Noise Trader Sentiment and Futures Price Behavior: An Empirical Investigation

by

Dwight R. Sanders, Scott H. Irwin,

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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 suggest that noise traders do not create a systematic bias in futures prices, and market returns are not predictable using the level of noise trader sentiment.

Introduction

> 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.

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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 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) traditionally argue that speculation is stabilizing and that uninformed speculators are quickly dispatched by their rational counterparts. Other well-known economists (e.g., Keynes) 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, 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, the results of a futures market variant of De Long, Shleifer, Summers, and Waldmann's (1990a) noise trader sentiment model are presented. The model's market pricing equation 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]

In the theoretical model, there are two types of two-period-lived agents: rational investors, i, and noise traders, n. The agents can invest in a unsafe asset, u, with a price of p_t or a safe asset, s. Both assets have a real yield of r, and the unsafe asset's true fundamental value is 1. The rational investors have rational expectations concerning the distribution of p_t, and they are present in measure $1-\mu$ ($\mu \in [0,1]$). 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.

After solving for each agent's optimal demand function, the resulting system of demands and the market clearing condition is solved for a pricing function. In turn, the pricing function is solved recursively for the steady-state equilibria. The final equilibria pricing rule is derived as:

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

and

$$\sigma^2_{p_t} = \frac{\mu^2\sigma^2_\rho}{(1+r)^2}\ . \tag{2}$$

Equation (1) is the equilibrium pricing function and (2) is the price variance. It is clear in Equation (2) that futures price volatility is increasing with the proportion of noise traders and in the variability of their sentiment. In equation (1), noise trader sentiment impacts the pricing of futures contracts. The first term of (1) indicates that the futures price equals fundamental value in the absence of noise traders. The second and third terms of (1) 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 (1), 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 (1) can be rewritten to display the time series characteristics and equilibrium pricing respectively:

[1]For the sake of brevity, the full theoretical model is not presented in this paper. The results are straight-forward and flow naturally from the original model presented by DeLong, *et al.* (1990a). The full futures market model can be referenced in Sanders (1995).

$$R_t = p_t - p_{t-1} = -[\frac{\mu\rho^*}{r} + \frac{\mu(\rho_{t-1} - \rho^*)}{1+r}] \ , \qquad (3)$$

and taking expectations,

$$E(R_t) = E(p_t - p_{t-1}) = -\frac{\mu\rho^*}{r} \ . \qquad (4)$$

where, R_t is the continuously compounded percentage change in the futures price.

From equation (3), 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).

In equation (4), 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-1}. Consequently, the futures price will rise on average towards fundamental value.. The predictions in equations (3) and (4) 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

Cross-Sectional Test for Systematic Forecast Bias

Under the rational expectations hypothesis the expected bias in futures prices is zero.[2] 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 (3) 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.

[2]This assumes futures prices do not reflect a "rational" risk premium.

Let $\bar{\rho}^i$ be a sample estimate of the mean noise trader sentiment in market i. The cross-sectional model implied in equation (4) can be empirically estimated as,

$$\bar{R}^i = \alpha + \beta\bar{\rho}^i + \epsilon^i \; . \tag{5}$$

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 (5) is estimated over N cross-sectional observations. This process is repeated for each J length non-overlapping subperiods in the entire sample.

The separate OLS cross-sectional regressions are pooled using the Fama and MacBeth procedure. 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. 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 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:

$$R_t = \alpha + \beta_1 HI_{t-1} + \beta_2 LO_{t-1} + \epsilon_t \tag{6}$$

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:[3]

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

$$R_t = k_0 + \sum_{i=1}^{m} \alpha_i R_{t-i} + \sum_{j=1}^{n} \beta_j \rho_{t-j} + \epsilon_t \ . \tag{7}$$

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 (7) 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.

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:

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

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. 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.

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.[4]

Empirical Results

Cross Sectional Test Results

The cross-sectional equation (5), is estimated with OLS using weekly observations of the CBSI along with weekly futures returns.[5, 6] 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 1. The rational expectations (null) hypothesis predicts that β=0, while the noise trader model predicts that the slope coefficient is negative, β<0. Looking at the individual regression results in Table 1, 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 to 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 null hypothesis of no systematic bias, β=0, in futures prices cannot be rejected in favor of the noise trader alternative, β<0. Although not presented, 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

Equation (6) is estimated with OLS using weekly data with K_H=80 and K_L=20. The results are presented in Table 2.[7] 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

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[4]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 indicate that noise traders are predominately positive feedback traders (see Sanders, Irwin, and Leuthold).

[5]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, $\ln(p_t/p_{t-1})$.

[6]A battery of diagnostic tests did not reveal any significant violations of OLS assumptions.

[7]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 estimated using White's heteroskedastic consistent covariance estimator, and if the errors are autocorrelated then the Newey-West covariance estimator is utilized (see Hamilton).

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%.[8]

Causality Test Results

The specified model is estimated with OLS, and the residuals are tested for heteroskedasticity and autocorrelation.[9] 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 3. 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 3 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%

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[8]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).

[9]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. The lag lengths, m and n, are determined with the search procedure suggested by Beveridge and Oickle.

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.[10]

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.

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, and futures prices contain a systematic bias that is proportional to the average level of noise trader sentiment.

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 generally do not support the noise trader model. That is, there is little evidence that noise trader sentiment creates a systematic bias in futures prices or that it is useful in predicting futures returns. 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).

[10]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.

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Table 1. 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 2. Cumby-Modest Test Results for Individual 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
Corn(C)*	76	-0.1472 (-1.09)	0.7522 (1.03)	-0.0672 (-0.18)	1.09	0.579
Wheat(W)	92	-0.0869 (-0.71)	0.4283 (0.82)	0.6477 (1.89)	4.05	0.131
Soybeans(S)	47	-0.1400 (-1.03)	0.5031 (0.49)	0.7299 (2.27)	5.36	0.068
Soy Meal(SM)	106	0.0198 (0.12)	-0.3885 (-0.55)	-0.1124 (-0.38)	0.42	0.801
Soy Oil(BO)	126	0.0538 (0.29)	0.5080 (0.50)	-0.5283 (-1.60)	2.99	0.223
Live Cattle(LC)	23	0.1659 (1.88)	-0.0224 (-0.06)	2.0730 (3.13)	9.83	0.007
Fdr Cattle(FC)	78	0.0831 (1.02)	0.1825 (0.71)	0.2078 (0.56)	0.72	0.696
Live Hogs(LH)	23	0.2596 (2.02)	-0.9115 (-0.61)	-0.0704 (-0.10)	0.39	0.822
Pork Bellies(PB)	88	-0.3557 (-1.49)	1.3560 (0.84)	0.1414 (0.22)	0.74	0.689
Coffee(KC)	113	-0.2414 (-1.24)	0.3544 (0.23)	0.1850 (0.40)	0.21	0.901
Sugar(SB)	117	-0.4081 (-1.36)	0.8003 (0.87)	-0.9866 (-1.21)	2.54	0.279
Cocoa(CC)	110	-0.4495 (-2.36)	0.9907 (0.91)	0.9082 (2.05)	4.82	0.089
Orange Juice(OJ)	161	0.2338 (1.18)	0.5623 (0.83)	-0.5112 (-1.63)	3.73	0.154
Cotton(CT)	101	0.1648 (1.13)	0.5484 (0.99)	-0.4501 (-1.46)	3.54	0.170
Lumber(LB)	120	0.0235 (0.12)	-1.2387 (-1.08)	-0.0762 (-0.18)	1.18	0.553

Table 2 (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
D-Mark(DM)	105	0.0626 (0.74)	0.7518 (0.21)	-0.7747 (-0.40)	0.23	0.890
Swiss Franc(SF)	115	0.0103 (0.11)	0.2532 (0.73)	0.0434 (0.21)	0.56	0.756
J-Yen(JY)	98	0.1735 (2.38)	-0.2310 (-0.70)	-0.3250 (-1.71)	3.22	0.198
Brit. Pound(BP)	130	0.0355 (0.39)	0.3856 (1.46)	-0.0264 (-0.11)	2.23	0.328
Can. Dollar(CD)	98	0.0582 (2.13)	-0.1064 (-0.72)	-0.1877 (-2.46)	6.29	0.043
T-Bill(TB)	98	0.0019 (2.21)	0.0305 (1.34)	-0.0190 (-0.48)	2.17	0.337
T-Bond(US)	39	0.0173 (2.44)	-0.5901 (-0.11)	-0.4312 (-1.44)	2.09	0.351
Gold(GC)	101	-0.0180 (-2.00)	0.4368 (0.84)	0.0685 (0.24)	0.75	0.687
Silver(SI)	68	-0.4169 (-2.81)	0.7366 (0.80)	0.5552 (0.96)	1.58	0.452
Platinum(PL)	114	-0.4510 (-0.32)	0.3082 (0.29)	-0.5878 (-1.76)	3.26	0.196
Heat Oil(HO)	130	0.0923 (0.43)	-1.1126 (-1.08)	-0.6281 (-0.12)	1.18	0.553
Crude Oil(CL)	67	0.3340 (1.38)	-0.8007 (-0.94)	-1.7014 (-1.67)	3.36	0.186
Gasoline(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. Ticker Symbols are presented in parenthesis, and they are used in the text and tables to identify the particular markets.

Table 3. 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.

Optimal Marketing Decisions for Cattle under Price Risk

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Optimal marketing decisions for cattle in Georgia are of critical importance to the profitability a continued economic survival of producers because of the low profit margins common to cat production in the Southeast. Many Georgia producers sell calves in November rather than retaini ownership, feeding until May, and selling as stocker cattle. This allows producers to avoid pri risk, but may cause them to miss profit opportunities. We examine five different marketi strategies and assess their expected profitability and riskiness. These expectations are employed compute the expected utility of profit and allow a producer to choose an optimal marketing strate for a specific level of risk aversion. Empirical results for a representative Georgia cattle operatic of 130 calves show that optimal decisions in the last three years have been either selling i November or feeding until May while using a futures hedge. For example, in 1996 the techniqu recommends feeding until May while selling two futures contracts as a hedge to reduce risk following this advice would have earned a producer an extra $1594 (or $12 per head). Given tha Georgia producers commonly earn about $30 per head if they sell in November, these extra profit are economically significant.

Introduction

One of the most significant sectors of Georgia's agricultural economy is beef ca 1994, farm cash receipts for cattle totaled $269 million, ranking fifth in agricultural behind broilers, peanuts, cotton, and eggs. There are three phases in the cattle industry: co stocking and feedlot operations. Cattle producers face decisions at several points in time they must either sell the cattle or continue to feed them until they reach the next size class. calves in Georgia, only 25 percent are retained for stockering. So there is a great potent enterprises to increase their farm income by carrying a larger portion of the state's calf c heavier weights by stockering.

There are two kinds of risk for a Georgia stocker cattle producer. One source market, which produces price variability, and the other one is production variability resulting environmental conditions and production practices. The cattle industry is characterized by h variable returns. According to McKissick and Ikerd (1996), during 1950 to 1996 the net re of winter stockering in Georgia ranged from -$9.28/cwt to $27.89/cwt, the net returns of the calf plus winter stockering and yearling feeding ranged from -$47.14/cwt to $33.19/cwt. also show that stocker operations seem to show an essentially random pattern of profit anc

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between sharp market breaks regardless of whether cow-calf operations are in the profit or loss phase of the cycle.

Abstracting from production risk in this paper, we examine a set of five marketing strategies in a search for optimal marketing decisions that balance the producer's desire for higher profits with an aversion for decisions that produce too much risk. The first strategy is to sell the calves in November (assumedly to someone who will stocker the cattle at another location). Because the marketing decision is made in November with observable cash prices, this decision is risk-free and can serve as a basis for comparison for the four other strategies. The second strategy is to stocker the cattle from November to May and then sell for the current cash price. The third through fifth strategies all include stockering the calves until May and selling for cash, but add a selection of hedging strategies. In the third strategy the producer employs a futures hedge (selling two futures contracts); in the fourth strategy the producer buys two puts; in the fifth, the producer buys two puts and sells two calls, using a straddle to reduce risk.

These strategies are evaluated here for a representative Georgia cow-calf operation for the years 1994 through 1996 and shown to be reasonably effective at assisting producers in choosing optimal marketing strategies that can raise their profits without unduly burdening them with returns risk.

The Representative Producer

For the purposes of evaluating the five marketing strategies considered here, a representative Georgia cattle operation is created. The farm is assumed to have 100 acres available for pasture and other cattle-related operations. The producer starts with 131 calves at the beginning of the annual operation, only has one death, therefore having 130 calves to market in November. Weight in November is taken to be 450 pounds per head, or 58,500 pounds total. The feeding period if ownership is retained past November is taken to be 180 days, with the stockered cattle then being sold on May 1. Total selling weight is assumed to be 97,110 pounds on May 1, implying average weight of 747 pounds per head. Marketing shrink is assumed to be 3 percent. Because the size of this operation would entail about 2.4 contracts to fully hedge, two contracts are assumed to be used in all positions in the futures and options markets. This keeps the example more realistic than if we allowed for partial contracts which are not possible for real world producers.

For assessing the five marketing strategies under conditions experienced in 1994, 1995, and 1996, variable costs of production are defined to include the cost of raising the calves until November, the foregone revenue that could have been realized by selling in the cash market on November 1, and, for the strategies where the cattle are retained until May, the cost of feeding/grazing the calves until May 1. This definition of variable costs results in profit always being equal to zero for the strategy of selling in November.

Evaluation of the Five Strategies: The Methodology

To evaluate the five marketing strategies, the representative Georgia catt assumed to choose a strategy that maximizes his expected utility of profit, where u is defined as

(1) $U(\pi) = \pi - (\phi/2)\mathrm{var}(\pi).$

In the above utility function ϕ is a constant absolute risk aversion coefficient. Sma ϕ imply less aversion to risk, with values generally being between 0.001 and 0.000($\phi = 0$ equating to the risk-neutral case. For this analysis of cattle marketing optic $= 0.0001$ which implies a fair amount of risk aversion fitting for Georgia cattle pr operate on such thin profit margins. The expected utility of profit is simply the ex of the expression in equation (1),

(2) $E[U(\pi)] = E(\pi) - (\phi/2)\mathrm{var}(\pi).$

Because the profit of the first strategy, selling the calves for cash in Novembe to be zero in all years, the expected utility of profit for that strategy is also zero (E($\mathrm{var}(\pi) = 0$). To compute the expected utility of the other four strategies is som complicated because the profits are random. To compute the variances and expectec these strategies, we must make assumptions about the distribution of returns associate of them.

For the second strategy (feeding until May and selling in the cash market), t variable whose distribution must be accounted for is the cash price on May 1. Fc strategy (feeding until May, selling in the cash market, and selling two futures cor hedge against falling prices), the random variable is the basis. In each case a sin regression model was built to predict cash price or basis on May 1. The May 1 cash p has a constant and cash prices from November (current) and the most recent May as r the basis model consisted of a constant, November cash price, and the basis in the prev Data from 1973 to 1996 were used to estimate the models, with only data that was obs the time of a decision used in estimation when computing the expected values that a evaluating the strategies (that is, the model is re-estimated with one additional year of d evaluating the strategies for the next year). To compute the expected utility of profit f strategies, Monte Carlo integration was used (Geweke, 1989, 1995). This consisted of g 10,000 random values of May cash price or May basis from the distribution implied by regression models (and assumed to be multivariate normal). These random values are i to compute 10,000 random values of profit for each strategy accounting for the variab production and the cost of selling futures contracts for the third strategy. The 10,000 profit under each of these two strategies are then used to calculate the expected value of p the variance of profit. Because these empirical values of profits are randomly genera their distributions, the expected value and variance of profit can be calculated using the standard formulas for random samples (e.g., the expected value is the simple arithmetic average of the 10,000 random values).

The computation of expected utility for the fourth and fifth strategies is different due to the much shorter time period of available data on cattle options. Nine years of data are available on the returns from puts and calls (including all premia and transaction costs); these historical returns are treated as an empirical distribution of these random variables with equal weight placed on each sample point. These nine points are used to compute the expected value and variance of these two strategies.

Evaluation of the Strategies: Three Years of Experience

Using the methodology described above, the five strategies were evaluated for the years 1994, 1995, and 1996 using only information available on November 1 of the respective year. The expected utilities of each strategy for each year are shown in table 1. A producer should choose the strategy that has the maximum expected utility in a given year. The empirical results suggest that a Georgia cattle producer should choose strategy three in 1994 and 1996 and strategy one in 1995. Recall that strategy three is to feed through May 1 while selling two futures contracts and strategy one is to sell in November.

Table 1. Expected Utilities of the Five Strategies

	1994	1995	1996
d1	0	0	0
d2	-5269	-6842	-2347
d3	1312	-2064	10390
d4	-8504	-9821	-4603
d5	-9271	-10203	-4608

Note: d1 is the first strategy, d2 is the second, and so on. Strategies are as described in the text.

To evaluate the effectiveness of this method, ex post, the actual profits that w been earned by the representative producer under each of the strategies for these three shown in table 2 along with the expected profits that would have been computed ex a table shows that the suggested strategies performed reasonably well. In 1994, the future strategy turned out to be second best (to selling in November). Because the strategy of November has no risk and higher ex post profit, it must be superior to the futures strategy. In 1995, the recommended strategy of selling in November turned out to be o post. In 1996, the results are disappointing. The two strategies utilizing options have l post profits and lower variances of profit (not shown) than the recommended strategy c hedging. Thus, the producer would have accepted more risk in choosing strategy thre received the hoped for payoff in higher profit. However, even though the recommen strategy of futures hedging was not optimal ex post, if followed it still would have pro additional $1594 of profit over choosing the common strategy of selling the cattle in N

Conclusions

We have demonstrated a method for evaluating a variety of cattle marketing strate are especially relevant to producers in Georgia and the Southeastern United States. In a t demonstration, the method recommended the best strategy considered in 1995, the secon 1994, and the third best in 1996. While the method is obviously not perfect, it shows in helping producers boost their thin profit margins. Future plans are to add product related to the uncertainty of weight gain and to investigate incorporating such measure probability of suffering a loss into the utility function.

Table 2. Expected and Actual Ex Post Profit

	1994		1995		1996	
	expected	actual	expected	actual	expected	actual
d1	0	0	0	0	0	0
d2	-3384	-6890	-4653	-9971	4488	-8535
d3	2267	-3278	-312	-5155	17764	1594
d4	-7046	-5162	-7393	-5650	2240	1845
d5	-7733	-3368	-8012	-1076	2225	5904

Note: All figures are in dollars.

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