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A Trading Simulation Test for Weak-Form Efficiency in Live Cattle Futures

Terry Kastens and Ted C. Schroeder*

Potential for downward bias or inefficiency in live cattle futures has been an issue of concern for about as long as this market has existed. Past research exists to support whatever preconception a researcher may have. Although using statistical tests to reject null hypotheses is usually a necessary condition for concluding market inefficiency, the sufficient condition is demonstration of the potential extraction of abnormal profits from that market (Garcia et al. 1988b; DeCoster, Labys, and Mitchell 1992). This paper clarifies the vagueness of that sufficient condition by examining trading simulations over time. The objective is to provide a credible trading simulation test of live cattle futures efficiency.

Previous Literature

Futures prices are *expected* prices (Gardner 1976; Working 1958). Agents holding price expectations different from the futures could act upon their expectations, bidding the market up or down until futures reflected aggregate expected prices. Several studies have used futures prices as producer price expectations (Gardner 1976; Helmlinger and Akinyosoye 1984; Hurt and Garcia 1982). Empirical evidence supports the contention that producers use futures prices as expected prices. In a recent example, Eales et al. (1990) determined that soybean and corn futures prices were consistent with mean price expectations of a sample of Illinois grain producers and merchandisers.

Viable futures markets should be efficient, or at least unbiased in the long run. If a market is biased (tendency to move up or down into contract expiration), profits could be extracted by trading the market. This activity would remove the bias. However, in reality, to attract traders, sufficient departure from this "efficiency" equilibrium must exist to allow for perception of a profit opportunity. The empirical issue involves testing the magnitude of that departure. The word "perception" belies the subjective nature of the tests involved. This study attempts to remove some of that subjectivity, so that the ongoing philosophical and empirical debate might move forward objectively.

Intuitively, futures market efficiency should be tied to ability of that market to forecast. But Working (1958) was reluctant to denote futures prices as forecasts. Tomek and Gray (1970) suggested that cash prices of non-storable commodities may forecast deferred prices better than do futures prices. Livestock futures in particular, are poor distant price forecasts (Garcia et al. 1988b; Just and Rausser 1981; Leuthold and Hartmann 1979; Martin and Garcia 1981; Shonkwiler 1986).¹ Koontz et al. (1992) argued that one should not expect distant live cattle futures prices to be good forecasts of future prices. During the time that supply of cattle placed on feed can be altered, production decisions can cause the forecast to be inaccurate. High prices stimulate increased placements, which cause expected delivery

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¹ The term "poor" refers to relatively large forecast mean squared errors (e.g., Just and Rausser (1981) found forecast root mean squared percentage errors of 22 percent and 27 percent for four-quarter-ahead live cattle and live hog futures prices, respectively, compared to typically less than 15 percent for grains).

date prices to fall. "The futures market will not forecast if doing so elicits behavior that will prove the forecast wrong" (Koontz et al. 1992, p. 235).

But poor forecasting does not necessarily make a market inefficient. The futures market may still be the best forecast available. Thus, the mere existence of "poor" forecasts is not sufficient to contradict efficiency. Although, how cash could out-perform futures as a forecast may be difficult to imagine, since futures could always duplicate the cash forecast, and the converse certainly is not true.

How then is market efficiency defined? A philosophical approach would simply be a declaration that what is *is*, and hence must be efficient. The definition used here however, is more descriptive than it is definitive; and it allows for empirically based analyses. Fama (1970) suggests that a futures market is efficient if price contains all relevant information. He describes efficiency in terms of whether abnormal trading profits can be earned conditional upon three possible sets of information. A *weak form* test examines whether profits can be earned by trading a system which bases its forecasts only upon past futures prices. A *semi-strong form* test includes all relevant publicly available information. The *strong form* test adds proprietary information to the previous two sets. Rejection of weak-form efficiency should be more difficult than rejection of strong-form efficiency, as it should be easier to demonstrate trading profits using proprietary information than it is using only public information.

Futures market efficiency has been debated in the literature enough to merit a study of the studies (Garcia et al. 1988a). Several studies have generally supported livestock futures market efficiency (e.g., Kolb and Gay 1983; Garcia et al. 1988b). Others found the market inefficient at times (Helmuth 1981 (this study has been subject to criticism - see Palme and Graham 1981); Koppenhaver 1983; Pluhar et al. 1985). Elam and Wayoopagtr (1992) suggested that the live cattle futures market may have become more efficient in recent years. However, some inefficiency may be inherent within the cattle futures markets (Koontz et al. 1992).

Overall, previous studies have mixed results regarding live cattle futures market efficiency. Although there are no general tendencies that completely reject efficiency of the market, there are studies that found time periods when live cattle futures have been suspected of being biased.

Concept of Futures Market Efficiency

Tests for futures efficiency usually begin with a statistical analysis of prices. The most common test posits futures prices to be unbiased forecasts, even if not particularly good forecasts. This test involves regressing a nearby futures contract's prices on the same contract's prices at some point in the past. The model is:

$$(1) \quad FP_t = \alpha + \beta FP_{t-i} + \varepsilon_t,$$

where FP_t is the nearby futures price at time t ; FP_{t-i} is the same contract's price at time $t-i$; ε_t is a random disturbance. If a market is efficient, α is expected to equal 0, and β is expected to equal 1. The model has been suspect of truly measuring efficiency because of possible unreliability of the F-test of the parameters, or the violation of other OLS assumptions (Elam and Dixon 1988; Shen and Wang 1990; Kenyon et al. 1993). Nonetheless, the model is often cited as the conceptual model of choice.

Statistical tests of market efficiency abound, from variants on the model in (1) (Kenyon et al. 1993; Martin and Garcia 1981; Koppenhaver 1983; Kolb and Gay 1983), to cost-of-production driven

models which check for rational price formation (Koontz et al. 1992). Among the most comprehensive statistical tests were those recently reported by Kolb (1992). Daily data were used to examine 29 different commodities, with data ranging from the 1950's through 1988. A total of 3330 contracts and 980,800 daily settlement prices were analyzed. The research was principally a study of normal backwardation (downward bias). Keynes (1930), who discussed the concept of normal backwardation over 60 years ago, believed that a risk premium was inherent within the futures market. That is, long speculators must make a profit over time that is commensurate with the risks they take.

After performing four different statistical tests, Kolb (1992) concludes that Keynes (1930) was wrong--normal backwardation is not normal in the futures markets. But in each of the four tests, Kolb (1992) concluded that live cattle futures were biased downward. For each test, the live cattle futures market was among the top three out of the 29 commodities analyzed, in terms of statistical confidence in the presence of a downward bias. In related research, Bessembinder (1993) reports that, of the commodities having significant downward bias, live cattle futures was the largest. These studies are indicative of long-term bias in the live cattle futures market.

Statistical inefficiency, though related, is certainly not synonymous with economic inefficiency. Unfortunately, with the large number of statistical tests of market efficiency have not come an equally large number of market trading simulation studies which might corroborate, in an economic sense, the findings of the statistical tests. Perhaps what prevails are economists' propensities towards elegant models with exquisite formulae. Or maybe trading simulations are so fraught with difficulties that they are seldom taken seriously.

An often cited cattle futures trading simulation by Helmuth (1981), is usually cited in conjunction with its rebuttal, Palme and Graham (1981). Helmuth (1981) used a limited data series (1978-1980). He used an estimated basis that was generated in-sample. After devising a trading system that was 100 percent accurate over the trading period, the conclusion of "biased" was reached.

A more intricate trading simulation was reported by Garcia et al. (1988b). However, once again the data set was limited, with only three years of trading, using monthly data. Though their simulations on the average generated profits, no analysis of those profits was undertaken. Because of "large" variances of the profits generated, they concluded that "... results do not show strong evidence of inefficiency in the live cattle futures market" (p. 169). As with any such forecasting/trading simulations, distinctions between forecast model specification and market efficiency are difficult.

Trading Simulation Design

A trading system is defined here as the set of rules that determine a trader's choices given existing market conditions. Trading systems are ordinarily designed from historical, data-based research, involving statistical tests, trading simulations, or both. The expected profitability from using a trading system in the future is the same issue as its reliability in demonstrating historical inefficiency. The following issues are important in validating trading simulations.

Length of Time Over Which Trading Occurs

Though no definitive rule exists, the longer the time periods of the trading signals, the longer the data set needs to be. For example, broad generalizations are difficult to draw from a three year test of monthly-generated trades. Trades should also more or less "fill the trading space". A system that

signals one trade in five years, even if by a weekly or even daily signal, offers little information. On the other hand, with a system that allows only daily trades, if numerous trades are signaled during a year, even a short data set covering a few years may instill confidence in the conclusions reached over the trading period. But even in this case, if market efficiency is the issue, statements about market efficiency over only a few years, though perhaps definitionally accurate, have little economic relevance.

Optimization of a Model's Parameters

Only out-of-sample trading simulation is informative. The parameters of either a trading or a forecasting model must be determined *ex ante*. Trading space parameter optimization is not permitted. This condition is perhaps the least understood and the most often breached "rule" of trading simulation. A researcher should be mindful of *time*, within the forecasting or trading model. A trade that is taken in one period should not be established on the basis of a trading rule discovered or modified in the next period.

Complexity of the Trading Simulation Model

The more rules a system has, or the more conditions that have to be met for a supposed trade to occur, the less likely an identical situation will occur in the future. Even if the exact situation is duplicated in the future, a duplication of the trading strategy may not be warranted because the trading rule was presumably chosen from a limited sample size in the first place (limited by a large number of conditions that had to be met). A complex trading system looks suspiciously like trading space parameter optimization.

Historical Realism of the Model

Historical realism is the same issue as future realism. Critique of a trading system calls for the researcher to judge the system on the basis of rationality at each point in time. The relevant question is: Would it have been reasonable for a trader to react in a specific fashion given the conditions of that moment in time? Historical realism has one additional condition that must be met, compared to future realism, and that is technological feasibility. A study that spans a relatively long period of time must concern itself with this issue, especially in light of the computer evolution of the last 20 years.

Historical inefficiency and future trading system reliability are the same issue. A study that purports to have uncovered a profit-generating trading system from past data, using today's tools, may or may not have a viable system into the future, given that those tools are now available to extract the supposed profits. The only relevant inefficiency, relevant meaning that profits could be acquired, is inefficiency that has a chance of persisting into the future. If the only way one can uncover inefficiency, is by using technology that is now available and will be available in the future, the case against future efficiency is diminished. On the other hand, if research tools are used that were available throughout the time period studied, and inefficiency was still found, then that inefficiency might continue into the future.

Abnormality of Trading Profits

The relevant questions are: Did the simulation generate trading profits? If "No", and all of the other conditions have been met, the research supports a null hypothesis of "efficiency". If "Yes", then a second question arises: Were those profits sufficiently large that they should have enticed investment capital into that market during the time period studied? If so, this suggests market inefficiency.

But what are abnormal profits? The profits must somehow take into account risk. Trading profits should be compared with a benchmark investment over the time period studied. The benchmark used here is a composite stock market investment.

Trading System Technique

Trading simulation requires a large number of seemingly *ad hoc* choices. First, the data to be analyzed must be chosen. That data can include historical futures prices and/or fundamental data such as cattle-on-feed numbers. Choices must be made regarding the sample size used in building the forecast model, as well as the sample set of the forecasts. How long will a model be used to make forecasts before it is re-optimized? What model-building techniques will be used, linear regression, simple moving average, or some non-linear technique like neural networking? Trading rules must also be defined. The point of entry and exit must be determined.

An analysis of the abnormality of trading profits requires still more rules--those involving money management. The number of contracts to be traded and the amount of money required for each contract, need to be determined. Analysis is complicated further by the fact that interest-bearing U.S. Treasury instruments may be used to meet trading account margin requirements.

With the multitude of choices, the credibility of the trading simulation approach to testing market inefficiency is often questioned? This may explain why research often ends with statistical price analysis. This study uses a set of trading rules that attempts to meet the five criteria mentioned.

Data

The data include live cattle futures prices from January, 1965 through August, 1993. Using only futures prices makes our test weak-form. Weekly data, specifically the opening price on the second trading day of the week, which is usually a Tuesday, are employed. The opening price was used because a market order placed before the open will generally be filled somewhere around the opening price range. In addition, the opening price may be compatible with the bulk of the underlying movement within the daily cash market (Liu et al. 1992). Tuesdays were used because most of the underlying cash cattle movement takes place early in the week (Jones et al. 1992). All margin calls are also figured on Tuesday's open.

Trading Signals

Any trading signal can be considered to have a forecasting component. There is an implicit forecast involved which says that the price should end up in a range which will cause the trade to earn a profit. In this case, all trades are considered to be driven explicitly from forecasts. In order to further reduce the trading rules, all trades are reduced to timed trades, 19 weeks in duration, corresponding to the length of a typical cattle finishing period.²

² To informally examine the consistency of our research, all analyses involving 19-week trades were also completed for both 9- and 29-week trades. Since the results of the 9- and 29-week analyses were qualitatively similar to those of the 19-week analyses, the paper proceeds in a 19-week framework.

The trading signal is simple. If a forecasted price projects a profit (by going either long or short) sufficient to cover a fixed commission charge of \$60 per contract, and there is enough money in the account to do so, the trade is taken. The position is held for a fixed 19 weeks.

Since futures prices predict the eventual cash price at delivery, and since nearby futures may be considered a proxy for cash, only those dates in a contract's life which are part of the "nearby" time period are forecasted. The nearby time period is defined as that period beginning with the week whose Monday is at least the 14th of the month two months preceding the delivery month, and continuing until the week whose Monday is the 13th or earlier within the delivery month. Therefore, trades are initiated on deferred contracts, and closed when those contracts are nearby.

Forecasts

To allow time for initialization of the models the first forecast was for the week of July 3, 1967. This forecast would have been made, and the trade entered, on February 20, 1967. Forecasting rules were established using only data that could have been observed on or before the entry date. The last price forecasted, and hence traded upon, is the price for the week August 30, 1993. The total number of forecasts generated, and the maximum possible number of trading signals, is 1366, which is the number of weeks from July 3, 1967 to August 30, 1993.

The forecasting techniques used are divided into three categories: 1) naive, 2) linear regression, and 3) neural network. Though neural networks have existed conceptually for many years, their use in economics has been limited to the last few years. Computer technology was insufficient over the last 25 years to trade futures with neural nets. They are not included here to evaluate market efficiency, but because they are on the forefront of forecasting and could influence future trading strategies.

Four different naive forecasts were completed. The first, denoted N-C for "naive" and "cash", assumes that the best forecast of the future price is today's cash price, with "cash" referring to nearby futures. For example, a forecast made on March 15 of the August contract price on August 1, would use the April contract price, which is the current nearby in March. The second naive forecast (N-CT) adds to the cash forecast in N-C a trend component. The trend component is the average weekly movement in cash price from the beginning of the data (8/16/65) until the date the forecast is made. With each succeeding forecast, the trend is the average over a larger number of weeks. The weekly trend, is multiplied by the number of weeks in the trade, and added to the cash price N-C, to become the N-CT forecast. The third naive forecast (N-CS) adds to the cash forecast of N-C a seasonal component, rather than a trend component. The year is split into 6 seasons, corresponding to the 6 live cattle futures contract months traded.³ The fourth naive forecast (N-CTS) incorporates with the cash of N-C, both the trend depicted in N-CT, along with the seasonal depicted in N-CS.

The regression model used to forecast is as follows (referred to as R model):

³ An April index, for example, is constructed in the following manner. The mean of all April cash prices that have occurred up to the forecast date (typically spanning from around 2/15 to 4/15 each year), is divided by the mean of *all* cash prices that have occurred up to the forecast date. The seasonal component of the N-CS forecast of 6/1 price, calculated on 1/15, would be the cash price of 1/15, times the 1/15 observation of the February index, divided by the 1/15 observation of the June index.

$$(2) \quad FP_t = \beta_0 + \beta_1 FP_{t-T} + \beta_2 CP_{t-T} + \varepsilon_t,$$

where FP_t is the nearby futures price at time t , FP_{t-T} is the same contract's price at time $t-T$, and CP_{t-T} is the cash price at time $t-T$ (here the nearby futures price). As described, T here is set equal to 19. The β 's are parameters to be estimated, and ε_t is a random error with zero mean.

A second regression model (referred to as RD) adds contract dummies to allow for seasonality:

$$(3) \quad FP_t = \beta_0 + \beta_1 FP_{t-T} + \beta_2 CP_{t-T} + \beta_{j+2} CONTR_j + \varepsilon_t,$$

where, the $CONTR_j$, $j=1, \dots, 5$ are contract dummy variables, with 1 being February, 2 April, 3 June, 4 August, and 5 October. The R and RD models, estimated at time t , are the equations for forecasting FP_{t+T} .

Once a decision is made regarding the variables to include in the regression models, the difficult decision regards the length of the sample period to include in estimation. The key would be to have a sample period long enough to capture long term characteristics of the market being studied, and yet short enough to assure sensitivity to change. *Ad hoc* 50-, 100-, and 150-week sample periods, corresponding roughly to 1, 2, and 3 years in the sample period, were selected. There is no apparent economic basis for these choices, and they were the only ones tested.

The regression forecasts include only the most recent data. The estimated equation, along with today's pertinent information, is then used to construct a forecast of the futures price T weeks into the future. That forecast signals today's trading decision. There are not enough data available to use the full 100 or 150 weeks sample size to design the 7/3/67 forecast. Therefore, a smaller sample size was used until the data became available. For descriptive purposes, RD-50, RD-100, and RD-150 refer to the RD models, using 50, 100, and 150 week sample periods.

The neural network models are back-propagation models (the B models) as described by Eberhart and Dobbins (1990). A sketch of the Eberhart-Dobbins approach is found in Grudnitski and Osburn (1993), and the mathematical theory behind the process in Kosko (1992). To limit the *ad hoc* parameter choices, Kosko's theory was used to define the error adjusting coefficient (at $1/K$, where K is the iteration number), and the momentum coefficient was set at 0.9, according to the suggestion of Rumelhart and McClelland (1986). One hidden layer was used, made up of either three or five neurodes. The neural nets used the same explanatory variables and sample periods used in the R models. One exception was that, because of the amount of computer time involved in neural estimation, five forecasts were conducted before a forecasting model was re-estimated, as compared to only one forecast per estimation in the regression models. For description, B3-100 refers to the back propagation model with three hidden neurodes, using a 100-week sample period.

Money Rules

The trading account is assumed to begin with \$10,000 on 2/20/67, the first date on which a trade may be made, and 19 weeks prior to the first forecasted date, 7/3/67. The account is closed 8/30/93, with the last possible position entered 19 weeks prior to that date. Since T-bills are used for

margin requirements, each account is assumed to draw, in addition to trading profits or losses, an interest rate equivalent to the weekly quoted T-bill rate, as reported in the Federal Reserve Bulletin.

The most difficult of the money rules is determining the capital required to trade a single contract. The capital required to effectively trade a contract is greater than the exchange initial margin requirement. Minimum equity to trade a contract was assumed to be 50% of the cash value of the contract being considered. A conservative equity requirement was used because our hypothetical "fund" is only allowed to trade live cattle futures. Commercial futures funds typically diversify into numerous commodities. The 50% is also consistent with the equity required for trading corporate stock on margin, a common practice in stock investment.

The equity requirement works as follows.. A futures price of \$50/cwt., coupled with a 400 cwt. contract, implies a per-contract equity requirement of \$10,000. After-commission trading equity is monitored weekly. Each open position has an equity requirement, made up of the equity required at the time the trade was made, coupled with the profit or loss that would accrue to the position if it were liquidated. Any equity not required for open positions may be used to establish new positions. The maximum possible amount of the "not-earmarked-for-equity-requirements" capital is used at the very next trading signal. In the example just given, if the account showed anywhere between \$20,000 and \$29,999 that was not needed for equity on open positions, the very next trading signal would initiate two new contracts to be traded, instead of one.

Forecast Updates

Traders could use any of the myriad of forecasts and trading schemes just discussed. Regardless of how profitable a system was in hindsight, it is unrealistic to assume that a trader would blindly follow it into huge loss situations. A more likely situation is that a trader would follow some type of forecast switching technique based upon either statistical or monetary criterion.

Two forecast switching techniques are examined. The first employs the forecast which has the lowest root mean squared forecast error (RMSE) to date, realizing that there is a 19-week lag in being able to act upon the RMSE information. A second method uses the forecast series which has generated the greatest profits to date. These two methods are used first for the naive and regression forecasts, and secondly, with the back-propagation methods included. Descriptively, EQ designates the equity-based forecast switching technique, *excluding* the back-propagation forecasts. Alternatively, RM-B designates the RMSE-based technique, *including* back-propagation forecasts. With the forecast switching techniques just described, we have reduced the number of comparisons we must make with the benchmark, down to only four.

Abnormal Profits Benchmark

The benchmark is a hypothetical composite stock market portfolio, with a beginning value of \$10,000. An "inclusive-of-dividend" NYSE and AMEX daily composite index was extracted from The CRSP (Center for Research in Security Prices) database. As with futures, the second business day of

the week was used.⁴ Of course \$10,000 could not be divided directly among all of the stocks on the NYSE and AMEX. But by investing in stock index funds, one could get close. Stock fund investing has a cost associated with it. *Forbes* shows annual stock fund costs in 1993 to be 1.45%. Since an index fund is presumably cheaper to operate than a more advisor-oriented fund, an annual cost equal to 0.75% is assumed. The \$10,000 initial value, is coupled with both the Tuesday index, as well as the assumed cost structure, to fabricate the hypothetical stock market portfolio that is compared with the futures simulations.

Results and Discussion

The results of the basic efficiency model (equation 1) are reported in table 1. The model is estimated for combinations of 19-week forecasts, along with various sample periods. Results show that large sample sizes virtually assure that efficiency will be rejected. For example, efficiency is rejected 100% of the time, any time the sample period is greater than 90 weeks. Even with small sample periods of only 10 weeks, efficiency is rejected over 90% of the time.

Table 1. Results of Equation (1) Tests for Market Efficiency. Forecasted Weeks: August 16, 1965 through August 30, 1993.

Weeks Ahead Forecasted	Weeks In Sample Period	Number of Samples Tested	Percent of Time Efficiency Rejected ^a
19	10	1455	90.03
19	30	1435	95.12
19	50	1415	97.10
19	70	1395	98.64
19	90	1375	100.00

^a F-test at the 0.05 level of significance.

Table 2 shows the results of the forecasting/trading models, as well as information regarding the stock market benchmark, and a similarly established T-bill benchmark. Also shown is a hypothetical system of always taking a long position. This system is not included in analyses, because there is no *a priori* reason to go long and not short. This merely shows an after-the-fact description of the market tendency. Because the money rules determine the number of contracts traded, there is little connection between the number of signals given, and the number of contracts traded.

The top line shows the RMSE of futures as a forecast of itself. N-C is cash (nearby futures) as a forecast of futures. Although the RMSE of Futures appears lower than the RMSE of N-C, indicating that deferred futures provided a better forecast of itself than did the nearby futures price, a

⁴ CRSP data was unavailable for 1/1/93 to 8/30/93. Thus, after 1/1/93, the NYSE composite Tuesday index was coupled with a 3.002 annual dividend rate (this was the S&P average dividend rate from 1/92 to 10/92).

formal statistical comparison with the Ashley, Granger, and Schmalensee (1980) procedure, did not confirm this. A weekly return is defined to be $100 * [(Value\ of\ Account\ at\ time\ t / Value\ of\ Account\ at\ time\ t-T) - 1]$, with T equal to 1 or 52. The lower volatility of the T-bill investment, relative to the stock market, can readily be seen by comparing the respective standard deviations of the means. But a comparison of the various futures means relative to their standard errors, with those of the stock market, shows that the stock market is about as volatile as futures, and in many cases, even more volatile.

Several points support either or both market inefficiency or downward bias in live cattle futures. Only 1 of the 20 systems reported has either a 1-week or 52-week mean that is lower than the stock market. None of the four forecast-switching systems has a lower 1-week or 52-week mean than the corresponding stock market figure. In each of the systems, the number of long positions traded was much greater than the number of short positions. In all systems the long trades have mean profits while the short trades have mean losses. These last two points provide evidence in support of downward bias. Though not a contribution to the proof, the results of the "always long" system, as seen in the last line of table 2, provide a striking description of the tendency for cattle futures to increase over a contract's life. The "always-long" returns are among the highest in the table.

Because the futures systems offer slightly more volatile returns than the stock market, it cannot be immediately concluded that they should be preferred by a risk-averse agent. A formal comparison must ultimately transcend statistics and involve a discussion of the risk involved with trading the various systems. A comparison of the four forecast-switching systems with the stock market series showed that none of the futures weekly return series stochastically dominates the corresponding stock market series at either the second or first degree levels. The weekly return series of all systems failed a statistical test for normality. Not wanting to impose the restriction of quadratic utility functions, the mean-variance analysis of the possible investments is not appropriate.

The weekly returns of each of the forecast-switching models were formally compared to the stock market weekly returns, using "stochastic dominance with respect to a function" (SDWRF). This technique is discussed by King and Robison (1981), and by Meyer (1977). The absolute risk aversion function is defined by Pratt (1964) as: $R(x) = -U''(x)/U'(x)$, which is the ratio of derivatives of the decision maker's utility function $U(x)$, where x may be considered to be either wealth or income.

The SDWRF procedure places no restrictions on the functional form of the utility function, nor any restrictions on whether an agent is risk-loving or risk-averse. Upper and lower bounds to the absolute risk aversion function (ARAF) may be established which would ensure that agents, whose ARAF's lie everywhere between these bounds, would unanimously prefer one distribution to another. Here, the distributions in question are the weekly returns for T-bills, the stock market, and the forecast-switching systems.

Table 2. Results of 19-Week Live Cattle Futures Trading Systems and Benchmarks,
February 20, 1967 - August 30, 1993.

Fore- cast Method	No. Long Conts	No. Short Conts	\$ Profit per Long	\$ Profit per Short	Mean of 1-Wk Returns %	Std Dev of 1-Wk Mean	Mean of 52-Wk Returns % ^a	Std Dev of 52 Wk Mean	Frst RMSE \$/cwt
Futures									5.31
<u>Naive Models</u>									
N-C	234	139	986.15	-576.23	0.32	0.10	17.75*	0.81	5.63
N-CT	403	167	828.05	-576.79	0.34	0.10	19.16*	0.81	5.67
N-CS	157	107	755.92	-817.61	0.27	0.11	12.71*	0.63	5.68
N-CTS	275	138	776.42	-772.90	0.32	0.11	16.56*	0.77	5.67
<u>Regression Models</u>									
R-50	2942	747	942.52	-143.21	0.49	0.09	27.57*	0.64	5.57
RD-50	665	314	1024.66	-477.17	0.39	0.10	21.27*	0.70	5.38
R-100	178	69	534.38	-843.25	0.28	0.12	13.24*	0.73	5.95
RD-100	137	81	759.59	-868.94	0.28	0.12	12.62*	0.68	6.26
R-150	81	45	578.91	-1146.49	0.19	0.11	9.00	0.68	6.20
RD-150	232	99	881.16	-724.93	0.31	0.10	16.73*	0.83	6.34
<u>Neural Models</u>									
B3-50	579	210	948.50	-324.53	0.38	0.09	20.88*	0.74	6.27
B5-50	264	120	888.74	-564.57	0.32	0.10	18.12*	0.86	6.86
B3-100	1278	480	1001.77	-332.23	0.43	0.09	24.56*	0.77	5.86
B5-100	266	122	892.12	-519.90	0.31	0.09	16.90*	0.77	6.16
B3-150	74	43	860.32	-1074.23	0.21	0.11	13.18*	1.02	5.88
B5-150	650	246	877.04	-402.18	0.38	0.09	20.89*	0.78	5.85
<u>Forecast Switching Models</u>									
EQ	380	94	904.36	-356.85	0.36	0.11	18.87*	0.67	5.44
RM	279	136	868.84	-663.76	0.33	0.11	16.84*	0.73	5.76
EQ-B	335	89	890.03	-377.03	0.36	0.11	18.31*	0.69	5.42
RM-B	279	136	867.84	-663.76	0.33	0.11	16.84*	0.73	5.76
<u>Stock Market and T-Bills</u>									
Stock Market					0.20	0.06	10.87	0.46	
T-Bills					0.12	0.002	6.64	0.08	
<u>Long Only</u>									
Long	485	0	533.76	0.00	0.42	0.14	21.04*	0.97	

* Higher return than stock market by 1-tail T-test, 0.05 level of significance.

^a There are 52 less observations in this analysis than in the weekly analysis.

With these three returns series, and SDWRF, we can establish the upper bound on the ARAF, below which agents would unanimously prefer the stock market over the low-risk T-bill market. In addition, we can determine *how* risk averse agents must be to hold them in the stock market when they might see superior returns in the live cattle futures market. With these boundary conditions we can establish a range of risk aversion that would appear consistent with the stock market investment. More risk-averse agents would prefer T-bills, whereas less risk-averse agents would prefer cattle futures. This procedure helps to determine whether it might have been plausible for money to have moved from the stock market to the cattle futures market over the last 28 years. If the range of consistency is narrow, and if stock market investing is compatible with a wider range of risk aversion, especially in the direction of *less* risk averse, then it would seem that money "should" have moved from the stock market to the futures in order to equilibrate the latter. The results of these simulations are reported in table 3. To facilitate comparison, each of the returns was first multiplied by 1000. The comparisons are then between the money made or lost each week on a \$1,000 investment in each of the markets.

Table 3. Boundaries On Risk Aversion Functions Consistent With Investment Preference.^a

Futures Series Preferred	Lower Bound	Stock Market Preferred	Upper Bound	T-Bills Preferred
EQ	< .0028 <=	Stk Mkt	<= .0029 <	T-Bills
RM	< .0021 <=	Stk Mkt	<= .0029 <	T-Bills
EQ-B	< .0026 <=	Stk Mkt	<= .0029 <	T-Bills
RM-B	< .0021 <=	Stk Mkt	<= .0029 <	T-Bills

^a Agents less risk averse than left numbers unanimously prefer corresponding futures series to stock market. Risk aversion greater than right numbers implies unanimous T-bill preference over the stock market.

The range denoted by the lower and upper bounds on the ARAF's that would be consistent with stock market investment, are narrow (though "narrow" is not formally defined). Typically, a given management or investment plan is compatible with a rather wide range of ARAF bounds, often many orders of magnitude apart (see for example Williams 1988). In our analysis the risk aversion boundaries separating futures trading with T-bill preference virtually coincide. Thus, money would have been expected to move from the stock market to the cattle futures market over the last 28 years.

Conclusions

Recent empirical work provides statistical evidence for downward bias in the live cattle futures over the last 25 years. Simple trading systems, designed with no *a priori* knowledge of the market, designed to take advantage of trends, could have extracted abnormal profits from that market. Fama's (1970) description of futures market efficiency was extended by suggesting a possible source of the equilibrating trading capital. The psychological difficulties of trading systems were accounted for, by providing simple forecasting-switching techniques. Results are not consistent with the null hypothesis of weak-form live cattle futures efficiency. Inconsistency with both semi-strong and strong-form efficiency would immediately follow. It would appear that it is time to invest money in this market.

References

- Ashley, R., C.W.J. Granger, and R. Schmalensee. "Advertising and Aggregate Consumption: An Analysis of Causality." *Econometrica* 48(1980):1149-1167.
- Bessembinder, Hendrik. "An Empirical Analysis of Risk Premia in Futures Markets." *The Journal of Futures Markets* 6(1993):611-630.
- Center for Research in Security Prices. Database. Graduate School of Business, University of Chicago.
- DeCoster, G.P., W.C. Labys, and D.W. Mitchell. "Evidence of Chaos in Commodity Futures Prices." *The Journal of Futures Markets* 12(1992):291-305.
- Eberhart, R.C., and R.W. Dobbins. "Implementations". In *Neural Network PC Tools*. R.C. Eberhart and R.W. Dobbins, editors. San Diego:Academic Press. 1990.
- Eales, J.S., B.K. Engle, R.J. Hauser, and S.R. Thompson. "Grain Price Expectations of Illinois Farmers and Grain Merchandisers." *American Journal of Agricultural Economics* 72(1990):701-708.
- Elam, E., and B.L. Dixon. "Examining the Validity of a Test of Futures Market Efficiency." *The Journal of Futures Markets* 8(1988):365-372.
- Elam, E., and C. Wayoogagtr. "A Reexamination of the Systematic Downward Bias in Live Cattle Futures Prices." *The Journal of Futures Markets* 12(1992):329-338.
- Fama, E.F. "Efficient Capital Markets: A Review of Theory and Empirical Work." *Journal of Finance* 25(1970):383-417.
- Federal Reserve Bulletin. Washington, D.C. Several Issues.
- Forbes. August 30, 1993: p. 112.
- Garcia, P., M.A. Hudson, and M.L. Waller. "The Pricing Efficiency of Agricultural Futures Markets: An Analysis of Previous Research Results." *Southern Journal of Agricultural Economics* 20(1988a):119-130.
- Garcia, P., R. Leuthold, T.R. Fortenbery, and G. Sarassoro. "Pricing Efficiency in the Live Cattle Futures Market: Further Interpretation and Measurement." *American Journal of Agricultural Economics* 70(1988b):162-169.
- Gardner, B.L. "Futures Prices in Supply Analysis." *American Journal of Agricultural Economics* 58(1976):81-84.
- Grudnitski, G. and L. Osburn. "Forecasting S&P and Gold Futures Prices: An Application of Neural Networks." *The Journal of Futures Markets* 6(1993):631-643.

- Helmberger, P.G. and V. Akinyosoye. "Competitive Pricing and Storage under Uncertainty with an Application to the U.S. Soybean Market." *American Journal of Agricultural Economics* 66(1984):119-130.
- Helmuth, J. "A Report on the Systematic Downward Bias in Live Cattle Futures Prices." *The Journal of Futures Markets* 1(1981):347-358.
- Hurt, C.A. and P. Garcia. "The Impact of Price Risk on Sow Farrowings, 1967-78." *American Journal of Agricultural Economics* 64(1982):565-568.
- Jones, R., T. Schroeder, J. Mintert, and F. Brazle. "The Impacts of Quality on Cash Fed Cattle Prices." *Southern Journal of Agricultural Economics* 24(1992):149-162.
- Just, R.E. and G.C. Rausser. "Commodity Price Forecasting with Large-Scale Econometric Models and the Futures Market." *American Journal of Agricultural Economics* 63(1981):197-208.
- Kenyon, D., E. Jones, and A. McGuirk. "Forecasting Performance of Corn and Soybean Harvest Futures Contracts." *American Journal of Agricultural Economics* 75(1993):399-407.
- Keynes, J.M. *A Treatise on Money* (vol 2). London:Macmillan. 1930.
- King, R.P., and L.J. Robison. "An Interval Approach to Measuring Decision Maker Preferences." *American Journal of Agricultural Economics* 63(1981):510-520.
- Kolb, R.W. "Is Normal Backwardation Normal?" *The Journal of Futures Markets* 12(1992):75-91.
- Kolb, R.W., and G.D. Gay. "The Performance of Live Cattle Futures as Predictors of Subsequent Spot Prices." *The Journal of Futures Markets* 3(1983):55-63.
- Koontz, S.R., M.A. Hudson, and M.W. Hughes. "Livestock Futures Markets and Rational Price Formation: Evidence for Live Cattle and Live Hogs." *Southern Journal of Agricultural Economics* 24(1992):233-249.
- Koppenhaver, G.D. "The Forward Pricing Efficiency of the Live Cattle Futures Market." *The Journal of Futures Markets* 3(1983):307-319.
- Kosko, B. *Neural Networks and Fuzzy Systems*. Englewood Cliffs, NJ: Prentice-Hall, Inc. 1992.
- Leuthold, R.M. and P. Hartmann. "A Semi-Strong Form Evaluation of the Efficiency of the Hog Futures Market." *American Journal of Agricultural Economics* 63(1979):482-489.
- Liu, S.-M., B.W. Brorsen, C.M. Oellermann, and P.L. Farris. "Forecasting the Nearby Basis of Live Beef Cattle." *Applied Commodity Price Analysis, Forecasting, and Market Risk Management*, proceedings of the NCR-134 Conference, 1992, pp. 231-245.

- Martin, L. and P. Garcia. "The Price-Forecasting Performance of Futures Markets for Live Cattle and Hogs: A Disaggregated Analysis." *American Journal of Agricultural Economics* 63(1981):209-215.
- Meyer, J. "Choice Among Distributions." *Journal of Economic Theory*. 14(1977):326-336.
- Palme, L.A., Jr. and J. Graham. "The Systematic Downward Bias in Live Cattle Futures: An Evaluation." *The Journal of Futures Markets* 1(1981):359-366.
- Pluhar, D.M., C.E. Shafer, and T.L. Sporleder. "The Systematic Downward Bias in Live Cattle Futures: A Further Evaluation." *The Journal of Futures Markets* 5(1985):11-20.
- Pratt, J.W. "Risk Aversion in the Small and in the Large." *Econometrica*. 32(1964):122-36.
- Rumelhart, D.E., and J.L. McClelland. *Parallel Distributed Processing, Explorations in the Microstructure of Cognition, Vol. 1: Foundations*. Cambridge, MA: MIT Press. 1986.
- Shen, C. and L. Wang. "Examining the Validity of a Test of Futures Market Efficiency: A Comment." *The Journal of Futures Markets* 10(1990):195-196.
- Shonkwiler, J.S. "Are Livestock Futures Prices Rational Forecasts?" *Western Journal of Agricultural Economics* 11(1986):123-128.
- Tomek, W.G., and R.W. Gray. "Temporal Relationships Among Prices on Commodities Futures Markets: Their Allocative and Stabilizing Roles." *American Journal of Agricultural Economics* 52(1970):372-380.
- Williams, J. "A Stochastic Dominance Analysis of Tillage and Crop Insurance Practices in a Semiarid Region." *American Journal of Agricultural Economics* 70(1988):112-120.
- Working, H. "A Theory of Anticipatory Prices." *American Economic Review* 48(1958):188-99.