamental value. Thus, returns can be predicted using the level of noise trader sentiment. The null rational expectations hypothesis is tested against the noise trader alternative using a commercial market sentiment index as a proxy for noise trader sentiment. Fama-MacBeth cross-sectional regressions test if noise traders create a systematic bias in futures prices. The time-series predictability of futures returns using known sentiment levels is tested in a Cumby-Modest market timing framework and a more general causality specification. The empirical results lead to the following conclusions. First, there is no evidence that noise trader sentiment creates a systematic bias in futures prices. Second, predictable market returns using noise trader sentiment is not characteristic of futures markets in general. Third, futures market returns at weekly intervals are characterized by low-order positive autocorrelation with relatively small autoregressive parameters. In those instances where there is evidence of noise trader effects, it is at best limited to isolated markets and particular specifications.

Noise Traders, Market Sentiment, and Futures Price Behavior

> I analyze the gold market by using monthly, weekly, and daily charts. I then look at what the moving averages are doing with stochastic studies and either window envelopes or Bollinger Bands...The 18 day moving average...is my "Bell Weather" moving average. When the market is above it, I am bullish, when the market is below it, I am bearish.... Fibonnaci retracement levels are taken from finding a high to a low point, or a low to a high point and then dividing the market into quadrants. I use those quadrants to find support and resistance lines in the markets. History shows that this type of analysis has merit. When all of this is put together an analysis is made (Ira Epstein).

Do traders such as Mr. Epstein, who trade on non-fundamental information, impact the behavior of futures prices? This question is central to our understanding of futures markets and, consequently, for effective market participation and regulation. The following research, couched within the noise trader paradigm, provides empirical insight into noise traders, market sentiment, and the subsequent behavior of futures prices.

Black defines "noise" as non-information and "noise trading" as trading on noise as if it were information. He asserts that noise traders may not be eliminated from the market because rational arbitrage against them is costly and, thus, limited. Noise traders are not rational Bayesian forecasters; thus, they make markets less efficient. Yet, noise traders are also beneficial because they also provide market liquidity. The topic of irrational speculation is not new, as economists have long debated the effects of noise traders on asset prices. For instance, neoclassical economists (e.g., Friedman; Working) traditionally argue that speculation is stabilizing and that uninformed speculators are quickly dispatched by their rational counterparts. Other well-known economists (e.g., Keynes; Fisher) argue that public speculation is a destabilizing mania. Recent theoretical models support the possibility that noise traders can persist in markets, and thereby, exert a destabilizing influence on prices (e.g., De Long, Shleifer, Summers, and Waldmann, 1989, 1990a, 1990b, 1991; Lux; Palomino). In this research, new empirical evidence is brought to bear on theoretical noise trader models.

Previous empirical research concerning noise trading tends to focus on the symptoms rather than the cause. That is, market behavior is examined for characteristics that suggest the presence of noise traders (e.g., Liu, Thompson, and Newbold). For instance, autocorrelation (e.g., Taylor) or mean-reversion (e.g., Ma, Dare, and Donaldson) in futures returns can be generated by noise traders; but, they may also arise from a disequilibrium adjustment process (Beja and Goldman) or some time-varying risk premium (Bessembinder). These studies test market rationality, but they do so without a clearly defined alternative hypothesis. Researchers that do hypothesize well-defined noise trader alternatives often must rely on somewhat *ad hoc* empirical measures of noise trader sentiment (e.g., Ma, Peterson, and Sears; Kodres).

In this paper, a futures market variant of De Long, Shleifer, Summers, and Waldmann's (1990a) noise trader sentiment model is developed. The model provides a clear alternative to market rationality. The model's predictions are tested using a commercial measure of market sentiment, which is based on surveys of market participants' price outlook. Consequently, noise trader sentiment reflects actual retail speculators' expectations. Using the bullish consensus index as a proxy for noise trader sentiment, the research seeks to determine if noise trader sentiment creates a direct and systematic price pressure effect on futures prices, where price pressure materializes as a systematic forecast bias or in the time series predictability of returns.

A Noise Trader Risk Model for Futures Markets

De Long, Shleifer, Summers, and Waldmann (DSSW, 1990a) develop an overlapping generations model that provides considerable insight into the behavior of asset prices in markets populated by noise traders. However, the model is not directly applicable to futures markets. Most notably, the unsafe asset in the economy is fixed in supply; whereas, there is a net zero supply of futures contracts. A simple modification is made within the model to derive the impact of noise trader sentiment on zero net supply investments. The resulting model is more applicable to futures markets.[1]

DSSW's model is a parsimonious overlapping generations model with no labor supply decision, bequest, or first period consumption.[2] There are two assets: a safe asset, s, and an unsafe asset, u. The safe asset is in perfectly elastic supply, pays a real dividend, r, in every period, and has a fixed price of 1. The unsafe asset pays the same real dividend, r, in every period as the safe asset, and it has a price of p_t. In DSSW's model, the unsafe asset is in perfectly inelastic supply normalized at one unit. Here, in the spirit of a futures market, the unsafe asset has a net zero supply.

There are two types of two-period-lived agents: rational investors, I, and noise traders, n. The rational investors have rational expectations concerning the distribution of p_t and are present in measure 1-μ ($\mu \in [0,1]$). Noise traders are present in measure μ and misperceive the distribution of p_t by an i.i.d. normal variable $\rho_t \sim N(\rho^*, \sigma^2_\rho)$. The mean misperception, ρ^*, is the average bullishness or bearishness of noise traders, and the variance, σ^2_ρ, is the volatility of noise trader sentiment. Market sentiment can arise from technical trading rules, extrapolation of price changes, or investment fads.

Both agent types choose portfolios when young (i.e., first period of life) to maximize perceived expected utility given their beliefs about the *ex ante* distribution of u when they are old, t+1. Each agent has a constant absolute risk aversion utility function: U=-exp $^{-(2\gamma)w}$, where, γ is the coefficient of absolute risk aversion. Each agent maximizes the expected utility of final wealth, w, which is equivalent in a mean-variance framework to maximizing: E(U) = $\bar{w}$- γ σ^2_w.

The representative sophisticated investor rationally perceives the distribution of returns, and chooses amount λ^i_t of the risky asset, u, to maximize expected utility:

$$E(U)=c_0+\lambda_t^i[({}_tp_{t+1}-p_t)-r(1-p_t)]-\gamma(\lambda_t^i)^2({}_t\sigma^2_{p_{t+1}}) \ . \tag{1}$$

The first term in brackets is the expected capital gain from investing in the unsafe asset, and the second term in brackets is the effective dividend of the unsafe asset due to purchasing it at a discount or premium to its fundamental value. The constant, c_0, is a function of first period labor income.[3,4] Following DSSW we can rearrange (1) to get the following expression for the sophisticated investor's expected utility:

$$E(U)=c_0+\lambda_t^i[r+{}_tp_{t+1}-p_t(1+r)]-\gamma(\lambda_t^i)^2({}_t\sigma^2_{p_{t+1}}) \ . \tag{2}$$

Like the sophisticated investor, the representative noise trader chooses the amount of the unsafe asset, λ^n_t, to maximize expected utility:

$$E(U)=c_0+\lambda_t^n[r+{}_tp_{t+1}-p_t(1+r)]-\gamma(\lambda_t^n)^2({}_t\sigma^2_{p_{t+1}})+\lambda_t^n(\rho_t) \ . \tag{3}$$

The difference between the two representative traders' expected utility is the last term in (3): the noise trader's misperception of capital gains due to irrational sentiment, ρ_t.

The representative rational and noise traders maximize their expected utility, resulting in demands (4) and (5), respectively.

$$\lambda_t^i = \frac{r + {}_t p_{t+1} - (1+r)p_t}{2\gamma({}_t\sigma^2_{p_{t+1}})} \quad , \tag{4}$$

$$\lambda_t^n = \frac{r + {}_t p_{t+1} - (1+r)p_t + \rho_t}{2\gamma({}_t\sigma^2_{p_{t+1}})} \quad , \tag{5}$$

$$\mu(\lambda_t^n) + (1-\mu)\lambda_t^i = 0 \quad . \tag{6}$$

Demands are increasing in perceived returns and decreasing in perceived variance.[5] The difference in (4) and (5) is noise traders' sentiment, ρ_t, where bullish sentiment (ρ_t>0) causes an increase in noise trader demand. Equation (6) is the market clearing condition for the speculative asset in zero net supply. The three equation system is solved for a pricing function,

$$p_t = \frac{r + \mu\rho_t + {}_t p_{t+1}}{(1+r)} \quad . \tag{7}$$

Recursively solving for the steady-state equilibria (assuming the unconditional distribution of p_{t+1} equals the conditional distribution of p_t), the final equilibria pricing rule is derived:

$$p_t = 1 + \frac{\mu\rho^*}{r} + \frac{\mu(\rho_t - \rho^*)}{1+r} \quad , \tag{8}$$

and

$$\sigma_{p_t}^2 = \frac{\mu^2 \sigma_\rho^2}{(1+r)^2} \ . \qquad (9)$$

Equation (8) is the equilibrium pricing function and (9) is the price variance. Comparing (8) with DSSW's pricing rule result (DSSW's equation 12), one difference is immediately obvious; noise traders cannot "create their own space" in the futures market. That is, there is not a premium for assuming noise trader risk in futures markets. This stems from the fact that the futures investment is really just a side bet on price movements, and therefore, requires no net risk sharing capacity within the economy. For instance, in (8) if $\rho_t=\rho^*=0$, then no side bets are made between noise traders and rational traders; thus, the unsafe asset u equals its fundamental value because no noise trader risk is borne.

The other general results from DSSW's model pertain to the futures market. Examining (9), it is clear that futures price volatility is increasing in the proportion of noise traders and in the variability of their sentiment. In equation (8), noise trader sentiment impacts the pricing of futures contracts. The first term of (8) indicates that the futures price equals fundamental value in the absence of noise traders. The second and third terms of (8) capture the price pressure effects of noise traders. If noise traders are on average bearish ($\rho^*<0$), then the price is lower (on average) than fundamental value. Also, if noise traders are more bullish than average at time t ($\rho_t>\rho^*$), then they are able to push prices above fundamental value. From equation (8), the equilibrium pricing of futures contracts and the time series characteristics of returns can be derived.

Assuming that the futures price is equal to fundamental value of 1 at expiration, and applying iterative expectations (e.g., Samuelson), the pricing equation (8) can be rewritten to display the time series characteristics and equilibrium pricing respectively:

$$R_t = p_t - p_{t-n} = -[\frac{\mu\rho^*}{r} + \frac{\mu(\rho_{t-n} - \rho^*)}{1+r}] \ , \tag{10}$$

and taking expectations,

$$E(R_t) = E(p_t - p_{t-n}) = -\frac{\mu\rho^*}{r} \ . \tag{11}$$

where, R_t is the continuously compounded percentage change in the futures price over the interval n.[6]

From equation (10), the noise trader model suggests that the forecast error at any time t is not random, but contains a deterministic bias, $-(\mu\rho^*)/r$, as well as time-varying component, $-\mu(\rho_t-\rho^*)/(1+r)$. The pricing error at time t (i.e., the deviation from fundamental or final value) is inversely proportional to the sentiment of noise traders at time t. If noise traders are unduly bullish at time t, $(\rho_t>\rho^*)$, then the futures forecast is too high and prices will decline. Likewise, bearish time t noise traders, $(\rho_t<\rho^*)$, are associated with rising futures prices, $R_t>0$. To the extent that ρ_t is known, then the futures price violates the efficiency or orthogonality condition of traditional rational models (Muth).

Additionally, in equation (11), futures prices are on average biased forecasts of fundamental value, and the expected bias equals $-(\mu\rho^*)/r$. That is, the deterministic bias in futures prices is proportional to the average level of sentiment among noise traders. The more bearish noise traders are on average (the lower ρ^*) for a particular commodity, then the greater the downward bias in the futures price, p_{t-n}. Consequently, the futures price will rise on average towards fundamental value. The predictions in equations (10) and (11) provide distinct, empirically testable, alternatives to a rational expectations hypothesis. The following sections discuss two approaches to empirically testing the noise trader predictions: cross-sectional and time series.

Empirical Methodology

A central prediction of the noise trader model presented above is that noise traders force prices away from fundamental value. That is, when noise traders are bullish, prices are pushed above their rationally expected value. It is inherently difficult to determine *ex ante* the fundamental value of an asset, however, the *ex post* realization of price serves as a guide. That is, within the context of futures markets, the current futures price provides a forecast for the cash price expected to prevail at contract expiration. In a rational market (in the Muthian sense) with no risk premium, the futures price is an unbiased and efficient forecast. In contrast, the noise trader model predicts that forecast errors will be influenced by the sentiment of noise traders. Couched within a rational expectations framework, cross-sectional regressions are specified to test if noise traders introduce a systematic bias in futures prices, and time series models of return predictability are specified to test for forecast efficiency. These tests improve upon prior methodology (e.g., Ma, Donaldson, and Sears) by directly testing the impact of noise trader sentiment under a well-defined alternative hypothesis.

Cross-Sectional Test for Systematic Forecast Bias

Under the rational expectations hypothesis the expected bias in futures prices is zero.[7] However, the systematic bias for market I under the noise trader model is expressed as a function of the model's parameters, $-(\mu^i\rho^{*I})/r$. Assuming that μ^i and r are constant across commodities and time, then the noise trader model (11) predicts that the equilibrium futures return is inversely proportional to the mean noise trader sentiment in market I, ρ^{*I}. This prediction can be tested with the cross-sectional regressions of Fama and MacBeth.

Let $\bar{\rho}^I$ be a sample estimate of the mean noise trader sentiment in market I. The following cross-sectional model is derived from equation (11),

$$E(R_t^i) = \alpha + \beta\rho^{*i} \ , \tag{12}$$

and can be empirically estimated as,

$$\bar{R}^i = \alpha + \beta\bar{\rho}^i + \epsilon^i \ . \tag{13}$$

The average forecast bias, $\bar{R}^I$, is a function of the average level of noise trader sentiment in market I. Following the procedure set forth by Fama and MacBeth, the cross-sectional regressions are estimated using *ex ante* estimates of ρ^{*I}. That is, $\bar{\rho}^I$ is estimated over K periods, then this *ex ante* estimate is the independent variable in explaining the average forecast bias, $\bar{R}^I$, in the subsequent J periods, where J need not equal K. So, for each market I, $\bar{\rho}^I$ is calculated for the first K periods of the sample. Then, the bias, $\bar{R}^I$, is calculated over the following J periods in market I. Tabulating these data for I=1,2,..,N markets, the regression in (13) is estimated over N cross-sectional observations. This process is repeated for each J length non-overlapping subperiods in the entire sample.

For example, consider a sample of one hundred weekly observations on fifteen markets, and let K=10 and J=10. Then, for each market, $\bar{\rho}^{I}$ is calculated over observations one through ten, and this is the independent variable in the cross-sectional regression explaining $\bar{R}^{I}$, which is calculated over observations eleven through twenty. The second cross-sectional regression for this data set would use $\bar{\rho}^{I}$ calculated over observations eleven through twenty to explain $\bar{R}^{I}$ calculated over observations twenty-one through thirty. This procedure would be repeated through all one hundred time series observations, resulting in nine cross-sectional regressions (15 observations each) for the entire sample.

The individual regression results can be pooled, and inferences are drawn from the M separate OLS cross-sectional regression equations using the Fama and MacBeth procedure,

$$\bar{\beta} = \frac{1}{M}\sum_{m=1}^{M} \beta_m; \quad st.\ err.\ (\bar{\beta}) = \frac{\sigma_{\bar{\beta}}}{\sqrt{M}} \ . \tag{14}$$

Using the distribution of the average slope coefficient, $\bar{\beta}$, the null hypothesis of no predictable bias across markets, $\beta \neq 0$, can be tested using a two-tailed t-test calculated with the average slope estimate and its standard error.[8] Note that a finding of $\beta<0$ supports the noise trader alternative, whereas a finding of $\beta>0$ rejects the null hypothesis but is not supportive of any particular alternative hypothesis.

Time Series Tests for Predictability

The rational expectations hypothesis posits that the futures' forecast error is orthogonal to the available information set. Consequently, the futures return, R_t, is random, and the forecast is efficient with respect to available information. In contrast, the noise trader model in (11) indicates that the forecast error, and subsequently R_t, is not orthogonal to all information. Rather, R_t is correlated with and can be predicted by noise trader sentiment at time t-n, ρ_{t-n}. Specifically, if noise traders are bullish (bearish), then the futures' forecast is overly optimistic (pessimistic) and the subsequent return is predicted to be negative (positive). The first test of return predictability is a relatively simple specification of market timing developed by Cumby and Modest, and the second is a more general specification of predictability associated with Granger.

The Cumby-Modest Test

The usefulness of sentiment in predicting price changes can be evaluated in the market timing framework proposed by Cumby and Modest (C-M). Empirically, sentiment provides market signals through extremely high levels, K_H, and low levels, K_L. The (C-M) test evaluates the ability to be on the correct side of major price changes with the following OLS regression:

$$R_t = \alpha + \beta_1 HI_{t-1} + \beta_2 LO_{t-1} + \epsilon_t \tag{15}$$

where, $HI_{t-1}=1$ if $\rho_{t-1}>K_H$, =0 otherwise, and $LO_{t-1}=1$ if $\rho_{t-1}<K_L$, =0 otherwise. If the mean return conditioned on extreme optimism ($\alpha+\beta_1$) or pessimism ($\alpha+\beta_2$) is different from the unconditional mean (α), then timing ability is demonstrated. The null hypothesis of no timing ability, H_0: $\beta_1=\beta_2=0$, is tested against the alternative of significant timing ability, H_A: $\beta_1\neq 0$ or $\beta_2\neq 0$. Specifically, the noise trader model suggests that $\beta_1<0$ or $\beta_2>0$, indicating that sentiment has a negative impact on returns.

Causality Tests

A general method of exploring the linear linkages between price and sentiment is to test for "Granger causality." Hamilton suggests the following direct or bivariate Granger test:[9]

$$R_t = k_0 + \sum_{i=1}^{m} \alpha_i R_{t-i} + \sum_{j=1}^{n} \beta_j \rho_{t-j} + \epsilon_t \ . \qquad (16)$$

where, R_t and ρ_t are futures returns and noise trader sentiment, respectively, and ϵ_t is a white noise error term. Sentiment leads returns in equation (16) if market sentiment is useful in predicting returns, and it is tested under the null of $\beta_j=0\ \forall\ j$. Furthermore, the theoretical model suggests that $\sum \beta_j < 0$. That is, high sentiment portends low returns as prices decline to fundamental value. Rational expectations is also tested under the full orthogonality condition: $\beta_j=\alpha_i=0\ \forall\ i,j$.

Recognizing the low statistical power of these tests against the null hypothesis (see Summers), the power of the tests is increased by estimating them over pooled cross-sectional time series data. That is, individual markets are designated into related commodity groups (e.g., grains), and the empirical models are estimated with time series data pooled across the related markets. Pooling time series data across markets not only increases the power of the tests, but also provides a concise way of presenting and testing for common noise trader effects in similar markets.

Choosing the appropriate lag lengths (m and n) is of practical significance in performing the causality test (see 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 (16) the model is estimated by varying the own-lag length of R_t from $m=1,2,...m^{max}$, and the lag length of ρ_t from $n=1,2,...,n^{max}$ such that a total of (m^{max} x n^{max}) regressions are estimated. The m,n lag length combination that minimizes Akaike's information criteria (AIC) is chosen as the final model specification. This search procedure is conducted for equation (16) for each individual market within a commodity group (results not shown). Then, the lag-lengths for the pooled regressions are specified by choosing the maximum m and the maximum n from among the individual market specifications within a group. For instance in the grain group the maximum m was 5 (for the corn model) and the maximum n was 1 (for the wheat and soybean models); therefore, the pooled grain model's lag structure is 5,1. 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.[10]

Measuring Noise Trader Sentiment

A commercial investment services firm, Consensus Inc. compiles a market sentiment index. Market advisory services, newsletters, electronic bulletin boards, and hotlines are surveyed as to whether they are bullish or bearish on particular commodities. The methodology Consensus Inc. 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 Inc. 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 Inc. 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 Inc. receives 100 newsletters that comment on the U.S. Treasury bond market and 25 of those think that bond prices are going to increase, then the CBSI is 0.25 or 25 percent.[11] The index is compiled on 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*.

The CBSI is available weekly for twenty-eight futures markets from May 1983 through September 1994 (591 observations). The availability of sentiment data on a broad cross-section of markets will strengthen general conclusions and avoid erroneous implications based on the nuances of a particular market. For pooled estimation purposes and to facilitate the presentation of results, 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; livestock;

food/fiber; financial; and metal/energy. A complete listing of groups and markets is presented in Table 1.

As a maintained hypothesis, it is assumed that the indices compiled by Consensus Inc. reflect the sentiment of noise traders--not rational or informed market participants. That is, the market views subsumed within the indices are those of smaller retail speculators who are acting on non-information: technical trading rules, extrapolation, or old news that is already incorporated into the market price. This maintained hypothesis is supported by reviewing the decision-making rules of small traders and their information sources.

Surveys by Canoles, Smidt, The Chicago Board of Trade (see Draper), and *Barron's* (see Draper) find that the average amateur futures trader is highly educated and trades for the leverage and excitement. Furthermore, these speculators generally do not bring new information to bear on the markets; rather, they collect much of their information from focused media sources such as those surveyed by Consensus. 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 *CONSENSUS*, such as in the introduction to this paper, indicate that market advisors rely heavily on technical indicators for decision-making and simply pass along this information to their retail subscribers. A minority of newsletters are fundamental in nature, relaying government reports, seasonal tendencies, and pertinent cash market conditions. Although these newsletters often contain detailed interpretations of relevant supply and demand factors, the fundamental analysis tends to reiterate public information, and it provides rather vague price predictions.

The non-informational nature of the market newsletters, coupled with the evidence that retail investors rely on this advise in making decisions, supports the maintained hypothesis: the sentiment indices are reasonable proxies for noise trader sentiment. To the extent that "systems" and pseudo-signals are correlated across the advisors, then this group of noise traders will act in concert and can potentially impact market prices.[12]

Noise Trader Impact on Futures Prices

Cross Sectional Test Results

The cross-sectional equation (13), is estimated with OLS using weekly observations of the CBSI along with weekly futures returns.[13, 14] The $\bar{\rho}^i$ are calculated over fifty week formation periods (K=50), and the $\bar{R}^i$ are calculated over the subsequent fifty weeks (J=50). The fifty-week formation and testing periods were chosen instead of (say) 52 weeks to maximize the number of complete samples that could be drawn from the data set. This results in eleven independent cross-sectional regressions formed from May 1983 through September 1994.

The eleven individual cross-sectional regressions are presented in Table 2. The rational expectations (null) hypothesis predicts that $\beta = 0$, while the noise trader model predicts that the slope coefficient is negative, $\beta < 0$. Looking at the individual regression results in Table 2, it is clear that the individual models have relatively little explanatory power, and the estimated β coefficient is seldom different from zero (except samples 2 and 8). The individual coefficients are pooled according the method proposed by Fama and MacBeth and presented in the last row of the table. Although the average slope coefficient is negative, as predicted by the noise trader model, it is not statistically different from zero.

The results of the cross-sectional tests can be sensitive to the size of both the formation (K) and testing periods (J). There is no strong justification for using a fifty week period. So, to test the model's sensitivity to alternative formation and testing period lengths, the cross-sectional regressions are estimated with K, J values of (50,100), (25,25), (25,50), and (5,5). The alternative Fama-MacBeth estimation results are presented in Table 3. The results are not materially different from the (50,50) pooled model in Table 2. Average slope coefficients are negative in three of the five cases, but none are statistically different than zero.

The null hypothesis of no systematic bias, $\beta=0$, in futures prices cannot be rejected in favor of the noise trader alternative, $\beta<0$, using cross-sectional Fama-MacBeth estimation of equation (13). This result is robust to alternative lengths of both the formation and test period (i.e., values of K and J). In general, the average level of noise trader sentiment has no discernable ability to explain cross-sectional variation in futures market returns.

Cumby-Modest Test Results

The C-M model, equation (15), tests if the mean return following extremely high (K_H) or low (K_L) sentiment levels is significantly different from the unconditional mean return (i.e., when sentiment is between the extremes levels). The C-M test allows for different market reactions at high and low sentiment levels. Specifying the C-M model requires a definition of extreme sentiment. Consensus Inc. suggests that sentiment outside the range of (25,75) indicates a market approaching extreme conditions. For the C-M test, extreme sentiment is defined by these levels plus a factor of five to assure that the extremes compose a small percentage of the total observations, and hence, K_H = 80 and K_L = 20.

Equation (15) is estimated with OLS using weekly data. The OLS error terms are tested for heteroskedasticity using White's test and autocorrelation using the Lagrange multiplier test. If the errors are heteroskedastic then the model is estimate using White's heteroskedastic consistent covariance estimator, and if the errors are autocorrelated then the Newey-West covariance estimator is utilized.[15]

The C-M test results for the individual markets are presented in Table 4. The t-statistic for each parameter equaling zero is presented in parentheses, and the Chi-squared statistic tests the joint null that both slope coefficients equal zero (p-value provided). For individual markets, the number of extreme observations constitute from 4.3% (23) to 30% (161) of the 536 total observations. Based on Chi-squared statistics, the null hypothesis of no timing ability ($\beta_1=\beta_2=0$) is rejected at the 5% level in three of the twenty-eight markets (LC, CD, HU). This is more than would be expected by chance (0.05 X 28 = 1.25 rejections). The null hypothesis is rejected for two more markets (S, CC) at the 10% level.

While there is evidence of a significant relationship between extreme sentiment and returns, the direction of the relationship generally is not as expected from noise trader theory. Recall that β_1 is expected to be negative and β_2 positive, as returns reverse after extreme levels of noise trader sentiment. It is found that β_1 is negative for only 10 of the 28 markets, and β_2 is positive for only 10 markets. If anything, the relationship is one of continuation, where returns increase (decrease) after high (low) sentiment, rather than reversal. In addition, there is variation in the coefficient signs for those markets where the null is rejected. For instance, if the CBSI is below 20, then the following week nearby live cattle (LC) returns increase by 2.07% on average, while Canadian dollar (CD) returns fall 0.187%.[16]

To reveal noise trader effects that are systematic within related markets, the C-M test is estimated as a pooled cross-sectional time series using Kmenta's cross-sectionally correlated, heteroskedastic, and time-wise autoregressive GLS estimation technique. Pooling restricts the estimated parameters to be the same for each market. In doing so, it reveals noise trader effects that are uniform and systematic across the markets.[17]

The pooled C-M tests with $K_H = 80$ and $K_L = 20$ are presented in Panel B of Table 5. Of the five market groups, the null of no market timing is rejected at the 5% level for the grains and at the 10% level for the financials. Again, the coefficient signs are not entirely consistent with theory, as only 3 of the ten signs are as predicted. As an example, the estimated coefficients indicate that weekly grain futures returns increase by 0.0689% after sentiment readings below 20 percent and increase by 0.4029% after sentiment readings above 80 percent.

Parameter sensitivity is explored by altering the definition of extreme sentiment. In Panel A of Table 5, $K_H = 75$ and $K_L = 25$, while in Panel C, $K_H = 85$ and $K_L = 15$. When the extreme sentiment definitions are widened (Panel C), none of the pooled models reject the null hypothesis, and at decreased extremes (Panel A) the grain model still displays statistically significant timing ability. These results suggest that the impact of noise trader sentiment is sensitive to alternative definitions of extreme index values.

Causality Test Results

Equation (16) provides a more general means of testing the orthogonality condition implied by market rationality versus the alternative noise trader hypothesis. The noise trader model suggests that the futures forecast error (i.e., returns) can be predicted by the level of noise trader sentiment in the market. Specifically, the model predicts that there is a negative relationship between sentiment and returns. That is, high (low) sentiment results in negative (positive) returns. If this is true, it should be captured in (16) by finding that sentiment leads returns, i.e., sentiment can be used to forecast market returns, and the cumulative impact of sentiment on returns should be negative. This is tested against the rational expectations null hypothesis that forecast errors are uncorrelated with available information.[18]

The empirical model's lag structure is specified using the search procedure described earlier. The specified model is estimated with OLS, and the residuals are tested for heteroskedasticity and autocorrelation.[19] The null hypothesis that ρ_t does not lead R_t (i.e., $\beta_j = 0$ $\forall$ j) is tested with a Wald Chi-squared test. The aggregate sign of causality (positive or negative) is addressed by summing the impact of lagged returns, $\sum \beta_j$, and testing if it equals zero using a two-tailed t-test. If $\sum \beta_j < 0$, then it supports the noise trader model.

The Granger causality test results for individual markets are presented in Table 6. The first Chi-squared statistic tests the null that sentiment does not lead returns, and the t-statistic tests if the sum of lagged sentiment coefficients equals zero. The second Chi-squared statistic tests the null full orthogonality condition, i.e., all coefficients equal zero. Looking at the first Chi-squared test, the null hypothesis that sentiment does not lead returns is rejected at the 5% level for two markets (LB and TB). The null is rejected for four more markets (FC, CC, JO, and LH) at the 10% level. The noise trader model predicts an inverse relationship between sentiment and returns. However, the t-statistics for H_0: $\sum \beta_j = 0$ are not consistently negative. In fact, 9 of the 14 t-statistics are positive, again indicating a tendency toward continuation instead of reversal.

The second Chi-squared statistic in Table 6 tests the null hypothesis that neither sentiment nor past returns lead future returns, i.e., returns are not predictable with the information contained in past returns and sentiment. This null is rejected in 13 markets 10% level or higher. Of the 13 rejections, 8 are in markets where the first Chi-squared test did not reject the null, and the rejections are concentrated among the food/fiber and metal/energy groups. Although not presented, the markets where the full orthogonality null is rejected, the rejection primarily stems from low-order positive autocorrelation in returns.[20]

Collectively, the individual causality models provide some evidence that noise trader sentiment is useful in predicting market returns. However, the null hypothesis that sentiment leads returns is rejected in a minority of the markets. Furthermore, the direction of sentiment's impact is not consistently negative as indicated by the theoretical model. Evidence against the full orthogonality condition, i.e., returns are not predictable with either lagged returns or sentiment, is much more prevalent. In particular, the weekly return series seem to be characterized by low-order positive autocorrelation.

It is difficult to draw general conclusions from the relatively inconsistent results across the individual markets. Therefore, common noise trader effects are tested with pooled cross-sectional time series models estimated with Kmenta's cross-sectionally correlated and heteroskedastic GLS procedure.[21] Lag specification is determined by using the maximum m and the maximum n specified among the individual markets comprising the commodity group.

The estimated pooled models are presented in Table 7. The first Chi-squared statistic (p-value in parenthesis) tests the null that sentiment does not lead returns, and the second Chi-squared statistic tests the full orthogonality condition. The first Chi-squared test rejects the null hypothesis for the food/fiber group only. The full orthogonality null hypothesis is rejected at conventional levels for all groups except livestock. Returns in general, and the food/fiber and grain groups in particular, are characterized by positive autocorrelation at short lags with autoregressive parameters along the order of 0.05 to 0.07 in magnitude.

As with the individual market models, the direction of sentiment's impact on returns generally is not consistent with noise trader theory. For example, the food/fiber group’s sentiment coefficients are statistically negative at one lag and statistically positive at lags two and five. If sentiment increases by 100 percent, then returns decrease 1.35% one week later, *ceteris paribus*. The full return response with a one standard deviation shock to weekly sentiment is plotted in Figure 1 for the food/fiber group. The figure shows there is not a well-defined response structure for sentiment leading returns. That is, the response function takes both positive and negative values before converging to zero after 7 weeks.

Summary and Conclusions

In this research, the noise trader sentiment model of DSSW (1990a) is applied to futures markets. The theoretical results predict that overly optimistic (pessimistic) noise traders result in market prices that are greater (less) than fundamental value. Thus, returns can be predicted using the level of noise trader sentiment. Specifically, the noise trader model indicates that futures prices contain a systematic bias that is proportional to the average level of noise trader sentiment, and market returns contain a predictable time-varying component that is inversely related to the level of noise trader sentiment. These predictions pose distinct alternatives to Muth's rational expectations hypothesis.

The null rational expectations hypothesis is tested against the noise trader alternative using commercial market sentiment indices as proxies for noise trader sentiment. Fama-MacBeth cross-sectional regressions test if noise traders create a systematic bias in futures prices. The time-series predictability of futures returns using known sentiment levels is tested in a Cumby-Modest market timing framework and a more general causality specification.

The empirical results lead to the following conclusions. First, there is no evidence that noise trader sentiment creates a systematic bias in futures prices. Second, predictable market returns using noise trader sentiment is not characteristic of futures markets in general. Third, futures market returns at weekly intervals are characterized by low-order positive autocorrelation with relatively small autoregressive parameters. In those instances where there is evidence of noise trader effects, it is at best limited to isolated markets and particular specifications.

The finding that noise trader sentiment has little (or at least an inconsistent) impact on futures prices is compatible with previous research (e.g., Kodres). Based on this limited evidence, it is unlikely that noise traders impose a large cost on society in terms of systematic pricing errors and the subsequent misallocation of resources (Stein). Thus, concerns about and attempts to curb futures market speculation, particularly trend-following fund activity, may be unfounded (see France, Kodres, and Moser). However, the cost and impact of noise traders on market micro-structure (see Ma, Peterson, and Sears) warrants further examination; yet, it must be weighed carefully against the liquidity enhancement provided by noise traders (Black).

Endnotes

1.The other major abstraction in DSSW's model from a futures market is that the unsafe asset pays a real dividend, r; whereas, there are no cash flows associated with the ownership of futures contracts. This is a necessary abstraction for the overlapping generations structure of the model. If this aspect of the unsafe asset, u, is not kept, then the model does not have an equilibrium solution. That is, solving (10) recursively results in a geometric series that diverges in the limit.

2.See DSSW (1990a) for a detailed description and discussion of the model's assumptions.

3.Both assets, u and s, pay real dividend r in the second period. Thus, all of first period income earns r regardless of where invested. Thus, c_0 is total second period dividends as a function of invested first period income. The remainder of the terms adjust c_0 for capital gains and the increased (decreased) yield on u from purchasing it at a discount (premium) to fundamental value.

4.Prescripts on random variables represent expectations for the variable taken at the indicated time. For example, ${}_tp_{t+1}$ is the expectation at time t for p at time t+1.

5.Both rational and noise traders are allowed to take short positions in u.

6.Henceforth, R_t is referred to interchangeably as the futures forecast bias or pricing error, where $R_t>0$ implies that $p_t>p_{t-n}$ or the futures price at time t-n was below fundamental value.

7. This assumes futures prices do not reflect a "rational" risk premium.

8.Alternative, methods of estimating and pooling the regression equations exist; however, the Fama-MacBeth regressions have shown to be statistically powerful and are still widely used in the literature (see Elton and Gruber, pp. 325-349).

9.Note, mis-specification of equation (16) due to co-integration and an omitted error-correction term is not a problem, as sentiment clearly is stationary I(0) in levels.

10.Alternative lag-length specification procedures were utilized; but, the results were nearly identical to those presented.

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

12. An in-depth analysis of the characteristics of the CBSI sentiment data was done. This analysis revealed several salient features: a) the sentiment data are quite volatile with large standard deviations and extremes of above 90 and below 10, b) the sentiment data display a high level of cross-market correlation within commodity groups, and c) the sentiment data indicates that noise traders are predominately positive feedback traders.

13.Weekly futures returns are calculated for the closest to expiration contract where the maturity month has not been entered. To correspond with the release of the sentiment index, returns are calculated Friday-to-Friday using closing prices. Returns, $R_{t,}$ are calculated as the log-relative change in closing prices, $\ln(p_t / p_{t-1})$.

14.A battery of diagnostic tests did not reveal any significant violations of OLS assumptions.

15.The Newey-West estimator is also consistent if the error terms are both heteroskedastic and autocorrelated. One operational problem with the Newey-West estimator is that the order of autocorrelation must be specified (see Greene, p. 423). This is done by examining the Lagrange multiplier statistic at each individual lag length. Then, the order of autocorrelation is set to the longest lag length with a LM statistic significant at the 5% level.

16.In the text, the C-M coefficients are always referred to as the change in returns or expected percent price change, relative to the unconditional return. This is in contrast to the total expected return. For instance, when the CBSI is below 20, the expected weekly LC return increases by 2.07%; but, the total expected return is 2.23% (2.07 + 0.16).

17.An alternative is to estimate the individual market regressions together in a seemingly unrelated regression (SUR) system. This estimation procedure was implemented, but the results were not materially different from the individual OLS regressions. Thus, the models are instead estimated as a pooled cross-sectional time series to not only highlight the common noise trader effects across markets, but also to facilitate the presentation and discussion of the results.

18.It is implicitly assumed that all relevant information is contained in past returns and sentiment.

19.As in the C-M tests, the OLS residuals are often heteroskedastic; thus, White's estimator is used in these cases. Autocorrelation is corrected by adding additional lags of the dependent variable.

20.For example, the LH model has a statistically significant (5% level) first-order autocorrelation coefficient of 0.124, and HO has second and third-order autocorrelation coefficients of 0.078 and 0.101, respectively.

21.The individual models were also estimated in a seemingly unrelated regression (SUR) framework, but the results were not materially different from the OLS estimations. Additionally, the SUR models did not enhance the presentation and estimation of common noise trader effects as does the pooled framework.

BIBLIOGRAPHY

Beja, A. and M.B. Goldman. "On the Dynamic Behavior of Prices in Disequilibrium." *Journal of Finance*. 34(1980):235-247.

Bessembinder, H. "Systematic Risk, Hedging Pressure, and Risk Premiums in Futures Markets." *Review of Financial Studies*. 5(1992):637-667.

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.

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.

Cumby, R.E. and D.M. Modest. "Testing for Market Timing Ability: A Framework for Forecast Evaluation." *Journal of Financial Economics*. 19(1987):169-189.

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.

Elton, J. and M.J. Gruber. *Modern Portfolio Theory and Investment Analysis*. Wiley, New York, 1984.

Epstein, I. "Ira Epstein and Company Futures Market Report." July 14, 1994. In *Consensus: National Futures and Financial Weekly*. 24, no. 28 (1994):34.

Fama, E. and J.D. MacBeth. "Risk, Return and Equilibrium: Empirical Tests." *Journal of Political Economy*. 81(1973):607-636.

Fisher, I. *The Theory of Interest*. MacMillan Company, New York, 1930.

France, V.G., L. Kodres, and J.T. Moser. "A Review of Regulatory Mechanisms to Control the Volatility of Prices." *Federal Reserve Bank of Chicago's Economic Perspectives*. 1994, pp. 15-28.

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.

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.

Kodres, L.E. "The Existence and Impact of Destabilizing Positive Feedback Traders: Evidence from the S&P 500 Index Futures Market." Working Paper, Board of Governors of The Federal Reserve System, 1994.

Liu, S-M, S. Thompson, and P. Newbold. "Impact of the Price Adjustment Process and Trading Noise on Return Patterns of Grain Futures." *Journal of Futures Markets*. 12(1992):575-585.

Lux, T. “Herd Behavior, Bubbles and Crashes.” *Economic Journal*. 105 (1995):881-896.

Ma, C.K., W.H. Dare, and D.R. Donaldson. "Testing Rationality in Futures Markets." *Journal of Futures Markets*. 10(1990):137-152.

Ma, C.K., R.L. Peterson, and R.S. Sears. "Trading Noise, Adverse Selection, and Intraday Bid-Ask Spreads in Futures Markets." *Journal of Futures Markets*. 12(1992):519-538.

Muth, J.F. "Rational Expectations and the Theory of Price Movements." *Econometrica*. 29(1961):315-335.

Palomino, F. "Noise Trading in Small Markets." *Journal of Finance*. 5 1 (1996):1537-1550.

Samuelson, P. "Proof that Properly Anticipated Prices Fluctuate Randomly." *Industrial Management Science*. 6(1965):41-49.

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

Stein, J.L. "Speculative Price: Economic Welfare and the Idiot of Chance." *Review of Economics and Statistics*. 63(1981):223-232.

Summers, L.H. "Does the Stock Market Rationally Reflect Fundamental Values?" *Journal of Finance*. 41(1986):591-601.

Taylor, S.J. "The Behavior of Futures Prices Over Time." *Applied Economics*. 17(1985):713-734.

Working, H. "The Investigation of Economic Expectations." *American Economic Review*. May(1949):159-170.

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. Individual Cross-Sectional Test Regressions.

$$\bar{R}^i = \alpha + \beta\bar{\rho}^i + \epsilon^i$$

The model is estimated with OLS over a cross-section of 28 markets. The estimate of $\bar{\rho}^i$ is made over fifty weekly observations, and the estimate of $\bar{R}^i$ over the following fifty weeks.

Sample Number	$\alpha \times 10^{-2}$	$\beta \times 10^{-4}$	adj. R^2
1	-0.5878 (-1.233)*	0.5499 (0.466)	-0.032
2	0.8958 (2.027)	-2.7115 (-2.255)	0.140
3	0.5828 (1.065)	-0.8738 (-0.714)	-0.018
4	0.0991 (0.267)	0.1097 (0.139)	-0.037
5	-0.3370 (-0.544)	0.7746 (0.628)	-0.022
6	0.1685 (0.339)	-0.3479 (-0.324)	-0.034
7	0.4416 (1.007)	-1.1333 (-1.114)	0.008
8	0.5566 (1.558)	-1.4977 (-1.787)	0.075
9	0.1299 (0.361)	-0.3432 (-0.431)	-0.031
10	-0.4275 (-0.773)	1.1353 (0.893)	-0.007
11**	0.0115 (0.015)	-1.6893 (-0.107)	-0.038
Average 1-11***	0.1393 (0.910)	-0.4290 (-1.187)	

*T-statistics in parenthesis test if coefficients equal zero. The first two samples contain 26 cross-sectional observations.
**The last test sample contains 43 weeks.
***The average slope coefficients and their standard errors are calculated using the Fama-MacBeth procedure.

Table 3. Cross-Sectional Test Results for Different Formation and Testing Periods.

$$\bar{R}^{i} = \alpha + \beta \bar{\rho}^{i} + \epsilon^{i}$$

The model is estimated with OLS over a cross-section of 28 markets. The estimate of $\bar{\rho}^{i}$ is made over K weekly observations, and the estimate of $\bar{R}^{i}$ over the following J weeks. The M individual cross-sectional OLS models are pooled using the method of Fama and MacBeth. T-statistics in parenthesis test if the coefficient is zero.

K, J	M	α x 10^{-2}	β x 10^{-4}	avg. adj. R^2
50,50	11	0.1393	-0.4290	0.000
		(0.910)	(-1.187)	
50,100	5	0.1513	-0.3832	-0.006
		(1.163)	(-1.159)	
25,25	23	-0.0528	0.0917	0.026
		(-0.330)	(0.279)	
25,50	11	0.0982	-0.3334	0.005
		(0.753)	(-1.286)	
5,5	117	-0.1973	0.3465	0.004
		(-1.561)	(1.383)	

Table 4. Cumby-Modest Test Results for Indidual Markets.

$$R_t = \alpha + \beta_1 HI_{t-1} + \beta_2 LO_{t-1} + \epsilon_t$$

The model is estimated with OLS, where HI_{t-1}= 1 if $\rho_{t-1} > K_H$, = 0 otherwise; and LO_{t-1}=1 if $\rho_{t-1} < K_L$, = 0 otherwise, and K_H= 80, K_L = 20. T-statistics testing that each parameter is zero are in parenthesis, and the Chi-square test is a joint test of the null, H_0: $\beta_1=\beta_2=0$.

Market	Ext. obs.	$\alpha \times 10^{-2}$	$\beta_1 \times 10^{-2}$	$\beta_2 \times 10^{-2}$	$\chi^2_{(2)}$	p-value
C*	76	-0.1472	0.7522	-0.0672	1.09	0.579
		(-1.09)	(1.03)	(-0.18)		
W	92	-0.0869	0.4283	0.6477	4.05	0.131
		(-0.71)	(0.82)	(1.89)		
S	47	-0.1400	0.5031	0.7299	5.36	0.068
		(-1.03)	(0.49)	(2.27)		
SM	106	0.0198	-0.3885	-0.1124	0.42	0.801
		(0.12)	(-0.55)	(-0.38)		
BO	126	0.0538	0.5080	-0.5283	2.99	0.223
		(0.29)	(0.50)	(-1.60)		
LC	23	0.1659	-0.0224	2.0730	9.83	0.007
		(1.88)	(-0.06)	(3.13)		
FC	78	0.0831	0.1825	0.2078	0.72	0.696
		(1.02)	(0.71)	(0.56)		
LH	23	0.2596	-0.9115	-0.0704	0.39	0.822
		(2.02)	(-0.61)	(-0.10)		
PB	88	-0.3557	1.3560	0.1414	0.74	0.689
		(-1.49)	(0.84)	(0.22)		
KC	113	-0.2414	0.3544	0.1850	0.21	0.901
		(-1.24)	(0.23)	(0.40)		
SB	117	-0.4081	0.8003	-0.9866	2.54	0.279
		(-1.36)	(0.87)	(-1.21)		
CC	110	-0.4495	0.9907	0.9082	4.82	0.089
		(-2.36)	(0.91)	(2.05)		
JO	161	0.2338	0.5623	-0.5112	3.73	0.154
		(1.18)	(0.83)	(-1.63)		
CT	101	0.1648	0.5484	-0.4501	3.54	0.170
		(1.13)	(0.99)	(-1.46)		
LB	120	0.0235	-1.2387	-0.0762	1.18	0.553
		(0.12)	(-1.08)	(-0.18)		

Table 4 (continued). Cumby-Modest Test Results for Individual Markets.

Market	Ext. obs.	$\alpha \times 10^{-2}$	$\beta_1 \times 10^{-2}$	$\beta_2 \times 10^{-2}$	$\chi^2_{(2)}$	p-value
DM	105	0.0626 (0.74)	0.7518 (0.21)	-0.7747 (-0.40)	0.23	0.890
SF	115	0.0103 (0.11)	0.2532 (0.73)	0.0434 (0.21)	0.56	0.756
JY	98	0.1735 (2.38)	-0.2310 (-0.70)	-0.3250 (-1.71)	3.22	0.198
BP	130	0.0355 (0.39)	0.3856 (1.46)	-0.0264 (-0.11)	2.23	0.328
CD	98	0.0582 (2.13)	-0.1064 (-0.72)	-0.1877 (-2.46)	6.29	0.043
TB	98	0.0019 (2.21)	0.0305 (1.34)	-0.0190 (-0.48)	2.17	0.337
US	39	0.0173 (2.44)	-0.5901 (-0.11)	-0.4312 (-1.44)	2.09	0.351
GC	101	-0.0180 (-2.00)	0.4368 (0.84)	0.0685 (0.24)	0.75	0.687
SI	68	-0.4169 (-2.81)	0.7366 (0.80)	0.5552 (0.96)	1.58	0.452
PL	114	-0.4510 (-0.32)	0.3082 (0.29)	-0.5878 (-1.76)	3.26	0.196
HO	130	0.0923 (0.43)	-1.1126 (-1.08)	-0.6281 (-0.12)	1.18	0.553
CL	67	0.3340 (1.38)	-0.8007 (-0.94)	-1.7014 (-1.67)	3.36	0.186
HU	120	0.4406 (1.82)	0.1653 (-2.44)	-0.8561 (-1.33)	6.87	0.032

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

Table 5. Pooled Cumby-Modest Test Results.

$$R_t = \alpha + \beta_1 HI_{t-1} + \beta_2 LO_{t-1} + \epsilon_t$$

The model is estimated over N cross-sections and T time series observations, where $HI_{t-1}= 1$ if $\rho_{t-1} > K_H$, = 0 otherwise; and $LO_{t-1}=1$ if $\rho_{t-1} < K_L$, = 0 otherwise. The t-statistics in parenthesis test that parameter values are zero, and the Chi-square tests the joint null H_0: $\beta_1=\beta_2=0$.

Panel A: K_H = 75, K_L=25

Group	$\alpha \times 10^{-2}$	$\beta_1 \times 10^{-2}$	$\beta_2 \times 10^{-2}$	$\chi^2_{(2)}$	p-value
Grains*	-0.0416	0.3687	0.0273	8.16	0.016
	(-0.43)	(2.83)	(0.36)		
Livestock	0.1239	0.2009	0.1462	3.69	0.157
	(1.57)	(1.53)	(1.20)		
Food/Fiber	-0.0245	-0.0703	0.0239	0.16	0.943
	(-0.28)	(-0.28)	(0.15)		
Financial	0.0096	0.0087	0.0089	0.36	0.834
	(1.16)	(0.37)	(0.51)		
Metal/Energy	-0.0263	0.1259	-0.1833	3.78	0.151
	(-0.29)	(0.74)	(-1.75)		

Panel B: K_H = 80, K_L=20

Group	$\alpha \times 10^{-2}$	$\beta_1 \times 10^{-2}$	$\beta_2 \times 10^{-2}$	$\chi^2_{(2)}$	p-value
Grains	-0.0308	0.4029	0.0689	6.44	0.039
	(-0.32)	(2.43)	(0.73)		
Livestock	0.1519	-0.0070	-0.0338	0.04	0.978
	(1.95)	(-0.04)	(-0.20)		
Food/Fiber	-0.0463	0.4979	0.0116	2.36	0.307
	(-0.58)	(1.54)	(0.06)		
Financial	0.0117	0.0549	-0.0209	4.65	0.098
	(1.52)	(1.82)	(-1.02)		
Metal/Energy	-0.0362	0.2118	-0.2311	4.07	0.131
	(-0.41)	(0.86)	(-1.80)		

Table 5 (continued). Pooled Cumby-Modest Test Results.

Panel C: K_H = 85, K_L=15

Group	α x 10^{-2}		β_1 x 10^{-2}		β_2 x 10^{-2}		$\chi^2_{(2)}$	p-value
Grains	-0.0113		0.4166	0.0027	2.49	0.286		
	(-0.12)	(1.58)		(0.02)				
Livestock	0.1563	-0.0598		-0.2856		1.72	0.423	
	(2.02)		(-0.22)	(-1.29)				
Food/Fiber	-0.0362		-0.0515		0.1294	0.36	0.833	
	(-0.46)	(-0.11)	(0.58)					
Financial	0.0122	0.0561	-0.0156		1.91	0.385		
	(1.60)		(1.19)		(-0.65)			
Metal/Energy	-0.0393		0.1591	-0.2148		1.98	0.372	
	(-0.45)	(0.47)		(-1.32)				

[*]All models are estimated over 536 weekly observations, except the metal/energy group which are estimated over 438 observations. Each pooled regression has N x T cross-sectional time series observations, where T = 536 (or 438) and N is the number of markets composing the group.

Table 6. **Granger Causality Test Results for Individual Markets**.

$$R_t = k_0 + \sum_{i=1}^{m} \alpha_i R_{t-i} + \sum_{j=1}^{n} \beta_j \rho_{t-j} + \epsilon_t$$

The model is estimated with OLS, and the first Wald Chi-squared statistic tests the null, H_0: $\beta_j=0$ $\forall$ j. The t-statistic tests that the sum of the lagged sentiment coefficients equals zero, $\sum \beta_j=0$. The second Chi-squared statistic tests full orthogonality, H_0: $\alpha_i=0$ and $\beta_j=0$, $\forall$ i,j.

Market	m,n	$\chi^2_{(n)}$	p-value	t-stat.	$\chi^2_{(m+n)}$	p-value	adj. R^2
C*	5,0	----	----	----	5.72	0.334	0.017
W	0,1	0.17	0.679	-0.41	0.17	0.679	-0.001
S	3,1	2.30	0.129	-1.51	4.82	0.306	0.008
SM	3,0	----	----	----	4.31	0.230	0.009
BO	3,0	----	----	----	3.45	0.327	0.010
LC	6,0	----	----	----	11.95	0.063	0.015
FC	2,3	7.48	0.058	0.76	10.61	0.059	0.017
LH	1,3	6.39	0.094	-2.05	17.13	0.002	0.024
PB	1,0	----	----	----	0.72	0.393	-0.001
KC	1,0	----	----	----	0.221	0.638	-0.002
SB	0,1	2.11	0.146	1.45	2.11	0.146	0.002
CC	0,1	3.21	0.073	-1.79	3.21	0.073	0.004
JO	1,5	10.32	0.066	2.62	31.69	0.000	0.041
CT	4,0	----	----	----	12.69	0.012	0.028
LB	2,2	18.68	0.000	-0.49	25.24	0.000	0.059
DM	0,1	1.21	0.271	1.09	1.21	0.271	0.000
SF	3,0	----	----	----	6.19	0.102	0.009
JY	0,1	2.16	0.141	1.47	2.16	0.141	0.002
BP	3,0	----	----	----	6.86	0.076	0.009
CD	0,1	0.53	0.462	0.73	0.53	0.462	-0.001
TB	0,5	16.86	0.005	0.06	16.86	0.005	0.015
US	1,0	----	----	----	0.643	0.422	-0.001
GC	0,1	0.31	0.574	0.56	0.31	0.574	-0.001
SI	6,0	----	----	----	9.32	0.156	0.016
PL	6,1	2.55	0.111	1.59	13.72	0.056	0.015
HO	3,0	----	----	----	8.96	0.029	0.022
CL	3,0	----	----	----	6.79	0.078	0.013
HU	3,0	----	----	----	8.77	0.032	0.025

*The model is estimated over 536 weekly observations, except for those regressions involving CL and HU which have 438 observations.

Table 7. Pooled Granger Causality Test Results.

Independent Variables	coefficient x 10^{-2}				
	Grains	Livestock	Food/Fiber	Financial	Metal/Energy
intercept	0.0149 -0.0699 (0.10)*	-0.1658 (-0.40)	0.0178 -0.1596 (-0.83) (0.95)	(-0.99)	
R_{t-1}	0.4028 2.4092 (0.20)	6.5781 (1.05)	-2.7300 (3.34)	-3.7200 (-1.63)	(-1.84)
R_{t-2}	5.6255 -2.438 (2.77)	4.3187 (-1.05)	3.8714 3.6352 (2.07)	(2.29)	(1.75)
R_{t-3}	7.2097 2.5207 (3.59)	2.4519 (1.10)	2.8223 4.6910 (1.17)	(1.67)	(2.28)
R_{t-4}	0.4432 -0.1779 (0.23)	4.9758 (-0.07)	(2.39)	1.5412	(0.75)
R_{t-5}	-2.1835 (-1.11) (-2.22)	-4.975		(-2.25)	-4.5359
R_{t-6}		2.7824 (1.23)			-1.8822 (0.89)
ρ_{t-1}	-0.0005 (0.10)	0.0012 (0.32)	-0.0135 (-2.24) (0.25)	0.0001 (0.89)	0.0028
ρ_{t-2}		0.0040 (0.94)	0.0155 -0.0004 (2.16)	(-0.54)	
ρ_{t-3}		-0.0003 (-0.09)	-0.0099 (-1.38) (-0.65)	-0.0004	
ρ_{t-4}			-0.0010 (-0.14) (2.13)	0.0013	
ρ_{t-5}			0.0127 -0.0009 (2.32)	(-1.79)	
$\chi^2_{(n)}$	0.051 (0.821)**	2.76 (0.431)	15.08 (0.010)	5.40 (0.368)	0.80 (0.370)
$\chi^2_{(m+n)}$	22.28 (0.001)	13.75 (0.131)	35.69 (0.000)	15.26 (0.054)	19.98 (0.005)
Buse R^2	0.006	0.001	0.009	0.002	0.006

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

**First (second) Chi-squared statistic tests H_0: $\beta_j=0$ (and $\alpha_i=0$) $\forall$ i,j (p-values in parenthesis).