Accuracy in Forecasting Feeder Cattle prices: Results of a Competition

by

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Within the agricultural sector, erroneous forecasts cause producers, processors, suppliers, wholesalers and retailers to make faulty decisions regarding production, marketing and inventory carryovers. Wider knowledge of alternative forecasting procedures could help to increase predictive accuracy and enhance the efficiency of the forecasting function. Given the range of forecasting approaches and methods in use today, it is important to understand how procedures differ from each other and for what applications they are best suited. Performance evaluation of alternative forecasting procedures can provide a guide to relative predictive accuracy, costs, information requirements, and tradeoffs between those criteria.

Forecasts can be obtained by (a) purely judgmental approaches, (b) causal or explanatory methods, (c) extrapolative (time series) methods or (d) any combination of the above methods (Makridakis et al. 1982). Choice of the appropriate technique for a particular forecasting application is based on criteria such as cost of a methodology (e.g., modeler and computer time), data requirements, end-user needs and technical sophistication, and forecast horizon. The characteristics of an individual commodity market and availability of relevant data will also influence model selection. A technique appropriate to one commodity or time horizon may be unsuitable for forecasting another commodity or over a different horizon. A "best" forecasting method appropriate to all applications probably does not exist.

The objective of this research effort was to evaluate the forecasting performance of selected procedures used to generate out-of-sample predictions of Kansas City feeder cattle prices ($/cwt., average all weights and grades) at two levels of temporal aggregation (quarterly and monthly). The study was organized as a forecasting competition. Nine alternative forecasting procedures were used to predict the quarterly feeder cattle price series one-, two-, and three-quarters-ahead out-of-sample and the monthly feeder cattle price series one-, two-, and three-months-ahead out-of-sample. Accuracy of the out-of-sample forecasts was evaluated using standard techniques. The research also had the objective of developing an analytical framework for conducting this and later forecasting competitions using agricultural variables.

This empirical study did not attempt to define best or worst approaches to forecasting, but to evaluate relative predictive accuracy. The objective was to demonstrate strengths and weaknesses of the competing methods in forecasting quarterly and monthly values of one agricultural price variable.

Forecasting Competition Procedures

Nine forecasting techniques representing the broad spectrum of forecasting methodology were applied to both the quarterly and monthly data series. The nine quarterly models were initially estimated over the sample period 1960.1 through

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1980.4; out-of-sample forecasts were then generated for 1981.1, 1981.2, and 1981.3.[1] Actual observations for 1981.1 were added to the information set, coefficients were updated, the model was respecified (if necessary), and forecasts were generated for 1981.2, 1981.3 and 1981.4. The iterative process continued for each sample period over a rolling horizon through the last sample period (1960.1 - 1986.3). Forecasting continued through 1986.4.

The nine monthly models were estimated over the initial sample period 1960.01 - 1980.12, with forecasts first generated for 1981.01, 1981.02 and 1981.03.[2] Actual observations for 1981.01 were added to the information set, coefficients were updated, respecification was conducted (if necessary) and forecasts were produced for 1981.02, 1981.03 and 1981.04. The iterative process continued through 1986.11. The last forecast generated in the monthly application was for the period 1986.12 using the information set 1960.01 - 1986.11.

All forecasting was conducted ex ante from the standpoint of the model and the forecaster (i.e., the values of the variable being forecast were unknown at the time the prediction was made). No attempts were made to improve predictive performance by reworking a model and re-forecasting after comparison of the out-of-sample forecast and the actual value. Evaluation of quarterly forecasting accuracy was conducted using 24 one-quarter-ahead, 23 two-quarters-ahead and 22 three-quarters-ahead out-of-sample forecasts. The monthly forecasting models were evaluated using a set of 72 one-month-ahead, 71 two-months-ahead and 70 three-months-ahead out-of-sample forecasts. Quantitative and qualitative accuracy of the competing models were evaluated over all out-of-sample forecasting horizons.

Forecasting competitions similar to the one presented here have been conducted using 111 series over 8 forecasting horizons (Makridakis and Hibon) and 1001 series over 6 to 18 different forecasting horizons (Makridakis et al., 1982). These studies dealt with yearly, quarterly, monthly, micro, macro, industry, demographic, seasonal and non-seasonal data. Accuracy evaluation included the use of mean absolute percentage error, mean squared error, and a variation of Theil's Inequality Coefficient.

The Forecasted Series

The data series forecasted was Kansas City feeder steer ($/cwt., average all weights and grades). Monthly values of this variable are reported in USDA-ERS Livestock and Poultry Situation and Outlook Report. These data are also available in various issues of USDA-ERS Livestock and Meat Statistics. Quarterly values for this variable were obtained by a simple average of monthly variables.[3] The Kansas City feeder steer price has regional and national importance as a leading indicator of feeder animal prices. This price series, and all other data used in the study were obtained from published USDA sources.

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[1] 1960.1 = First quarter, 1960; 1960.2 = Second quarter, 1960; etc.

[2] 1960.01 = January, 1960; 1960.02 = February, 1960; 1960.03 = March 1960; etc.

[3] The Kansas City feeder steer price for the first quarter of each year was calculated as the simple average of the January, February and March observations; the second quarter value was calculated as the simple average of the April, May and June observations; etc.

The Forecasting Techniques

The models chosen for this forecasting competition represent the broad spectrum of explanatory and extrapolative techniques available. These methods were selected to represent a range of information demands and modeling complexity, and required modeler and end-user sophistication. The procedures are described below.

Classical Decomposition

Decomposition methods are based on the premise that a time series has four components: trend, cyclical, seasonal and the random element. After the systematic components (trend, cycle, season) have been identified, they are multiplicatively reintegrated to generate forecasts. This data-based tool is devoid of economic theory and does not have a statistical rationale, yet it is one of the oldest and most commonly used approaches to forecasting (Majani). More information on forecasting using classical decomposition can be found in Makridakis et al. (1983).

Exponential Smoothing

Exponential smoothing procedures are based on the notion that, as observations become older, their weight in predicting future observations declines exponentially. Thus, recent observations are given greater weight in forecasting than are older observations. The technique chosen for use in this study was Holt-Winters' Three Parameter Trend and Seasonality Method. This forecasting procedure incorporates three possible different smoothing coefficients: one to update the level, one for the slope and one for the seasonal components. A comprehensive discussion of the procedure is presented in Abraham and Ledolter, and Makridakis et al. (1983).[4]

Univariate Stochastic Models

Standard univariate Box-Jenkins modeling procedures of identification, estimation, diagnostic checking and forecasting were applied to the quarterly and monthly data series. The original data were transformed using regular and/or seasonal differencing to assure stationarity; natural log transformations were also performed for variance stabilization. The appropriate autoregressive and moving average building blocks were identified through the autocorrelation and partial autocorrelation functions.[5] Discussion of these procedures can be found in Pindyck and Rubinfeld. The portmanteau statistic proposed by Box and Pierce was used to test model adequacy throughout the sample periods. This statistic is described in Abraham and Ledolter.

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[4] Starting values for the trend, seasonal and overall updating equations were calculated using the first one third complete seasons of the data following Abraham and Ledolter. Values for the three smoothing coefficients are chosen by a grid search to minimize in-sample error.

[5] The univariate stochastic model used to predict quarterly feeder steer prices included moving average (MA) terms of orders 3, 5, and 6 for samples 1960.1-1980.4 through 1960.1-1982.3. An MA(18) term was then added and all four terms were included in the model for the remaining estimation samples (from 1960.1-1982.4 through 1960.1-1986.3). R^2 values ranged from .18 to .23 over the 24 sample periods. The univariate stochastic model used to predict monthly feeder steer prices included MA terms of orders 1, 11 and 15 for samples 1960.01-1980.12 through 1960.01-1982.10. An MA(36) term was added at sample 1960.01-1982.11 and included with the first three terms in all further sample periods. R^2 values ranged from .09 to .11 over the 72 sample periods.

Simple Linear/Multiple Regression Models

Parsimonious regression models were constructed to forecast quarterly and monthly Kansas City feeder steer prices. These models were designed to be as simple as possible to minimize information needs and time demands. The inclusion of other relevant explanatory variables into each of these models was severely limited by the need to lag them sufficiently to avoid forecasting exogenous variables. The presence of residual autocorrelation and multicollinearity also limited enriching these two specifications without abandoning the objective of maximum simplicity.[6]

Bivariate Stochastic Models

The bivariate stochastic modeling procedure chosen for application in this study is the approach proposed by Brandt and Bessler (1982). This procedure combines the forecast of the univariate stochastic model with a prediction of the error or residual term for each forecast period. The underlying assumption is, if it can be shown that one time series leads another, a dynamic regression model linking the two series may lead to increased forecasting accuracy. The methodology followed by Brandt and Bessler (1982) is basically that of Haugh and Box, and Helmer and Johansson, except for the more tractable dynamic shock model.

The average U.S. corn price ($/bushel) was selected as a variable expected to exhibit a time ordered association with feeder steer prices. The choice of corn price was supported by previous work by Spreen and Shonkwiler that demonstrated a lead-lag relationship between feeder steer prices and feed costs. Univariate stochastic filter models were identified and estimated, and residual series retained for the associated quarterly and monthly corn price series in each estimation period. Cross-correlation analysis was performed between the residuals of the univariate stochastic feeder steer models described above, and the corn price filter models. A linkage was formed by regressing the residuals of the output variables (i.e., quarterly and monthly feeder steer prices) on the statistically significant lags of the related input series residuals. The transfer function models were adjusted, reestimated and used to generate forecasts of the quarterly feeder steer price residual series one-,two-, and three-quarters-ahead over the rolling horizon. The monthly transfer function models were similarly treated and used to produce forecasts of the feeder steer price residual series one-, two-, and three-months-ahead. Predicted residuals were then combined with the forecasts of the univariate stochastic feeder steer price models for the adjusted forecast.[7]

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[6] The model used to generate forecasts of feeder steer prices was $QFSP_t = \beta_1 QFSP_{t-1} + \epsilon_t$, where QFSP is the quarterly Kansas City feeder steer price. This model was reestimated in each of the 24 sample periods with a consistent R^2 value of at least .95. The monthly regression model specified and reestimated in the 72 sample periods was $MFSP_t = \beta_1 MFSP_{t-1} + \beta_2 MFSP_{t-2} + \beta_3 t + \epsilon_t$, where MFSP is the monthly feeder steer price and t is a deterministic trend variable. The R^2 value was .98 throughout the sample periods.

[7] The univariate stochastic models described in note (5) above were used to filter the output variables. The filter model applied to quarterly corn prices included varying combinations of moving average terms of orders 4, 6, 24, 30 and 40. R^2 values ranged from .12 to .47 over the 24 estimation samples. The quarterly transfer function noise model included varying combinations of lagged terms of orders 3, 4, 6, 11 and 18. R^2 values for these equations ranged from .13 to .18. The filter model applied to monthly corn prices included autoregressive terms of orders 1, 4 and 12 in all estimation samples. The R^2 values for the 72 equations ranged from .09 to .14. The monthly transfer function noise model included lagged terms of orders 6, 18, 32 and 39. Noise model R^2 values ranged from .08 to .13.

Vector Autoregression Models

The VAR modeling procedures used in this study are those proposed by Tiao and Box, and Brandt and Bessler (1984). Economic theory and a brief review of past structural models used in forecasting applications helped to suggest alternative data series that would exhibit time-ordered relationships with the two series being forecasted. The time order associated variables selected for use in the quarterly feeder steer application were Omaha slaughter steer prices ($/cwt., average all grades) and average U.S. retail beef prices ($/lb.). The monthly VAR system included these two prices, U.S. average corn prices and slaughter cattle numbers (in thousands). Economic theory and empirical research suggests that beef prices at the feeder, slaughter and retail levels should exhibit lead/lag relationships (Barksdale et al., Spreen and Shonkwiler). Corn prices were included because a lead-lag relationship with feeder cattle prices was demonstrated by the residual cross-correlation analysis applied in the bivariate stochastic procedure. Slaughter cattle numbers were added to the monthly system because it was assumed there would be cyclical lead-lag interdependence with cattle and beef prices.

Block F-tests helped to indicate the potential strength of the time-associated variables in forecasting quarterly and monthly feeder steer prices. However, this test was not strictly followed because the time-associated variables could still affect the two forecasted variables through the other equations in each VAR system. A likelihood ratio test was used to formally pretest overall lag lengths used in estimation. Discussion of this procedure can be found in Brandt and Bessler (1984) and Sims.

Full, unrestricted, profligately large VAR systems were first estimated and used to generate forecasts of quarterly and monthly feeder steer prices in each of the 24 quarterly and 72 monthly sample periods. Parameter restrictions specified in a Bayesian framework were next applied to the two VAR systems. The prior specified for both systems functioned as a filter which suggested that coefficients on longer lags were likely to be close to zero; however, the data were allowed to override the prior restrictions if more distant lags were significant. The restricted full VAR system then generated forecasts one-, two-, and three-steps-ahead over the rolling horizons.

The two full VAR systems were also subjected to variable selection through the application of a full stepwise regression algorithm. This procedure was rerun and forecasts generated for each sample period over the rolling horizons. The critical significance levels for an independent variable to enter and stay in the models was set at the 80% confidence level. It was assumed the relatively liberal confidence interval would provide the stepwise-VAR forecasting models with additional, albeit marginal, predictive accuracy.[8]

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[8] The vector autoregression (VAR) system used to predict quarterly feeder steer prices was of order 9. The monthly VAR system was of order 12. These orders were selected through the application of the likelihood ratio statistic described in Sims. The two VAR systems estimated with Bayesian parameter restrictions had the following characteristics: 1) the prior distributions on the lags of the endogenous variables were independently normal; 2) the means of the prior distributions for all coefficients were zero, except for the first lag of the dependent variable in each equation; 3) the first lag of the dependent variable in each equation had a prior mean of one, serving to center the prior about a random walk process; 4) there was one tightness parameter used to specify how close all of the coefficients were to their prior mean; 5) the tightness value used was 0.20; and 6) all equations included a constant term.

Structural System Modeling

Two simple multi-equation structural models were developed for use in forecasting quarterly and monthly feeder steer prices. A review of past forecasting applications, using models based on behavioral and biological factors, provided a guide to specification of the equations. Literature helpful in specifying the two systems includes Maki, Rohdy et al., Myers et al., Kulshreshtha and Rosaasen, Westcott and Hull, McLemore and Gross, and Stillman.

The structural systems were designed to include a small set of appropriate variables. They were specified as simultaneous models, and estimated using three-stage least squares procedures. Feedback relationships were identified whereby current endogenous variables were allowed to enter other equations in the systems as exogenous variables.

The model specified for forecasting quarterly feeder steer prices incorporated lagged feeder steer prices; feedlot marketings and placements; disposable income; slaughter cattle numbers; corn, alfalfa and retail beef prices; precipitation; beef, pork and chicken consumption; and the quarterly cattle-on-feed inventory.[9] The system used to forecast monthly feeder steer prices included lagged feeder steer prices; Omaha slaughter steer prices; disposable personal income; retail beef, pork and chicken prices; alfalfa hay and corn prices; an index of prices received for feed grains and hay; and slaughter cattle numbers.[10]

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[9] The nine equations which comprised the quarterly model are:

(i) $QFSP_t = \beta_0 + \beta_1 QFSP_{t-1} + \beta_2 QMKTGS_t + \epsilon_t$, $R^2 = .95$;
(ii) $QSSP_t = \beta_1 QTDPI_{t-4} + \beta_2 QBFP_t + \beta_3 QMKTGS_{t-1} + \beta_4 QSLTR_t + \epsilon_t$, $R^2 = .99$;
(iii) $QBFP_t = \beta_1 QBFCON_{t-4} + \beta_2 QPKCON_{t-4} + \beta_3 QCHCON_{t-4} + \beta_4 QTDPI_{t-4} + \epsilon_t$, $R^2 = .95$;
(iv) $QUSHAYP_t = \beta_1 QFSP_t + \beta_2 QCRNP_t + \beta_3 QUSHAYP_{t-1} + \beta_4 QPRECIP_{t-4} + \epsilon_t$, $R_2 = .96$;
(v) $QSLTR_t = \beta_1 QBFCON_{t-4} + \beta_2 QSSP_t + \beta_3 QCRNP_t + \epsilon_t$, $R^2 = .85$;
(vi) $QCRNP_t = \beta_1 QUSHAYP_{t-1} + \beta_2 QCRNP_{t-1} + \beta_3 QPRECIP_{t-4} + \epsilon_t$, $R^2 = .93$;
(vii) $QCOFINV_t = \beta_0 + \beta_1 QCRNP_t + \beta_2 QCOFINV_{t-1} + \beta_3 QMKTGS_{t-1} + \beta_4 QPLCMTS_{t-1} + \epsilon_t$, $R^2 = .98$;
(viii) $QMKTGS_t = \beta_1 QCOFINV_{t-1} + \beta_2 QCOFINV_{t-2} + \beta_3 QPLCMTS_{t-1} + \epsilon_t$, $R^2 = .94$;
(ix) $QPLCMTS_t = \beta_1 QMKTGS_{t-1} + \beta_2 QFSP_{t-1} + \beta_3 QSSP_{t-1} + \beta_4 QFSP_{t-2} + \beta_5 QCRNP_t + \epsilon_t$, $R^2 = .65$.

QFSP is qtrly. Kansas City feeder steer price, QMKTGS is qtrly. feedlot marketings for the 13 major states, QTDPI is qtrly. U.S. total disposable income; QBFP is qtrly. U.S. avg. retail beef price, QSLTR is qtrly. U.S. cattle slaughter in thousands, QBFCON is qtrly. avg. U.S. per capita beef consumption, QPKCON is qtrly. avg. U.S. per capita pork consumption, QCHCON is qtrly. avg. U.S. chicken consumption, QCRNP is the qtrly. avg. U.S. corn price, QUSHAYP is the qtrly. avg. U.S. alfalfa hay (baled, $/ton) price, QPRECIP is qtrly. total western and midwestern states precipitation, QSSP is qtrly. Omaha slaughter steer price (all weights and grades), QCOFINV is the qtrly. cattle-on-feed inventory for the 13 major states, and QPLCMTS is qtrly. feedlot placements for the 13 major states.

[10] The six equations which comprised the monthly model are:

(i) $MFSP_t = \beta_1 MFSP_{t-1} + \beta_2 MFSP_{t-3} + \beta_3 MSSP_t + \beta_4 MSSP_{t-1} + \beta_5 MSSP_{t-2} + \epsilon_t$, $R^2 = .99$;
(ii) $MSSP_t = \beta_0 + \beta_1 MTDPI_{t-3} + \beta_2 MSSP_{t-1} + \epsilon_t$, $R^2 = .97$;
(iii) $MBFP_t = \beta_1 MBFP_{t-1} + \beta_2 MBFP_{t-2} + \beta_3 MTDPI_{t-3} + \beta_4 MPKP_{t-3} + \beta_5 MCHP_{t-3} + \epsilon_t$, $R^2 = .99$;
(iv) $MUSHAYP_t = \beta_1 MFSP_t + \beta_2 MUSHAYP_{t-1} + \beta_3 MUSHAYP_{t-2} + \epsilon_t$; $R^2 = .97$;
(v) $MSLTR_t = \beta_0 + \beta_1 MSSP_{t-1} + \beta_2 MCRNP_t + \beta_3 MSLTR_{t-1} + \epsilon_t$; $R^2 = .50$;
(vi) $MCRNP_t = \beta_1 MUSHAYP_{t-1} + \beta_2 MCRNP_{t-1} + \beta_3 MIPRECFG_{t-3} + \epsilon_t$; $R^2 = .97$.

MFSP is monthly Kansas City feeder steer price; MSSP is monthly Omaha slaughter steer price; MTDPI is monthly total U.S. disposable personal income; MBFP, MPKP and MCHP are U.S. monthly avg. retail beef, pork and chicken prices; MUSHAYP is monthly U.S. avg. alfalfa hay (baled) price; MSLTR is total U.S. cattle slaughter (in thousands); MCRNP is monthly avg. U.S. corn price; and MIPRECFG is the USDA monthly index of prices received for feed grains and hay.

Forecasting Performance Evaluation

The quantitative evaluation consisted of measurements of bias, absolute accuracy and relative accuracy of the competing models. Qualitative accuracy was compared using the contingency table method for classifying turning points proposed by Theil (1961) and Naik and Leuthold. The classification scheme used in discussing forecasting performance is as follows: (1) the two applications were quarterly feeder steer and monthly feeder steer prices; 2) there were eighteen cases (i.e., combination of forecasting procedure and application); 3) there were fifty-four case-horizons, or combinations of application, case and out-of-sample forecasting horizon.

Quantitative Evaluation

Comparison of forecast bias, absolute accuracy and relative accuracy are summarized in Table 1. Mean error (ME) was used to measure forecast bias in this study. Negative bias (i.e., forecasted values with a tendency to be greater than actual values) was noted in 93% of the case-horizons. In the quarterly application, least bias was noted for the univariate stochastic model and the structural system forecasts. The least biased forecasts in the monthly application were achieved with the univariate and bivariate stochastic models. Forecasts of the stepwise and unrestricted VAR procedures were highly biased in both the quarterly and monthly applications.

Root mean squared error (RMSE) was used to measure absolute accuracy of the forecasts. Minimum RMSE in the quarterly application was achieved using the structural system model. RMSE results for the monthly application were mixed, with slight differences between the procedures and across the forecasting horizons. Both ME and RMSE tended to increase as the out-of-sample forecasting horizon lengthened in both applications. An exception was noted for the quarterly structural system, where both ME and RMSE improved between the two- and three-quarters-ahead forecasting horizons.

Relative accuracy between the forecasting procedures and across commodities was evaluated using Theil's Inequality Coefficient (U_2). This coefficient compares each forecast with those of a naive model; U_2 values of one indicate the naive forecasting model is as good as the more sophisticated model. A U_2 score of zero would indicate perfect forecasting.

U_2 values tended to increase in all case-horizons as the forecasting horizon lengthened. The three quarterly VAR-based models showed the greatest increases in U_2 between the one- and three-quarters-ahead horizons. This breakdown of the VAR-based procedures was not found in the monthly application. The calculated Inequality Coefficient was less than one in 11% of the case-horizons.

The systematic nature of the error noted by the quantitative evaluation (i.e., negative bias) could have been corrected by subjective adjustment of the forecasts, as often happens under actual forecasting conditions. Bias would tend to be reduced under those conditions; however, in this forecasting competition, no learning was assumed, and all forecasts were evaluated only at the end of the competition.

Table 1. Quantitative Forecast Evaluation Results

METHOD	Quarterly Feeder Steer Price Forecasts (Quarters Ahead) 1	2	3	Monthly Feeder Steer Price Forecasts (Months Ahead) 1	2	3
Classical Decompostion						
Mean Error (ME)[a]	-.75	-1.66	-2.48	-0.28	-0.55	-0.80
Root Mean Squared Error (RMSE)[b]	3.72	5.23	4.83	2.38	3.36	4.29
Inequality Coefficient (U_2)[c]	1.02	1.42	1.32	0.99	1.39	1.75
Exponential Smoothing						
Mean Error	-0.61	-1.02	-1.48	-0.28	-0.50	-0.71
Root Mean Squared Error	3.88	5.34	4.92	2.38	3.31	4.18
Inequality Coefficient	1.05	1.44	1.33	0.99	1.37	1.70
Univariate Stochastic Model						
Mean Error	0.00	-0.08	-0.08	-0.07	-0.15	-0.24
Root Mean Squared Error	3.53	5.04	5.45	2.40	3.29	4.11
Inequality Coefficient	0.98	1.38	1.48	1.01	1.38	1.69
Regression Model						
Mean Error	-0.77	-1.54	-2.36	-0.46	-1.00	-1.56
Root Mean Squared Error	3.75	5.20	5.05	2.47	3.55	4.52
Inequality Coefficient	1.03	1.43	1.40	1.03	1.47	1.85
Bivariate Stochastic Model						
Mean Error	-1.34	-2.85	-4.53	-0.04	-0.08	-0.19
Root Mean Squared Error	4.00	6.27	8.09	2.48	3.28	4.12
Inequality Coefficient	1.09	1.73	2.23	1.04	1.37	1.71
VAR, No Restrictions						
Mean Error	-2.61	-5.54	-8.37	-0.62	-1.27	-1.91
Root Mean Squared Error	4.65	8.11	11.43	2.66	3.63	4.55
Inequality Coefficient	1.25	2.17	3.09	1.10	1.49	1.87
VAR, With Prior						
Mean Error	-1.69	-3.53	-5.51	-0.56	-1.17	-1.77
Root Mean Squared Error	3.51	5.74	7.71	2.35	3.31	4.24
Inequality Coefficient	0.94	1.56	2.10	0.97	1.37	1.74
VAR, Stepwise Selection						
Mean Error	-2.48	-5.14	-7.80	-0.68	-1.39	-2.14
Root Mean Squared Error	4.42	7.95	11.02	2.54	3.54	4.45
Inequality Coefficient	1.15	2.12	2.97	1.05	1.46	1.82
Structural System Model						
Mean Error	0.48	0.83	0.23	-0.75	-1.26	-1.88
Root Mean Squared Error	3.50	4.77	4.23	2.58	3.73	4.81
Inequality Coefficient	0.99	1.32	1.16	1.07	1.54	1.97

[a] $ME = [\Sigma_{t=1}^{n} (A_t - F_t)]/n$

[b] $RMSE = ((\Sigma_{t=1}^{n} (A_t - F_t)^2)/n)^{1/2}$

[c] $U_2 = \dfrac{(\Sigma_{t=1}^{n-1} \; ((F_{t+1} - A_{t+1})/A_t)^2)^{1/2}}{(\Sigma_{t=1}^{n-1} \; ((A_{t+1} - A_t)/A_t)^2)^{1/2}}.$

<u>Qualitative Evaluation</u>

A contingency table was used to compare turning point precision of the competing forecasting models. The summary of this evaluation is presented in Table 2.

The ratio of accurate forecasts (RAF) measured the number of times the forecasting model perfectly predicted the actual movement in direction. Except for the unrestricted VAR procedure, this measure was low for the one-quarter-ahead forecasting models. The RAF values for the monthly forecasting models were consistently higher than the quarterly models (with exception noted for the unrestricted VAR model). When forecasting three-quarters-ahead, the quarterly models tended to perform better than the monthly models forecasting three-months-ahead. The least data demanding procedures (classical decomposition, exponential smoothing, univariate stochastic model, and the regression model) used to predict quarterly feeder steer prices showed improvements in turning point precision between the one- and three-quarters-ahead forecasting horizons. This tendency was not registered across the monthly horizons.

The unrestricted VAR model forecasted one-quarter-ahead feeder steer prices accurately and inaccurately in the same proportions, but it avoided the worst cases (i.e., predicting a downturn when an upturn actually occurred, and vice-versa) such that the number of accurate forecasts was five times greater than the number of worst forecasts. The structurally-based quarterly model showed an increase in the ratio of accurate to worst forecasts (RAWF) as the horizon lengthened, but could not match the restricted VAR, univariate stochastic model, or exponential smoothing in the final horizon. There were few notable differences in turning point accuracy between the monthly models. All procedures except the unrestricted VAR technique demonstrated a decrease in turning point predictive accuracy as the monthly forecasting horizon lengthened.

General comments that can be made regarding the turning point evaluation concern the relatively good performance of the VAR-based models. The predictive abilities of these models were not impressive, based on the general forecast evaluation, yet the turning point evaluation revealed superior prediction in many cases and case-horizons. As in the general evaluation, the forecasting ability of the simpler procedures (i.e., classical decomposition and exponential smoothing) was better than expected.

Decomposition of Forecast Error

The quantitative and qualitative evaluations indicate which procedures were most and least successful in point and turning point prediction; decomposition analysis contributes to understanding the sources of poor predictive ability. The procedure applied here is that of Theil (1966) and is comparable to that used by Just and Rausser.

Results of the forecast error decomposition are summarized in Table 3. The evaluation procedure is based on decomposition of the mean squared error (MSE) into three inequality proportions. The three inequality proportions are: U^m, the proportion of MSE attributed to bias or errors in central tendency; U^s, the MSE proportion resulting from prediction errors caused by unequal variation; and U^c, the proportion of the MSE due to unequal covariation.

Table 2. Qualitative Forecast Evaluation Results

METHOD	Quarterly Feeder Steer Price Forecasts 1 (Quarters Ahead)	2	3	Monthly Feeder Steer Price Forecasts 1 (Months Ahead)	2	3
Classical Decomposition						
RAF[a]	0.09	0.14	0.40	0.40	0.33	0.29
RWF	0.27	0.24	0.15	0.14	0.14	0.18
RAWF	0.33	0.60	2.67	2.80	2.30	1.67
RIF	0.64	0.62	0.45	0.46	0.52	0.53
RWF+RIF	0.91	0.86	0.60	0.60	0.67	0.71
Exponential Smoothing						
RAF	0.09	0.19	0.40	0.40	0.33	0.31
RWF	0.18	0.19	0.05	0.14	0.14	0.16
RAWF	0.50	1.00	8.00	2.80	2.30	1.91
RIF	0.73	0.62	0.55	0.46	0.52	0.53
RWF+RIF	0.91	0.81	0.60	0.60	0.67	0.69
Univariate Stochastic Model						
RAF	0.05	0.24	0.50	0.39	0.39	0.19
RWF	0.27	0.24	0.05	0.16	0.16	0.37
RAWF	0.17	1.00	10.00	2.45	2.45	0.52
RIF	0.68	0.52	0.45	0.46	0.45	0.44
RWF+RIF	0.95	0.76	0.50	0.61	0.61	0.81
Regression Model						
RAF	0.14	0.05	0.40	0.46	0.33	0.26
RWF	0.14	0.52	0.15	0.14	0.16	0.26
RAWF	1.00	0.09	2.67	3.20	2.09	1.00
RIF	0.73	0.43	0.45	0.40	0.51	0.47
RWF+RIF	0.86	0.95	0.60	0.54	0.67	0.74
Bivariate Stochastic Model						
RAF	0.09	0.24	0.25	0.40	0.38	0.29
RWF	0.27	0.19	0.20	0.17	0.16	0.25
RAWF	0.33	1.25	1.25	2.33	2.36	1.18
RIF	0.64	0.57	0.55	0.43	0.46	0.46
RWF+RIF	0.91	0.76	0.75	0.60	0.62	0.71
VAR, No Restrictions						
RAF	0.45	0.29	0.30	0.27	0.35	0.37
RWF	0.09	0.14	0.10	0.23	0.26	0.16
RAWF	5.00	2.00	3.00	1.19	1.50	2.27
RIF	0.45	0.57	0.60	0.50	0.42	0.47
RWF+RIF	0.55	0.71	0.70	0.73	0.65	0.63
VAR, With Prior						
RAF	0.23	0.38	0.45	0.46	0.42	0.35
RWF	0.23	0.24	0.05	0.19	0.13	0.15
RAWF	1.00	1.60	9.00	2.46	3.22	2.40
RIF	0.55	0.38	0.50	0.36	0.45	0.50
RWF+RIF	0.77	0.62	0.55	0.54	0.58	0.65
VAR, Stepwise Selection						
RAF	0.27	0.33	0.40	0.50	0.45	0.31
RWF	0.09	0.19	0.20	0.16	0.13	0.19
RAWF	3.00	1.75	2.00	3.18	3.44	1.62
RIF	0.64	0.48	0.48	0.34	0.42	0.50
RWF+RIF	0.73	0.67	0.68	0.50	0.55	0.69
Structural System Model						
RAF	0.14	0.05	0.30	0.44	0.32	0.21
RWF	0.23	0.52	0.15	0.16	0.16	0.28
RAWF	0.60	0.09	2.00	2.82	2.00	0.74
RIF	0.64	0.43	0.55	0.40	0.52	0.51
RWF+RIF	0.86	0.95	0.70	0.56	0.68	0.79

[a] RAF = Ratio of Accurate Forecasts, the number of perfect model forecasts divided by the total number of forecasts. RWF = Ratio of Worst Forecasts, the number of model forecasts which were opposite the direction of actual movement. RAWF = Ratio of Accurate to Worst Forecasts, RAF divided by the RWF. RIF = Ratio of Inaccurate Forecasts, the number of turning points inaccurately predicted by the model (but not including the worst cases). RWF+RIF = total inaccurate forecasts, a summation of the ratios of inaccurate and worst forecasts.

Table 3. Decomposition of Forecast Error

METHOD	Quarterly Feeder Steer Price Forecasts 1	2 (Quarters Ahead)	3	Monthly Feeder Steer Price Forecasts 1	2 (Months Ahead)	3
Classical Decomposition						
$U^m\%$ [a]	4.01	10.06	26.25	1.34	2.66	3.50
$U^s\%$ [b]	12.46	8.42	1.47	5.13	6.81	6.28
$U^c\%$ [c]	83.53	81.52	72.28	93.53	90.53	90.22
r [d]	0.57*	0.13	0.18	0.81*	0.65*	0.44*
Exponential Smoothing						
$U^m\%$	2.51	3.64	9.07	1.43	2.27	2.91
$U^s\%$	14.04	12.28	6.22	4.90	6.61	6.33
$U^c\%$	83.45	84.08	84.71	93.66	91.12	90.76
r	0.54*	0.14	0.16	0.81*	0.65*	0.46*
Univariate Stochastic Model						
$U^m\%$	0.00	0.03	0.02	0.10	0.20	0.33
$U^s\%$	4.10	14.71	22.53	1.03	0.73	0.86
$U^c\%$	95.90	85.26	77.45	98.87	99.07	98.81
r	0.48*	0.23	0.29	0.78*	0.57*	0.33*
Regression Model						
$U^m\%$	4.23	8.75	21.81	3.52	7.95	11.99
$U^s\%$	2.62	3.50	4.08	0.92	0.70	0.47
$U^c\%$	93.15	87.76	74.12	95.55	91.35	87.53
r	0.41*	-0.05	0.18	0.77*	0.54*	0.27*
Bivariate Stochastic Model						
$U^m\%$	11.18	20.68	31.30	0.02	0.06	0.21
$U^s\%$	5.92	13.22	19.54	1.20	1.12	1.62
$U^c\%$	82.90	66.10	49.16	98.78	98.82	98.17
r	0.46*	0.14	0.15	0.76*	0.58*	0.35*
VAR, No Restrictions						
$U^m\%$	31.55	46.68	53.61	5.50	12.30	17.66
$U^s\%$	17.72	19.62	20.73	1.77	1.13	1.49
$U^c\%$	50.73	33.70	25.66	92.73	86.57	80.85
r	0.64*	0.41*	0.30	0.75*	0.55*	0.35*
VAR, With Prior						
$U^m\%$	23.30	37.77	50.99	5.57	12.48	17.53
$U^s\%$	4.53	8.51	13.20	0.47	0.50	0.79
$U^c\%$	72.17	53.72	35.81	93.96	87.01	81.68
r	0.62*	0.33*	0.36*	0.79*	0.61*	0.41*
VAR, Stepwise Selection						
$U^m\%$	31.32	41.75	50.12	7.06	15.48	23.26
$U^s\%$	19.39	20.60	23.82	0.61	0.50	0.80
$U^c\%$	49.30	37.65	26.07	92.33	84.02	75.94
r	0.68*	0.37*	0.35*	0.76*	0.57*	0.40*
Structural System Model						
$U^m\%$	1.84	3.07	0.30	8.48	11.41	15.26
$U^s\%$	0.99	1.08	0.15	1.04	1.73	1.77
$U^c\%$	97.17	95.85	99.54	90.48	86.86	82.98
r	0.42*	-0.10	0.02	0.77*	0.54*	0.27*

a $U^m\%$ = Bias Proportion of Mean Squared Error (MSE), $[(\bar{F} - \bar{A})^2 / MSE]*100$.
b $U^s\%$ = Variance Proportion of Mean Squared Error (MSE), $[(s_F - s_A)^2 / MSE]*100$.
c $U^c\%$ = Covariance Proportion of Mean Squared Error (MSE), $[2(1 - r)s_F s_A / MSE]*100$.
d r = Correlation coefficient of predicted and actual values. An asterisk (*) indicates r is significant at the 95% confidence level.

In the quantitative evaluation, negatively biased forecasts were noted in almost all of the case-horizons, however, error decomposition indicates bias is a relatively unimportant source of total forecast error in many of the case-horizons. Exception is noted for the quarterly VAR-based models. If U^m is relatively large, as in the case of the VAR techniques applied to quarterly feeder steer prices, forecasters should be able to reduce such errors over time as learning takes place. Large proportions of error resulting from bias provide support for the argument that model forecasts must first be subjectively adjusted before they can be used with confidence.

Incomplete covariance was the most important source of forecast error in most of the case-horizons. If the correlation coefficient is 1, U^c vanishes. Forecasters probably will not be able to predict such that all their points are located on a straight line; therefore, incomplete covariance is more untreatable than errors in central tendency. The covariance proportion of the mean squared error is the least manageable (through learning and adjustment) of the three inequality proportions. It is thus desirable to have the bulk of MSE resulting from incomplete covariance. The optimal outcome of the forecast error decomposition would have occurred if U^m was the only source of forecast error.

With the exception of selected quarterly models (univariate stochastic, unrestricted and stepwise selection VAR-based), unequal variance is a relatively unimportant source of total mean squared error. This indicates most of the forecasting techniques applied in the competition accounted for fluctuations in the actual data. These fluctuations could be caused by underlying factors such as the cattle cycle or the general business cycle. Learning over time could also reduce the contribution of U^s to total mean squared error. In both applications the incomplete covariation component decreased as a proportion of forecast error between the one- and three-steps-ahead forecasts. This trend was balanced by an increase in bias as a source of error as the forecasting horizon lengthened.

Using the correlation coefficient as a measure of linear association between the forecast and actual variables, the strongest relationships for both applications were shown for the one-step-ahead horizon. Based on this criterion, the VAR-based models had the best fit over the three-step-ahead horizon in the quarterly feeder steer price application, while the classical decomposition and exponential smoothing methods showed the strongest correlation between actual and forecast monthly feeder steer prices. Correlation between actual and forecast values showed less variability across procedures in the monthly application than in the quarterly application.

The decomposition of forecast error demonstrated the tradeoffs between the three error components across the competing procedures. These results should be interpreted with full awareness that all inequality proportions are relative to total MSE, with the overall forecasting accuracy objective that of MSE minimization.

Concluding Comments

There are numerous forecasting techniques available for use by decision makers and researchers. These procedures range from judgmental or intuitive methods to highly complex econometric models. The choice of forecasting methodology made by an individual, agency or firm will be based on criteria such as predictive accuracy, cost, modeler and end-user sophistication, data availability, end-user needs and aversion to risk, and the loss function selected for minimization. The major purpose of this paper was to deal with one of the most important aspects of choosing a forecasting methodology: post-sample predictive accuracy.

Accuracy in forecasting is important to agricultural economists. Inaccurate forecasts imply faulty decision making, resulting in economic and financial losses. The need to minimize the cost of the forecasting function requires that agricultural economists understand various approaches to forecasting, how the methods differ from each other, and their strengths and weaknesses. A forecasting competition provides a systematic procedure to comprehensively evaluate alternative methodologies. This forecasting competition used one agricultural price variable with two levels of temporal aggregation to test nine alternative procedures, comparing over three different out-of-sample forecasting horizons.

While it is difficult to generalize, the earlier forecasting competitions referenced above and the current one provide evidence that statistically or econometrically sophisticated methods do not necessarily produce more accurate forecasts than simpler methods. The studies conducted by Makridakis and Hibon and Makridakis et al. (1982) were much more exhaustive than this research effort. Their evaluations included many data series, with a wide variety of temporal and spatial aggregation levels. Such a comprehensive evaluation using agricultural data series could help understand when, and under what circumstances, one forecasting method is to be preferred over other methods.

This research effort has provided an analytical framework for conducting additional forecasting competitions. With further evaluation of competing forecasting techniques, the costs and benefits of alternative methodologies could be objectively compared. This would lead to more optimal use of the resources employed in the forecasting function at the individual, firm and governmental levels. As noted in Makridakis and Hibon, further research is required to understand why, under certain circumstances, simpler methods do as well or better than sophisticated ones. This knowledge could fine tune forecasting functions at all levels within the agricultural economy.

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