A TRADING SIMULATION TEST FOR WEAK-FORM EFFICIENCY IN LIVE CATTLE FUTURES

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INTRODUCTION

Potential for downward bias or inefficiency in live cattle futures has been a concern for about as long as this market has existed. Statistical tests are often used to test market efficiency. However, such tests only indicate statistical market inefficiencies. Economic market inefficiency is determined by the ability to extract abnormal (risk adjusted) profits using some trading technique (Garcia et al., 1988b; DeCoster, Labys, and Mitchell, 1992). The objective of this research is to examine whether certain realistic long-term futures trading systems could have been used to acquire abnormal profits from the live cattle futures market, when tested using out-of-sample data.

This research extends previous live cattle futures trading simulation studies in several important ways. First, a comprehensive trading simulation test of live cattle futures is completed by examining a period spanning 90% of the time over which live cattle futures have

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existed. Second, special attention is given to whether purported trading systems could have been followed historically. Third, the *abnormality* of the simulated trading profits is formally tested within an accepted investment theory framework, the capital asset pricing model (CAPM). The research is of interest to those who wish to corroborate statistical tests of market efficiency with plausible trading simulation tests. Results should also be of interest to those involved in forecasting futures prices, and to those who design and trade mechanical systems based upon those forecasts.

CONCEPT OF FUTURES MARKET EFFICIENCY

Viable futures markets should be efficient, or at least unbiased in the long run. If a market is biased (tendency to move either up or down into contract expiration), profits could be extracted by trading the market. This extraction of profits would, in the long run, remove the bias.[1] However, to attract traders, sufficient departure from this "efficient" equilibrium must exist to allow for the perception of a profit opportunity. The magnitude of departure needed to attract trader interest is an empirical issue.

Intuitively, futures market efficiency should be intimately tied to the ability of that market to forecast. However, Working (1958) was reluctant to call futures prices forecasts. Also, Tomek and Gray (1970) suggested that cash prices of nonstorable commodities may be able to forecast deferred prices better than do futures prices. More recently, livestock futures, in particular, were noted as being poor distant price forecasts (Garcia et al., 1988b; Just and Rausser, 1981; Leuthold and Hartmann, 1979; Martin and Garcia, 1981; Shonkwiler, 1986).[2] 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 the 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 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).

[1] *Bias* may be considered a subset of inefficiency. However, if the nature of inefficiency is unusually long-running trends, both up and down, each trend may be considered a bias.

[2] 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% and 27% for four-quarter-ahead live cattle and live hog futures prices, respectively, compared to typically less than 15% for grains].

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. How then is market efficiency defined? Fama (1970) suggested that a futures market is efficient if the prices contain 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 price data. 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, because it should be easier to demonstrate trading profits using proprietary information than it is using only public information. Grossman and Stiglitz (1980) extended Fama's definition by noting that where information has a cost, informationally efficient markets will be impossible. Essentially, their work adds that for *perceived* inefficiencies to be *real* inefficiencies, they must be large enough to merit the cost of trading them out. Fama (1970) acknowledged this as well. In addition, profit comparisons for efficiency testing should account for risk.

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

Statistical tests of market efficiency abound (Kenyon et al., 1993; Martin and Garcia, 1981; Koppenhaver, 1983; Kolb and Gay, 1983; Koontz et al., 1992). Among the most comprehensive statistical tests were tests for normal backwardation by Kolb (1992). Daily data were used to examine 29 different commodities from the 1950s through 1988. Keynes (1930) 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) concluded that Keynes (1930) was wrong—normal backwardation is not normal in the futures markets; but he also concluded that in each of the four tests, live cattle futures were inefficient and 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 of presence of a downward bias. In related research, Bessembinder (1993) reported that, of the commodities having downward bias, live cattle futures was the largest. These studies all find indications of long-term bias in the live cattle futures market.

Statistical inefficiently, though related, is not synonymous with economic inefficiency. Elam and Njukia (1993) calculated that the cost to cattle feeders of the statistically insignificant risk premium implicit within live cattle futures between 1979 and 1992 was around \$13 per head. Continuous cattle hedging would have turned the average unhedged profit of \$10 per head to a loss of \$3 per head. Such a risk management strategy does not appear plausible, even for highly risk averse individuals.

An often cited cattle futures trading simulation by Helmuth (1981) is usually cited in conjunction with its rebuttal by Palme and Graham (1981). Helmuth (1981) employed a limited data series (January, 1978 through January, 1980). He used an estimated basis that was generated in-sample. After devising a trading system that correctly predicted market direction 100% of the time over the trading period (32 trades, \$289 before-commission profit per trade), he concluded that the market was biased. Out-of-sample, however, the Helmuth technique failed to generate net trading profits. For the out-of-sample period, February, 1981 through December, 1982, nine trades showed a loss of \$313 per trade before commission (Pluhar, Shafer, and Sporleder, 1985). From January, 1983 through December, 1989 the technique resulted in 41 trades with a \$68 loss per trade before commission (Elam and Wayoopagtr, 1992). With each of the two post-Helmuth studies, the Helmuth trading technique could have been duplicated by adding one or two ex post established trading rules (filters). Therefore, it is a judgement call as to whether the addition of further trading filters caused the Helmuth technique to be supported or negated out-of-sample.

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. Although their simulations, on average, generated profits, because of the large variances of profits generated, they concluded that "...results do not show strong evidence of inefficiency in the live cattle futures market" (p. 169).

The appropriateness of futures market efficiency trading simulation tests depends upon forecast model specification and trading system design. A poorly specified model increases the likelihood of finding efficiency. On the other hand, implausible trading systems increase the likelihood of rejecting efficiency. Therefore, careful attention must be given to forecast model specification and trading system design.

TRADING SIMULATION DESIGN

A trading system is defined here as the set of rules that determine a trader's choices given market conditions. Trading systems are ordinarily designed from historical, data-based research, involving statistical tests and/or trading simulations. The expected profitability from using a trading system in the future is assumed to be the same issue as its reliability in demonstrating historical inefficiency. The following issues are important in construction of a valid trading simulation. The first four are discussed by Schwager (1984). The fifth one is necessary to tie a trading simulation to efficiency testing.

1. 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. 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, statements about market efficiency over only a few years, though perhaps definitionally accurate, have little economic relevance.

2. 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 in a later period.

3. 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 it is that 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 an over-fit model in the first place. After all, given enough trading rules or filters, it is possible to extract virtually every dime from an historical futures price series. A complex trading system looks suspiciously like trading space parameter optimization.

4. Historical Realism of the Model

Historical realism is the same issue as future realism, as are historical inefficiency and future trading system reliability. Critique of a trading system requires 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 at that moment in time? Additionally, technological feasibility is important for historical realism, especially in light of the computer evolution of the last 20 years. Historical trading profits, found using technology unavailable at the time, have little meaning.

5. Abnormality of Trading Profits

Did the simulation generate trading profits? If not, and all of the other conditions have been met, the research supports a null hypothesis of efficiency. If profits were generated, then two further questions arise. Were the profits large enough to cover the costs of system design? Were the 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 benchmarks used here are a composite stock market investment and a T-bill investment. The theoretical framework used is the capital asset pricing model (CAPM).

TRADING SYSTEM TECHNIQUE

Trading simulation requires numerous seemingly ad hoc choices. First, the data to be analyzed must be chosen. Data can include historical prices and/or fundamental data such as cattle-on-feed numbers. Though the data may include only futures prices, manipulation of that data is multifaceted. Choices must be made regarding the sample size used in estimating the forecast model, as well as how long a model will be used to make forecasts before it is reoptimized. What forecast model-building techniques will be used? Trading rules and entry and exit points must be determined.

An analysis of the abnormality of trading profits requires meticulous rules involving money management. The number of contracts to be traded and the amount of money required for each contract must 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 involved, it is easy to question the credibility of the trading simulation approach to testing market efficiency. Though it is impossible to remove all ad hoc choices in trading system design and simulation, this research concentrates on minimizing their number. Those ad hoc choices which remain can only be judged subjectively according to their reasonableness.

DATA

The data include weekly live cattle futures prices from January, 1965 through August, 1993. Only futures prices are used, which makes the efficiency test weak-form. The opening price on the second trading day of the week (usually Tuesday) is used for that week's price. The opening price is 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 are used because most of the underlying cash cattle movement occurs early in the week (Jones et al., 1992). All margin calls are also figured on Tuesday's open.

TRADING SIGNALS

Most trading signals contain an implicit forecast which says that the price should end up in a range which will allow the trade to earn a profit. In this case, all trades are considered to be driven explicitly from forecasts. To further reduce the trading rules, all trades are reduced to timed trades, being either nine, 19, or 29 weeks in duration. Nineteen weeks is the length of a typical cattle finishing period. The nine- and 29-week regimes are included for comparison purposes.

The trading signal is simple. If a forecasted price projects a profit (by going either long or short) sufficient to cover a combined commission and slippage charge of $60 per contract, and there is enough money in the account to do so, the trade is taken. The position is held until the allotted time (nine, 19, or 29 weeks, depending upon the analysis) has expired, at which time the position is closed. 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. This study is only interested in forecasting the price where a contract ends up (when it becomes the nearby), since that is when trades will exit. 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, and to allow for the same forecasted dates to apply to each of the nine-, 19-, and 29-week regimes, the first forecast is for the week, July 3, 1967. For the 29-week regime, the forecast would have been made and the trade entered 29 weeks prior, or on December 12, 1966. Forecasting rules are established using only data that could have been observed on or before the entry date. The last price forecasted and 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 (the number of weeks from July 3, 1967 to August 30, 1993). The forecasting techniques used are of two types: naive and linear regression.

Four different naive forecasts are completed for each of the nine-, 19-, and 29-week trading regimes. The first, denoted N-C for naive and cash, assumes that the suitable 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 would be the current nearby. 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 six seasons, corresponding to the six live cattle futures contract months traded.[3] The fourth naive forecast (N-CTS) adds both the trend and the seasonal components.

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

$$FP_t = \beta_0 + \beta_1 FP_{t-T} + \beta_2 CP_{t-T} + \varepsilon_t \qquad (1)$$

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 may take on values of nine, 19, or 29. The βs 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 as:

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

where $CONTR_j$ is a vector of contract dummy variables, with j going from 1 to 5, representing the February, April, June, August, and October futures contracts, respectively. 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 is 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 one, two, and

[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 (the April cash prices typically span 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 the 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.

three years in the sample period, are selected. There is no economic basis for these choices, and they are the only ones tested.

An 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-week sample size to design the 7/3/67 forecast. Therefore, a smaller sample size is used until the data become available. For descriptive purposes, RD-50, RD-100, and RD-150 refer to the RD models, using 50-, 100-, and 150-week sample periods.

One final forecast which is considered, for exemplary reasons only, is really just a signal. It merely directs the trader to always go long and never short.

MONEY RULES

The nine-week trading account is assumed to begin with $10,000 on 5/1/67, the first date on which a trade may be made, and nine weeks prior to the first forecasted date, 7/3/67. The beginning dates for the 19-week and 29-week accounts are respectively 2/20/67 and 12/12/66. All accounts are closed 8/30/93, with the last possible position entered nine, 19, or 29 weeks prior to that date. All accounts trade the same number of forecasts. 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 amount of capital required to trade a contract is greater than the exchange initial margin requirement. Minimum equity to trade is assumed to be 50% of the cash value of the contract being considered. A conservative equity requirement is used because the hypothetical fund trades only 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 carries with it an equity requirement, made up of the equity required at the time the trade is 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 uncommitted equity capital is used at the 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 next trading signal would initiate two new contracts to be traded, instead of just one.

FORECAST UPDATES

Traders could use any of the myriad of forecasts and trading schemes just discussed. Regardless of how profitable a system is in hindsight, it is unrealistic to assume that a trader would blindly follow it into huge loss situations. Additionally, it would be difficult to know which forecast procedure to follow early in the data period, with little or no history. A more likely situation is that a trader would follow some type of forecast switching or combining technique based upon either statistical or monetary criteria. Forecasts and profits based upon these criteria should be carefully considered when examining market efficiency, as they require little or no ex ante predisposition to a particular technique.

Three forecast updating techniques are examined. First, since it is difficult to know which system to follow early in time, one might simply average the forecasts from the ten forecasting models each time and use that average as the forecast upon which to act. The second updating procedure uses the forecast at each week which, had it been solely used up to that week, would have generated the highest profits to date of all of the ten systems. However, there is a nine-, 19-, or 29-week lag in being able to act upon the profit information. The third technique employs the forecast which has the lowest root mean squared forecast error (RMSE) to date, again allowing for the lags in being able to act upon the RMSE information. Descriptively, AV designates the forecast averaging procedure, EQ designates the equity-based (greatest profits-to-date) forecast updating technique, and RM designates the lowest-RMSE updating technique. With these forecast updating techniques, the number of *essential* comparisons that must be made with the benchmarks are reduced to only three for each of the nine-, 19-, or 29-week regimes.

HYPOTHETICAL FUTURES FUNDS AND PROFITS BENCHMARKS

A crucial part of any trading simulation test of market efficiency is testing for abnormality of profits. In this research, abnormality is judged by comparing futures trading profits with returns from investing in two alternative benchmarks, the stock market and T-bills. To facilitate comparison, it is useful to consider each of the alternative investments as funds, where capital can be added or subtracted at any point and associated returns on investment calculated. Accordingly, each of the futures forecast series has associated with it a hypothetical futures fund which grows (following the initial investment of $10,000) by accumulating the profits from the simulated trades and from T-bill interest.

The stock market benchmark is a hypothetical composite stock market portfolio, with a beginning value of $10,000. Because of the different starting dates of the trading schemes, a slightly different series is constructed that serves as a comparison to each of the futures trading systems. An inclusive-of-dividend NYSE and AMEX daily composite index is extracted from the CRSP (Center for Research in Security Prices) data base. As with futures, the second business day of the week is used.[4]

Ten thousand dollars cannot be divided directly among all of the stocks on the NYSE and AMEX. But by investing in stock index funds, one can get close. Stock fund investing has a cost associated with it. *Forbes* reports annual stock fund costs in 1993 to be 1.45% (*Forbes,* 1993). Since an index fund is presumably cheaper to operate than a more advisor-oriented fund, an annual cost equal to 0.75% is assumed. A $10,000 initial value is coupled with the Tuesday index and the assumed cost structure to fabricate the hypothetical stock market portfolio that is compared with the futures simulations.

For comparison purposes, a hypothetical T-bill fund is constructed. Initialized at $10,000, this fund grows commensurate with the weekly T-bill interest rate. Each of the hypothetical funds (the futures funds, stock market fund, and T-bill fund) assume that no money is removed during the time period studied. That is, all profits are reinvested. No allowance is made for income taxes in any of the funds. The *cash* dollar value of each fund is established each week, based only upon accumulated T-bill interest and closed trades. To better account for the risk associated with trading futures, the weekly *equity* dollar value is established also for each of the futures funds, reflecting the value of all open futures positions as well. At a futures fund inception and termination, or at any point in the interim where no trades are held due to lack of a signal or lack of

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

sufficient trading capital, the cash and equity values for that fund are equal. The cash or equity values for each fund can be used to establish returns over periods of interest for each fund. For example, the 52-week equity return for a futures fund in week 100 is the difference between the equity value for that fund in week 100 and week 48, divided by the equity value in week 48.

THE CAPM MODEL

The final step necessary for testing efficiency is to adjust generated trading profits for risk. The tendency for a market's price to move upward through time may be thought of as a risk premium that is paid to the holder of the underlying instrument as compensation for assuming risk. Alternatively, the risk premium could be thought of as the tendency for an investment to generate returns in excess of some risk-free rate. In this context, the trades underlying a hypothetical futures fund would not have to display a tendency to move upward through time; only the fund itself would have to show this tendency. One generally accepted model which is used to examine whether a given risk premium is reasonable is the capital asset pricing model (CAPM). In the spirit of Bjornson and Innes (1992) and Elam and Njukia (1993), the CAPM depicts risk as the covariation of an asset's return with the market's return. This covariation may be estimated with the model:

$$R_t - RF_t = \alpha + \beta(RM_t - RF_t) + \varepsilon_t \tag{3}$$

where R_t is the return on an asset in time, t; RF_t is the riskless rate of return; RM_t is the return on the market portfolio; and ε_t is a serially independent error term. The β-estimate is a measurement of an asset's systematic risk. Systematic risk cannot be diversified against since it is presumably caused by variables which affect both the asset and the market portfolio. The β for the market portfolio is 1.0. An asset with $\beta < 1$ is less risky than the market portfolio, since part of its risk can be diversified away by investing in a broad portfolio of investments. $\beta > 1$ implies that the asset is more risky than the market portfolio.

After estimating the βs for a number of investments, the mean returns may be expressed as a function of the βs in a linear regression to establish an empirical market security line (Bjornson and Innes, 1992):

$$\overline{r}_i = \gamma_0 + \gamma_1\beta_i + u_i \tag{4}$$

where $\overline{r}_i$ is the average *excess* (i.e., above risk-free rate) return of asset i; β_i is the β-estimate of asset i, as obtained from an estimate of the form displayed in eq. (3); u_i is a zero-mean normal disturbance; and γ_0 and γ_1 are the parameters to be estimated. Once eq. (4) is estimated, it can be used to predict an expected risk premium for an asset (given an estimate for that asset's β) that is compatible with the CAPM theory. An actual risk premium that is significantly greater than the CAPM-predicted risk premium would be an indication of market inefficiency.

RESULTS AND DISCUSSION

Tables I–III show the results of the forecasting/trading models, as well as information regarding the stock market and T-bill benchmarks. Each of the three tables corresponds to a different forecasting (and trading) length, either nine, 19, or 29 weeks. Each table also contains a hypothetical system of always taking a long position. This long-only system is not intended to represent a plausible trading simulation, because there is no a priori reason to only go long. It merely shows an after-the-fact description of the market tendency. Because the money rules determine the number of contracts traded with each position, there is little connection between the number of signals given and the number of contracts traded. A system that makes large profits will typically trade a lot of contracts, because the required capital is available.

The top line within each of the tables shows the RMSE of futures as a forecast of itself. N-C is cash (nearby futures) as a forecast of futures. In each of the three tables the RMSE of Futures is lower than the RMSE of N-C, indicating that a deferred futures price provides a more accurate forecast of itself than does the nearby futures price. However, a formal statistical comparison with the Ashley, Granger, and Schmalensee (1980) procedure fails to demonstrate that the difference is statistically significant in any of the three cases. In addition, the RMSE of futures is lower than any of the alternative forecasts.[5]

A 52-week return is defined to be 100* [(Value of Account at time t/Value of Account at time $t - 52$) $- 1$]. Equity returns rather than cash returns are reported for the futures funds to better capture their fund nature by eliminating the discrete stair-step type returns that would be more typical of cash returns. For the T-bill and stock market returns, equity returns equal cash returns. The lower volatility of the T-bill investment relative to the stock market, and the stock market relative to futures, can readily be seen by comparing the respective

[5]The trading signals are associated with forecasted direction, not magnitude. A profitable system can be grossly off target, as long as it has signaled the correct direction.

TABLE I

Results of Nine-Week Trading Systems and Benchmarks

Forecast Method	No. Long Contracts	No. Short Contracts	$ Profit per Long	$ Profit per Short	$ Profit per trade	Std Dev per Long	Std Dev per Short	Std Dev per Trade	Maximum Drawdown (%)	Mean of 52-Wk Returns (%)	Std Dev of 52 Wk Mean	Frcst RMSE ($/cwt)
Futures												4.24
Naive models												
N-C	886	492	624.91	−405.40	257.05	3553	3358	3519	61	21.86[a]	0.98	4.38
N-CT	3106	1367	568.89	−371.08	281.62	5419	6152	5669	62	29.51[a]	1.25	4.40
N-CS	540	362	650.85	−344.15	251.53	2406	2660	2556	61	19.09[a]	0.96	4.51
N-CTS	216	141	554.39	−483.80	144.35	1787	2227	2034	51	13.55	0.87	4.49
Regression models												
R-50	829	388	420.47	−436.04	147.40	2991	2810	2960	63	18.65[a]	0.81	4.94
RD-50	175	154	453.07	−516.68	−0.85	2125	1850	2056	58	11.41	0.89	4.98
R-100	1424	650	375.00	−449.33	116.65	3261	3675	3417	66	22.07[a]	1.01	4.54
RD-100	1203	892	523.42	−473.26	99.06	4401	3670	4134	57	22.14[a]	1.12	4.74
R-150	166	72	392.89	−533.78	112.55	1780	1568	1768	74	11.78	0.76	4.51
RD-150	270	199	373.70	−588.52	−34.58	2407	2283	2400	63	11.15	0.83	4.69
Forecast updating models												
AV	2383	1110	560.61	−456.73	237.32	5311	5643	5439	67	25.33[a]	1.05	4.09
EQ	334	143	561.78	−413.76	269.32	1820	2091	1955	63	15.01[a]	0.71	4.77
RM	282	161	596.75	−454.98	214.52	2320	2318	2371	61	16.16	1.00	4.69
Stock Market									46	10.89	0.46	
T-bills										6.66	0.08	
Long only	1279	0	331.49	0.00	331.49	2340	0	2340	84	23.91[a]	1.07	

[a]Higher return than stock market by one-tail Z-test, large sample Wilcoxon signed-rank, 0.05 level of significance.

TABLE II

Results of 19-Week Trading Systems and Benchmarks

Forecast Method	No. Long Contracts	No. Short Contracts	$ Profit per Long	$ Profit per Short	$ Profit per Trade	Std Dev per Long	Std Dev per Short	Std Dev per Trade	Maximum Drawdown (%)	Mean of 52-Wk Returns (%)	Std Dev of 52 Wk Mean	Frcst RMSE ($/cwt)
Futures												5.3[illegible]
Naive models												
N-C	234	139	1068.36	−576.23	455.50	2091	2644	2442	71	17.75[a]	0.81	5.63
N-CT	403	167	905.04	−576.79	470.89	2589	2752	2720	55	19.16[a]	0.81	5.67
N-CS	157	107	821.68	−817.61	157.27	1919	2195	2186	59	12.71[a]	0.63	5.68
N-CTS	275	138	824.80	−772.90	290.94	2427	2444	2544	73	16.56[a]	0.77	5.67
Regression models												
R-50	2942	747	1032.44	−143.21	794.38	7033	5136	6709	46	27.57[a]	0.64	5.57
RD-50	665	314	1089.05	−509.63	576.30	3205	4341	3682	54	21.27[a]	0.70	5.38
R-100	178	69	572.83	−843.25	177.25	2512	3067	2747	73	13.24[a]	0.73	5.95
RD-100	137	81	798.34	−875.36	176.46	2407	2371	2522	77	12.62	0.68	6.26
R-150	81	45	600.40	−1146.49	−23.49	1938	3886	2903	82	9.00	0.68	6.20
RD-150	232	99	941.66	−724.93	443.19	2470	2407	2564	66	16.73[a]	0.83	6.34
Forecast updating models												
AV	664	179	992.01	−355.82	705.82	3193	2885	3176	75	21.48[a]	0.72	5.00
EQ	380	94	980.67	−356.85	715.43	2425	1906	2390	75	18.87[a]	0.67	5.44
RM	279	136	914.09	−681.71	391.13	2168	2137	2632	78	16.84[a]	0.73	5.76
Stock Market									46	10.87	0.46	
T-bills										6.64	0.08	
Long only	485	0	591.14	0.00	591.14	2401	0	2401	86	21.04[a]	0.97	

[a]Higher return than stock market by one-tail Z-test, large sample Wilcoxon signed-rank, 0.05 level of significance.

TABLE III

Results of 29-Week Trading Systems and Benchmarks

Forecast Method	No. Long Contracts	No. Short Contracts	$ Profit per Long	$ Profit per Short	$ Profit per rade	Std Dev per Long	Std Dev per Short	Std Dev per Trade	Maximum Drawdown (%)	Mean of 52-Wk Returns (%)	Std Dev of 52 Wk Mean	Frcst RMSE ($/cwt)
Futures												5.71
Naive models												
N-C	281	151	1407.57	−656.05	686.26	2569	2435	2706	60	18.46[a]	0.65	5.88
N-CT	349	107	1194.76	−506.13	795.65	2823	2778	2901	36	18.21[a]	0.53	5.92
N-CS	549	587	1299.29	−681.71	619.21	3173	2868	3211	45	20.57[a]	0.57	5.88
N-CTS	147	48	881.88	−966.33	426.93	2211	2704	2467	81	15.52[a]	0.71	5.90
Regression models												
R-50	80	44	921.35	−977.45	247.58	1995	2632	2410	69	11.08	0.57	7.90
RD-50	272	116	1221.81	−487.45	710.79	2406	2700	2614	58	17.35[a]	0.60	7.10
R-100	192	83	1076.60	−743.28	527.33	2446	2950	2734	84	16.62[a]	0.80	8.61
RD-100	194	99	754.72	−1018.87	155.45	2499	2806	2734	80	14.51[a]	0.72	8.48
R-150	81	29	861.63	−967.59	379.38	2236	2549	2448	76	12.46[a]	0.72	8.64
RD-150	421	187	1133.93	−709.43	566.97	3141	3014	3215	68	18.62[a]	0.60	8.61
Forecast updating models												
AV	685	154	1183.19	−613.84	853.34	3467	3314	3507	74	22.26[a]	0.69	6.43
EQ	200	90	1105.38	−699.60	545.21	2290	2428	2475	70	15.41[a]	0.58	6.45
RM	172	88	888.37	−916.14	277.62	2459	2155	2507	60	13.76	0.56	6.67
Stock Market									46	10.93	0.46	
T-bills										6.61	0.08	
Long only	331	0	837.50	0.00	837.50	2722	0	2722	80	20.34[a]	0.90	

[a]Higher return than stock market by one-tail Z-test, large sample Wilcoxon signed-rank, 0.05 level of significance.

standard deviations of the means. Since the returns series are correlated with each other, and since they fail statistical tests for normality, the large sample Wilcoxon signed-rank test is used to establish statistical differences between means of each futures series and the corresponding mean of the stock market series.

Maximum cash drawdown for each of the funds is the percentage of an investment that an investor would have lost (before the fund turned around) if the investment would have been placed at the worst possible week of the series. In this respect, each of the funds shows substantial risk to an investor. Even the stock market showed a maximum drawdown of 46.5% (September 30, 1974). However, none of the funds went bankrupt. This could be attributed to the conservative equity requirements assumed by the futures funds.[6]

As noted earlier, the three forecast updating models should be considered the most historically plausible systems. For example, in Table II the simple 50-week regressions, R-50, generate the highest returns. If, however, an agent had used 150-week regressions (R-150), the returns would have been the lowest. Such situations illustrate the unreliability of trading simulations as vehicles to determine future trading strategies, or as tests for market efficiency.

When looking at this R-150 case (Table II) the question arises: How can a system which has an average trading loss of $23.49 per contract generate higher returns than the T-bill fund? This comes about because of timing. If large profits are generated early, there is a huge capital base with which to generate T-bill interest. This may offset trading losses which do not come until much later.

The timing of returns across alternative futures series is quite diverse. Figures 1–3 respectively display the timing of 52-week returns for the three forecast updating funds, AV, EQ, and RM of the 19-week analysis (Table II). In each figure the respective futures fund returns are compared to the stock fund returns. Choosing forecasts by averaging them (AV: Fig. 1) or on the basis of RMSE (RM: Fig. 3), results in a tendency to generate large profits during the bullish period of the late 1970s. This is not the case for the fund that chooses its forecasts on the basis of most profits to date (EQ: Fig. 2).

Of all the forecasting/trading systems examined, only the AV system is consistently good, based upon the returns generated. The AV system, constructed from the simple average of the preceding ten systems, is

[6]The maximum *cash* drawdowns for the futures funds, not reported, average 88% of the maximum equity drawdowns reported.

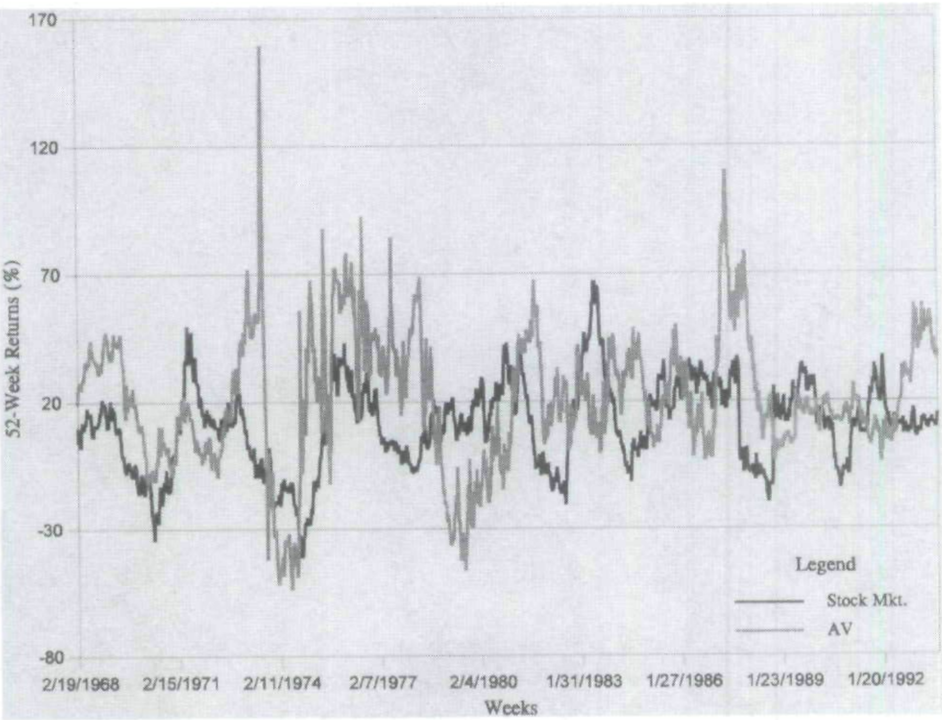

FIGURE 1
Stock market and AV returns.

the second ranked system in the nine- and 29-week analysis, and the top ranked system in the 19-week analysis. In addition, this method of choosing between competing forecasts is simple to implement and intuitively appealing.

As expected, the 52-week mean returns are negatively correlated with their corresponding RMSEs. Over the 39 comparisons in Tables I–III, the correlation coefficient is −0.33 (correlation between the 52-Wk Mean and RMSE columns, without the Stock Market, T-bill, and Long rows). Surprisingly, taking more risk in the form of accepting higher drawdowns does not imply higher returns (correlation coefficient of −0.12). On the other hand, returns are highly (0.75) correlated with the standard deviation per trade.

Several considerations within Tables I–III point to the possibility of market inefficiency and/or downward bias in live cattle futures. Only one futures fund (R-150, Table II) associated with the 39 alternative forecasts has a 52-week mean return that is nominally lower than the stock market. Thirty of the 39 futures funds have returns that are statistically higher than the stock market (0.05 significance). Seven of

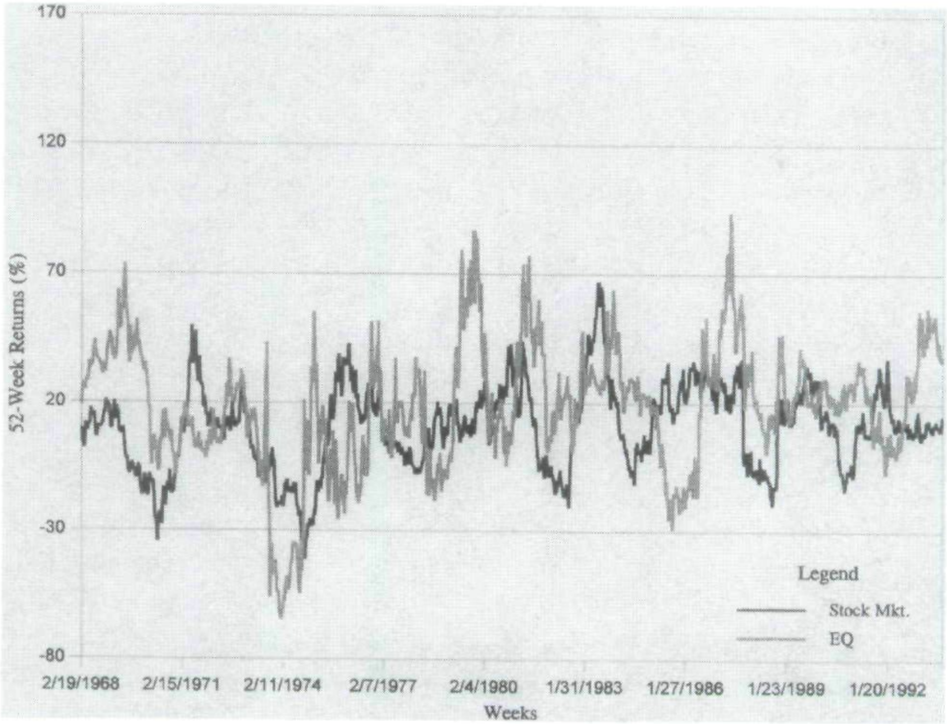

FIGURE 2
Stock market and EQ returns.

the nine forecast updating models show returns that are significantly higher than the stock market. The nine forecast updating models are considered to be the most plausible of the 39 models. In all but one of the systems (N-CS, Table III), the number of long trades is greater than the number of shorts. Overall, the number of long contracts completed within the 39 futures funds (22,064, profit/contract: \$823.81) is more than double the number of shorts (10,229, profit/contract: \$−621.85). In all systems, the long trades have mean profits while the short trades have mean losses. The 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 Tables I–III, 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 each of the tables.

A portion of the successes for the futures funds trading the long side of the market could be due to a perpetually unanticipated upward trend in the underlying cash market. During the period studied, the average nine-, 19-, and 29-week upward movements in the cash market

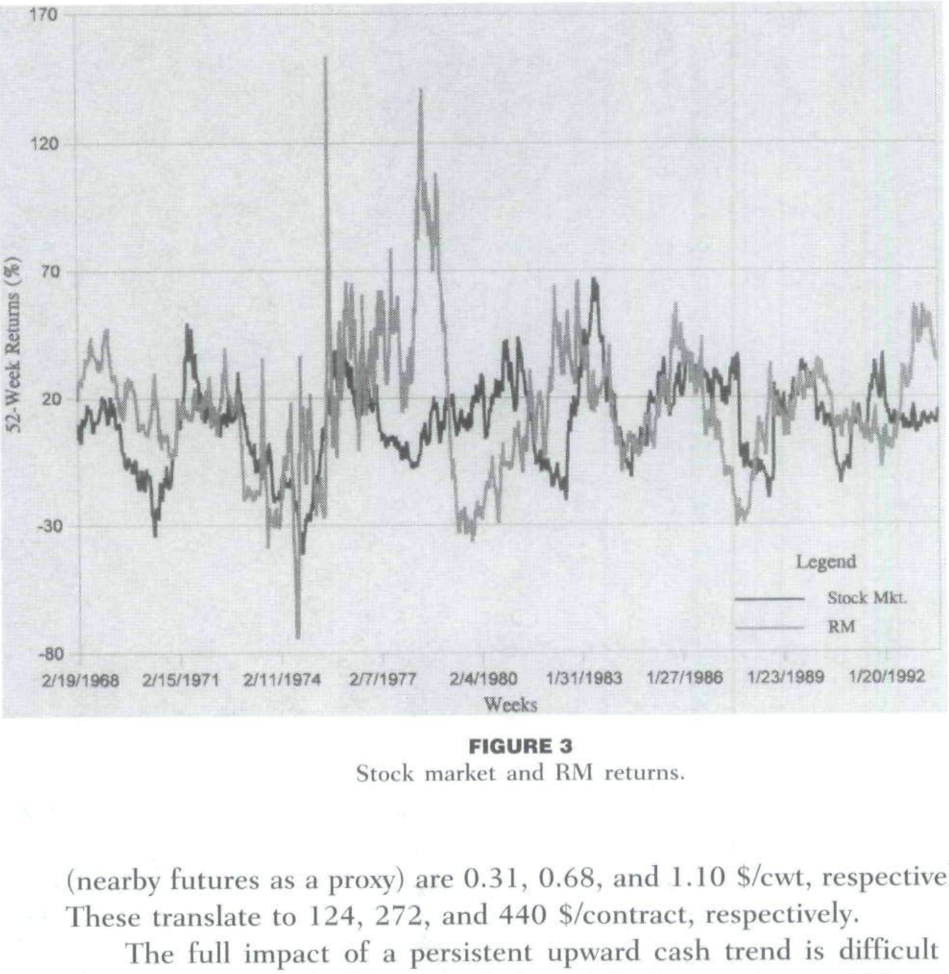

FIGURE 3
Stock market and RM returns.

(nearby futures as a proxy) are 0.31, 0.68, and 1.10 \$/cwt, respectively. These translate to 124, 272, and 440 \$/contract, respectively.

The full impact of a persistent upward cash trend is difficult to determine. Certainly, if it were eliminated the long trades would become less profitable. But the short positions would tend to lose less money as well. To establish a feel for this, the returns portion of the analyses is repeated for a time period that shows less tendency for cash prices to move upward. The period is 3/1/79 through 8/30/93. During this period, the average nine-, 19-, and 29-week upward movements in the cash market are −0.01, 0.08, and 0.31 \$/cwt, respectively (per contract equivalents: \$4, \$32, and \$124). Although the 52-week stock market returns during this period are much higher than the original period studied (15.5% instead of 10.9%), seven out of nine of the forecast updating futures funds have mean 52-week returns superior to those of the stock market. Additionally, the lowest mean return among the three always-long funds is still 19.9%.

A second explanation for finding the large profits of the futures funds relative to the stock market could be that the cost of building and maintaining the futures forecast models was prohibitively high. If that is true, then the presence of large potential profits does not imply an inefficient market. Beyond the obvious explicit cost of futures commissions, no attempt is made here to account for these costs. An heuristic argument can be made, however, that the costs should not have been prohibitively high. The data were readily available and involved only one futures price series: live cattle. The techniques of analysis were also readily available throughout the time period studied. The most complicated technique used is ordinary least squares regression. While it may be difficult to expect an individual to undertake an analysis such as this for a small investment, commercial public futures funds have been around since the early 1980s, and individual brokers or traders were trading for many persons besides themselves long before. In light of this, it would not seem that the cost of discovering and extracting the potential profits in the live cattle futures market should have precluded that extraction from occurring.

With trading profits and costs discussed, the final issue is risk. Bjornson and Innes (1992) estimated the empirical market line described by eq. (4) as (in monthly equivalent parameters)

$$RP = 0.00099 + 0.00032\beta \tag{5}$$

where RP (risk premium) is the expected excess return for an asset, given its β, that is commensurate with CAPM theory. In the CAPM context, RP is the expected risk premium that the asset should offer to entice investment capital to it. In percentages and 52-week equivalent form, eq. (5) becomes:[7]

$$RP = 1.188 + 0.384\beta \tag{6}$$

where RP is now the expected 52-week risk premium (in percent) for a futures fund investment, given an estimate of β for that fund. For this research, the expected risk premium is the expected difference between the return of a futures fund and the alternative T-bill fund (the *risk-free* fund).

Equation (3) is estimated using feasible generalized least squares, correcting for autocorrelation, for each of the futures funds reported in Tables I–III. The weekly 52-week returns for a futures fund are R. The weekly 52-week returns of the T-bill fund become RF, and

[7]Since it is not clear if Bjornson and Innes accounted for compounding when transforming their parameter estimates from annual to monthly figures, and since it makes only negligible difference for small βs, eq. (5) is merely multiplied by 1200.

the stock market returns are RM. Each of the returns are in terms of percent. The results of the estimations are reported in Table IV. As Elam and Njukia (1993) reported in a similar analysis, the associated R^2s are all low (the largest was 0.004). To avoid clutter, the R^2s and the standard errors for the coefficient estimates are not reported (significant coefficient estimates are noted). The average β-estimate for the nine-week models is 0.016, and 0.027 and 0.011 for the 19- and 29-week models, respectively. These estimates are smaller than those reported by Elam and Njukia (1993), but in line with the 0.03 β-estimate for steer investment reported by Arthur, Carter, and Abizadeh (1988).

The low β-estimates for the futures funds imply that most of the associated risk is unsystematic. The implication is that expected returns for futures funds should be somewhere between T-bill returns and stock market returns. Each fund-specific β-estimate in Table IV implies, through eq. (6), an expected risk premium (a scalar) associated with the 52-week returns (a series) for that fund. This expected risk premium is reported for each fund alongside the actual mean of the risk premium series for that fund. The difference between the two is tested with a one-tail t-test. In every case but one (R-150, 19 weeks) the actual risk premium demonstrated by a futures fund is significantly higher than the CAPM-predicted risk premium at the 0.001 level of significance. The one exception is significant at the 0.10 level.

The alternative time period (3/12/79 through 8/30/93) is examined also in the CAPM framework. For this period, 32 of the 39 forecast-driven futures funds display actual risk premia that are significantly higher (0.05 level) than the model-predicted risk premia. This is also true for eight out of nine of the forecast-updating models. Based on CAPM theory, the large risk premia displayed by the futures funds suggest inefficiency in the live cattle futures market. Alternatively, it could mean that the live cattle futures market is poorly integrated with the stock market, and that investors do not routinely mix the two investments.

CONCLUSIONS

This study constructs a trading simulation test for weak-form efficiency in the live cattle futures market. Specifically, the roughly 30 years in which live cattle futures have existed are examined to test if abnormal (risk-adjusted) profits could have been acquired using only the information provided by futures prices along with historically plausible price analysis procedures.

TABLE IV

Results of Nine-, 19-, and 29-Week CAPM Analysis[a, b]

Forecast Method	Nine-Week Analysis				19-Week Analysis				29-Week Analysis			
	Est. α	Est. β	Predicted RP (%)	Actual RP Mean (%)	Est. α	Est. β	Predicted RP (%)	Actual RP Mean (%)	Est. α	Est. β	Predicted RP (%)	Actual RP Mean (%)
Naive models												
N-C	15.45*	−0.0095	1.18	15.20	11.79	0.0086	1.19	11.12	11.84*	−0.0069	1.19	11.84
N-CT	22.43	0.0312	1.20	22.86	12.99	0.0641	1.21	12.53	11.47*	0.0251	1.20	11.60
N-CS	12.90	0.0272	1.20	12.43	6.36	0.0539	1.21	6.08	13.71*	0.0252	1.20	13.96
N-CTS	7.85	0.0658	1.21	6.89	10.26	0.0927	1.22	9.93	8.76	0.0548	1.21	8.91
Regression models												
R-50	12.53	0.0645	1.21	11.99	20.85*	0.0273	1.20	20.94	4.76	−0.0140	1.18	4.46
RD-50	5.51	0.0529	1.21	4.75	14.77*	0.0246	1.20	14.63	11.27*	0.0417	1.20	10.74
R-100	15.86*	−0.0692	1.16	15.42	7.35	−0.0138	1.18	6.61	10.91*	−0.1771*	1.12	10.00
RD-100	16.47	−0.0476	1.17	15.48	6.90	−0.0467	1.17	5.98	8.59	−0.0324	1.18	7.89
R-150	6.57	−0.00001	1.19	5.13	3.25	−0.0131	1.18	2.36	5.95	0.0592	1.21	5.85
RD-150	5.44	−0.0178	1.18	4.49	11.11	−0.0155	1.18	10.09	12.32*	−0.0065	1.19	12.00
Forecast updating models												
AV	19.46*	−0.0500	1.17	18.67	15.14*	0.0217	1.20	14.85	15.59*	−0.0157	1.18	15.65
EQ	9.16	0.0517	1.21	8.35	12.41*	0.0769	1.22	12.24	8.95*	0.0154	1.19	8.80
RM	10.22	−0.0241	1.18	9.50	11.01*	−0.0573	1.17	10.20	7.11	0.0399	1.20	7.14
Stock market				4.24				4.23				4.32
Long only	17.15	0.1422*	1.24	17.26	14.09	0.1542*	1.25	14.41	12.72	0.1512*	1.25	13.72

[a] Parameter estimates significant at the 0.05 level denoted with an asterisk.

[b] All actual risk premia (RP) are significantly higher (one-tail t-test) than associated predicted RP at 0.001 level except R-150, 19–weeks which is significant at 0.10 level.

Simple trend-following forecasting models are developed using ordinary least squares regression. The models provide nine-, 19-, and 29-week ahead futures price forecasts. Hypothetical futures funds, based upon simulated trading of the forecasting systems, are developed to translate futures forecasting into an economic framework suitable for analyses of resultant trading profits. To enhance the plausibility of dynamic forecast selection over such a long time period, three simple forecast selecting/combining techniques are used in choosing a forecast to act upon at any given week. These are: (1) the forecast associated with the lowest mean squared forecasting error to date; (2) the forecast that had generated the largest trading profits to date; and (3) an average of the model-based forecasts.

The trading profit series associated with each price forecast series is formally tested for abnormality by comparing it with a stock market returns series in a traditional CAPM framework. Generally, the futures trading profits are associated with risk premia substantially in excess of those predicted by the CAPM framework. The results reject the null hypothesis of weak-form live cattle futures efficiency. Likewise, both semi-strong and strong-form efficiency are rejected.

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