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ACCURACY IN FORECASTING: RESULTS OF A COMPETITION

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 objectives of this research effort were: (1) to develop an analytical framework for conducting this and future forecasting competitions using agricultural variables; and (2) apply that framework to evaluate the forecasting performance of selected procedures used to generate out-of-sample predictions of two agricultural price series. The study was organized as a forecasting competition. Nine alternative forecasting procedures were used to predict both price series one-, two- and three-quarters-ahead. Accuracy of the out-of-sample forecasts was evaluated using standard techniques.

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 two agricultural price variables.

Forecasting Competition Procedures

Nine forecasting techniques representing the broad spectrum of forecasting methodology were applied in this study. The models were initially estimated over the sample period 1960.1 through 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 or 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 was conducted through 1986.4.

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 forecasts and the actual value. Evaluation of forecasting accuracy was conducted using 24 one-quarter-ahead, 23 two-quarters-ahead and 22 three-quarters-ahead out-of-sample forecasts. Quantitative and qualitative accuracy of the competing models were evaluated over the three 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 two data series selected for the forecasting competition were Kansas City feeder steer ($/cwt, average all weights and grades) and average California alfalfa hay ($/ton, baled) prices. These two variables have strong regional and national importance as leading indicators of feeder animal and forage prices. These data series and all others used in the forecasting competition were obtained from published USDA sources.

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. This approach is represented as

(1) $$X_t = f(I_t, T_t, C_t, E_t),$$

where X_t is the observed value, I_t is the seasonal component, T_t is the trend component, C_t is the cyclical component and E_t is the random element.

After the systematic components $(I_t\ ,\ T_t\ ,\ C_t)$ have been identified, they are multiplicatively reintegrated to generate forecasts of the variable X.[2] 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).

The basic equations for the Holt-Winters' method are:

(2) $S_t = \alpha(X_t / I_{t-L}) + (1 - \alpha)(S_{t-1} + b_{t-1})$, for overall updating;

(3) $b_t = \Gamma(S_t - S_{t-1}) + (1 - \Gamma)b_{t-1}$, for trend component updating;

(4) $I_t = \beta(X_t / S_t) + (1 - \beta)I_{t-L}$, for seasonal component updating;

(5) $F_{t+m} = (S_t + b_t m)I_{t-L+m}$, for forecasting;

where S_t is the exponentially smoothed value, X_t is the observed value, I_t is the seasonal adjustment factor, F_{t+m} is the forecast for m periods ahead and b_t is the trend component.

α is the overall smoothing coefficient, Γ is the trend smoothing coefficient and β is the seasonal smoothing coefficient with $0 \leq \alpha, \Gamma, \beta \leq 1$; m is the number of periods ahead of time period t with $m = 1, 2, \ldots, L$; and L is the length of seasonality.[3]

Univariate Stochastic Models

Standard univariate Box-Jenkins modeling procedures of identification, estimation, diagnostic checking and forecasting were applied to the two 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. Detailed discussion of these procedures can be found in Pindyck and Rubinfeld.

The general representation of the integrated autoregressive-moving average or ARIMA(p,d,q) processes used for both data series is

(6) $\phi(B)\Delta^d y_t = \delta + \theta(B)\epsilon_t$, with

(7) $\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \ldots - \phi_p B^p$, and

(8) $\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \ldots - \theta_q B^q$,

where B is the backward shift operator.[4]

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.

Simple Linear/Multiple Regression Models

Parsimonious regression models were constructed to forecast Kansas City feeder steer and California alfalfa hay 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.

The model used to generate forecasts of feeder steer prices was a simple random walk model. The alfalfa hay price multiple regression model included lagged California alfalfa hay prices, a deterministic trend, and average total precipitation in the western and midwestern states[5] as independent variables.[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 simple 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.

Two data series exhibiting a time-ordered association with each of the two series being forecasted were identified. For Kansas City feeder steer prices, the associated series was average U.S. corn prices ($/bushel). Average total precipitation in the western and midwestern states was selected as the associated variable for California alfalfa hay prices. The choice of the corn price variable was supported by previous work by Spreen and Shonkwiler that demonstrated a lead/lag relationship between feeder steer prices and feed costs. The precipitation variable was selected for use in the alfalfa hay application based on prior observation of alfalfa hay markets in the western United States.

Univariate stochastic filter models were identified and estimated, and residual series retained for the two associated series in each estimation period. Cross-correlation analysis was performed between the residuals of feeder steer and corn price univariate models, and between the alfalfa hay price and precipitation univariate models. The feeder steer and alfalfa hay price univariate stochastic models described above were also used in this forecasting procedure. A linkage equation was formed by regressing the residuals of the output variables (i.e., feeder steer and alfalfa hay prices) on the statistically significant lags of the related input series residuals. The transfer function noise models were adjusted, reestimated and used to generate forecasts of the feeder steer and alfalfa hay residual series one-, two-, and three-quarters-ahead over the rolling horizon. The predicted residuals were then combined with the forecasts of the univariate stochastic filter models for the adjusted forecast.[7]

Vector Autoregression Models

The vector autoregression (VAR) approach to forecasting uses a set of time order associated variables to generate forecasts. The general representation of the VAR model has the form:

(9) $$y_t = \phi_0 + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \dots + \phi_m y_{t-m} + u_t,$$

where y_t is a $G \times 1$ vector containing the elements $y_{1t}, y_{2t}, \dots, y_{Gt}$. $y_{t-1}, y_{t-2}, \dots, y_{t-m}$ are the lagged values of y_t; ϕ_0 is a $G \times 1$ vector of constants; and $\phi_1, \phi_2, \dots, \phi_m$ are $G \times G$ matrices of vector autoregressive coefficients (Kmenta). The disturbance u_t is assumed to obey all classical assumptions.

Ordinary least squares estimation of the VAR system is appropriate because there are no current endogenous variables on the right hand side of the vector autoregression model. There is no distinction between endogenous and exogenous variables in the system, and there are no a priori restrictions on the coefficients. Every variable in the multivariate system is allowed to influence every other variable in the system with lags.

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 might exhibit time-ordered relationships with the two series being forecasted. The time order associated variables selected for use in the feeder steer application were Omaha slaughter steer prices ($/cwt., average all grades) and average U.S. retail beef prices ($/lb.). 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). California alfalfa hay prices were related to U.S. average corn prices ($/bushel) and average U.S. milk prices ($/cwt). These variables were selected because corn is a complementary feedstuff and the demand for alfalfa hay is (partially) derived from the demand for dairy products.

Block *F*-tests helped to indicate the potential strength of the time-associated variables in forecasting feeder steer and alfalfa 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 feeder steer and alfalfa hay prices in each of the 24 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-quarters-ahead over the rolling horizon.

The feeder steer and alfalfa hay 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 horizon. 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]

Structural System Modeling

Two relatively simple multi-equation structural models were developed for use in forecasting the two variables of interest. A review of past forecasting applications, using models based on behavioral and biological factors, provided a guide to specification of the equation systems. Literature helpful in specifying the two structural forecasting system include 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 relatively small set of appropriate variables. They were specified as simultaneous equation 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. There were numerous explanatory variables common to both systems; however, they were not linked in any way.

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

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 feeder steer and alfalfa hay 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. Mean error was calculated as

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

where A_t is the actual value for period t, F_t is the forecast value for period t, and n is the number of out-of-sample forecast periods analyzed.

Negative bias (i.e., forecasted values with a tendency to be greater than actual values) was noted in 85% of the case-horizons. In the feeder steer application, least bias was noted for the univariate stochastic model and the structural system forecasts. Minimum bias in the alfalfa hay price application was achieved with the VAR-stepwise selection model.

Root mean squared error (*RMSE*) was used to measure absolute accuracy of the forecasts, and was calculated as

(11) $RMSE = ((\Sigma_{t=1}^{n} (A_t - F_t)^2)/n)^{1/2}.$

Minimum *RMSE* in the feeder steer application was achieved using the structural system model. Least *RMSE* resulted from the VAR-stepwise selection in the one- and two-quarters-ahead cases for the alfalfa hay application, while the structural system model performed best in the three-quarters-ahead case.

Root mean squared percentage error (*RMSPE*) is a unitless measure of absolute accuracy which permits comparison across commodity applications. *RMSPE* is calculated

(12) $RMSPE = (RMSE/(\Sigma_{t=1}^{n} A_t /n))*100.$

Using this loss function, the structural model was the best predictor of feeder steer prices. Results were mixed for the alfalfa hay price application, but the simple (least data demanding) procedures did perform relatively well.

Relative accuracy between the forecasting procedures and across commodities was evaluated using Theil's Inequality Coefficient (U_2). This value is calculated as

(13) $$U_2 = \frac{(\Sigma_{t=1}^{n-1} \; ((F_{t+1} - A_{t+1})/A_t)^2)^{1/2}}{(\Sigma_{t=1}^{n-1} \; ((A_{t+1} - A_t)/A_t)^2)^{1/2}}.$$

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.

With respect to the one-quarter-ahead U_2 values, the alfalfa hay price forecasting models were better than the naive model 89% of the time. Forecasted feeder steer price U_2 values tended to be higher than those of the alfalfa hay application, with exception noted for the univariate stochastic model. As out-of-sample forecasting extended to three-quarters-ahead, an increasing trend in U_2 values was noted for both applications.

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.

Qualitative Evaluation

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. This measure was extremely low for the one-quarter-ahead forecasts generated by many of the feeder steer models. The least data demanding procedures (classical decomposition, exponential smoothing, univariate stochastic model, and the regression model) used to predict feeder steer prices showed large improvements in turning point precision between the one- and three-quarters-ahead forecasting 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 feeder steer price explanatory model showed an increase in turning point accuracy as the horizon lengthened, but could not match the restricted VAR, univariate stochastic model or exponential smoothing in the final horizon.

The stepwise selection VAR model was a relatively good turning point predictor in the alfalfa hay price application. This model had the highest *RAF* over all three horizons, and the minimum ratio of worst forecasts (*RWF*) in two of the three horizons. No worst forecasts were noted for the bivariate stochastic model predicting two-quarters-ahead and the VAR-stepwise selection model predicting three-quarters-ahead.

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 case-horizons. As in the general evaluation, the directional 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 calculation of the mean squared error (*MSE*), where total *MSE* is equal to the following decomposition of errors:

(14) $$MSE = (\bar{F} - \bar{A})^2 + (s_F - s_A)^2 + 2(1 - r)s_F s_A$$

where $\bar{F}$ and $\bar{A}$ are the means of the forecast (*F*) and actual (*A*) values; s_F and s_A are standard deviations of the forecast and actual values; and r is the linear correlation coefficient of the forecast and actual values. A convenient way to handle the decomposition is to divide each of the three terms by their sum. This leads to

(15) $1 = U^m + U^s + U^c$, where

(16) $U^m = (\bar{F} - \bar{A})^2 / MSE$,

(17) $U^s = (s_F - s_A)^2 / MSE$, and

(18) $U^c = 2(1-r)s_F s_A / MSE$.

Total *MSE* is divided into three inequality proportions. U^m is the proportion of mean squared error attributed to bias or errors in central tendency; U^s is the variance proportion, resulting from prediction errors cuased by unequal variation; and U^c is the proportion of the mean squared error due to unequal covariation. Multiplying equation (15) by 100 gives the *MSE* decomposition on a percentage basis.

In the quantitative evaluation, negatively biased forecasts were noted in almost all case-horizons; however, error decomposition indicates bias is a relatively unimportant source of total forecast error in both applications. If U^m is relatively large, as in the case of the VAR techniques applied to 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 many of the cases. 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 of correlation; 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 the unrestricted VAR technique, unequal variance is 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-quarters-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-quarter-ahead horizon. Based on this criterion, the VAR-stepwise selection model had the best fit in the feeder steer price application, while the results were mixed for the alfalfa hay 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 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 two data series to test nine alternative procedures, compared over three different out-of-sample forecasting horizons.

While it is difficult to generalize, earlier forecasting competitions 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 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.

Endnotes

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

2. MicroTSP™-Version 6 and a spreadsheet software program were used for all decomposition calculations.

3. Starting values for the trend, seasonal and overall updating equations were calculated using the first one third (*k*) 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.

4. The univariate stochastic model used to predict 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 alfalfa hay univariate stochastic model included an MA(1) and a seasonal moving average (SMA) term of order 4 in all estimation sample periods. An autoregressive (AR) term of order 6 was included intermittently throughout the first half of the sample periods, and in all sample periods after 1960.1-1983.1. R^2 values for the 24 estimations ranged from .47 to .54.

5. Western and midwestern states = Minnesota, Wisconsin, Michigan, Washington, Oregon, California, Montana, Wyoming, Idaho, Colorado, Utah, Nevada, Arizona, New Mexico, Texas, Oklahoma, Iowa, Missouri, Illinois, Indiana, Ohio, North Dakota, South Dakota, Kansas and Nebraska.

6. The model used to generate feeder steer price forecasts 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 alfalfa hay price multiple regression model specified and reestimated over the rolling horizon was $QHAYP_t = \beta_0 + \beta_1 QHAYP_{t-1} + \beta_2 QHAYP_{t-2} + \beta_3 QPRECIP_{t-4} + \beta_4 t + \epsilon_t$, where *QHAYP* is average California alfalfa hay price, *QPRECIP* is average total precipitation in the western and midwestern states, and *t* is the trend variable. The R^2 value for this equation was consistently greater than .95.

7. The univariate stochastic models described in note (4) above were used to filter the output variables. The filter model applied to 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 feeder steer-corn 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 precipitation included a seasonal moving average term (order 4) in all estimation samples, along with varying combinations of MA(1), MA(8), MA(12) and AR(1) terms. The R^2 values for the 24 equations ranged from .48 to .57. The alfalfa hay-precipitation transfer function noise model included combinations of lagged terms of orders 3, 5, 6, 7, 10, 15, 17, 18, 19 and 21. Noise model R^2 values ranged from .17 to .40.

8. The vector autoregression (VAR) system used to predict feeder steer prices was of order 9. The alfalfa hay VAR system was of order 11. 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.

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

10. The six equations which comprised the alfalfa hay model are:

(i) $QCAHAYP_t = \beta_1 QCAMLKP_t + \beta_2 QCAHAYP_{t-1} + \beta_3 QCAHAYP_{t-2} + \epsilon_t, R^2 = .95;$

(ii) $QFSP_t = \beta_1 QFSP_{t-1} + \beta_2 QSSP_{t-1} + \beta_3 QCRNP_{t-1} + \beta_4 QSSP_t + \epsilon_t, R^2 = .97;$

(iii) $QSSP_t = \beta_0 + \beta_1 QTDPI_{t-4} + \beta_2 QSSP_{t-1} + \epsilon_t, R^2 = .94;$

(iv) $QCAMLKP_t = \beta_1 QCAMLKP_{t-1} + \beta_2 QTDPI_{t-4} + \beta_3 QUSMLKP_{t-4} + \epsilon_t; R^2 = .92;$

(v) $QCRNP_t = \beta_1 QUSHAYP_{t-1} + \beta_2 QCRNP_{t-1} + \beta_3 QPRECIP_{t-4} + \epsilon_t; R^2 = .92;$

(vi) $QUSHAYP_t = \beta_1 QUSHAYP_{t-1} + \beta_2 QCAHAYP_t + \epsilon_t; R^2 = .98.$

QCAMLKP is the quarterly California milk price ($/cwt.), *QUSMLKP* is the quarterly U.S. milk price ($/cwt.), and *QCAHAYP* is the quarterly California alfalfa hay price (baled, $/ton). All other variables are as described in note (9).

Table 1. Quantitative Forecast Evaluation Results

METHOD	Feeder Steer Price Forecasts 1	2	3	Alfalfa Hay Price Forecasts 1	2	3
	(Quarters Ahead)			(Quarters Ahead)		
Classical Decomposition						
Mean Error	-.75	-1.66	-2.48	-2.35	-4.27	-5.85
Root Mean Squared Error	3.72	5.23	4.83	6.87	8.73	12.03
Root Mean Squared % Error	5.99	8.45	7.81	8.04	10.31	14.25
Inequality Coefficient	1.02	1.42	1.32	0.88	1.10	1.63
Exponential Smoothing						
Mean Error	-0.61	-1.02	-1.48	-1.95	-3.61	-5.05
Root Mean Squared Error	3.88	5.34	4.92	6.60	8.74	11.94
Root Mean Squared % Error	6.24	8.62	7.96	7.72	10.32	14.14
Inequality Coefficient	1.05	1.44	1.33	0.83	1.10	1.60
Univariate Stochastic Model						
Mean Error	0.00	-0.08	-0.08	-2.57	-5.05	-7.39
Root Mean Squared Error	3.53	5.04	5.45	10.65	12.15	17.02
Root Mean Squared % Error	5.68	8.14	8.82	12.46	14.34	20.15
Inequality Coefficient	0.98	1.38	1.48	1.33	1.62	2.25
Regression Model						
Mean Error	-0.77	-1.54	-2.36	-2.86	-6.15	-8.64
Root Mean Squared Error	3.75	5.20	5.05	6.57	10.09	12.83
Root Mean Squared % Error	6.03	8.40	8.17	7.69	11.91	15.19
Inequality Coefficient	1.03	1.43	1.40	0.80	1.27	1.71
Bivariate Stochastic Model						
Mean Error	-1.34	-2.85	-4.53	0.95	-3.43	-6.83
Root Mean Squared Error	4.00	6.27	8.09	7.38	11.49	14.86
Root Mean Squared % Error	6.44	10.13	13.09	8.63	13.57	17.60
Inequality Coefficient	1.09	1.73	2.23	0.95	1.54	2.03
VAR, No Restrictions						
Mean Error	-2.61	-5.54	-8.37	-0.19	-1.30	-2.33
Root Mean Squared Error	4.65	8.11	11.43	7.81	12.02	17.72
Root Mean Squared % Error	7.48	13.10	18.49	9.14	14.19	20.98
Inequality Coefficient	1.25	2.17	3.09	0.99	1.52	2.37
VAR, With Prior						
Mean Error	-1.69	-3.53	-5.51	0.58	-1.79	-2.91
Root Mean Squared Error	3.51	5.74	7.71	6.14	8.17	12.10
Root Mean Squared % Error	5.65	9.27	12.47	7.18	9.65	14.33
Inequality Coefficient	0.94	1.56	2.10	0.79	1.05	1.68
VAR, Stepwise Selection						
Mean Error	-2.48	-5.14	-7.80	1.03	0.07	-0.93
Root Mean Squared Error	4.42	7.95	11.02	5.91	6.99	11.80
Root Mean Squared % Error	7.11	12.84	17.83	6.91	8.25	13.97
Inequality Coefficient	1.15	2.12	2.97	0.77	0.92	1.70
Structural System Model						
Mean Error	0.48	0.83	0.23	-1.50	-3.77	-5.45
Root Mean Squared Error	3.50	4.77	4.23	7.38	9.87	11.28
Root Mean Squared % Error	5.63	7.70	6.84	8.63	11.65	13.36
Inequality Coefficient	0.99	1.32	1.16	0.92	1.23	1.53

Table 2. Qualitative Forecast Evaluation Results

METHOD	Feeder Steer Price Forecasts 1	2 (Quarters Ahead)	3	Alfalfa Hay Price Forecasts 1	2 (Quarters Ahead)	3
Classical Decomposition						
RAF [a]	0.09	0.14	0.40	0.36	0.57	0.30
RWF	0.27	0.24	0.15	0.18	0.05	0.15
RAWF	0.33	0.60	2.67	2.00	12.00	2.00
RIF	0.64	0.62	0.45	0.45	0.38	0.55
RWF+RIF	0.91	0.86	0.60	0.64	0.43	0.70
Exponential Smoothing						
RAF	0.09	0.19	0.40	0.36	0.52	0.25
RWF	0.18	0.19	0.05	0.09	0.10	0.05
RAWF	0.50	1.00	8.00	4.00	5.50	5.00
RIF	0.73	0.62	0.55	0.55	0.38	0.70
RWF+RIF	0.91	0.81	0.60	0.64	0.48	0.75
Univariate Stochastic Model						
RAF	0.05	0.24	0.50	0.18	0.43	0.55
RWF	0.27	0.24	0.05	0.23	0.10	0.10
RAWF	0.17	1.00	10.00	0.80	4.50	5.50
RIF	0.68	0.52	0.45	0.59	0.48	0.35
RWF+RIF	0.95	0.76	0.50	0.82	0.57	0.45
Regression Model						
RAF	0.14	0.05	0.40	0.32	0.57	0.35
RWF	0.14	0.52	0.15	0.09	0.05	0.25
RAWF	1.00	0.09	2.67	3.50	12.00	1.40
RIF	0.73	0.43	0.45	0.59	0.38	0.40
RWF+RIF	0.86	0.95	0.60	0.68	0.43	0.65
Bivariate Stochastic Model						
RAF	0.09	0.24	0.25	0.14	0.43	0.25
RWF	0.27	0.19	0.20	0.18	0.00	0.25
RAWF	0.33	1.25	1.25	0.75	1.00	0.77
RIF	0.64	0.57	0.55	0.68	0.57	0.50
RWF+RIF	0.91	0.76	0.75	0.86	0.57	0.75
VAR, No Restrictions						
RAF	0.45	0.29	0.30	0.36	0.48	0.35
RWF	0.09	0.14	0.10	0.09	0.14	0.15
RAWF	5.00	2.00	3.00	4.00	3.33	2.33
RIF	0.45	0.57	0.60	0.55	0.38	0.50
RWF+RIF	0.55	0.71	0.70	0.64	0.52	0.65
VAR, With Prior						
RAF	0.23	0.38	0.45	0.36	0.53	0.40
RWF	0.23	0.24	0.05	0.18	0.10	0.05
RAWF	1.00	1.60	9.00	2.00	5.50	8.00
RIF	0.55	0.38	0.50	0.45	0.38	0.55
RWF+RIF	0.77	0.62	0.55	0.64	0.48	0.60
VAR, Stepwise Selection						
RAF	0.27	0.33	0.40	0.36	0.67	0.60
RWF	0.09	0.19	0.20	0.05	0.05	0.00
RAWF	3.00	1.75	2.00	8.00	14.00	2.29
RIF	0.64	0.48	0.48	0.59	0.29	0.48
RWF+RIF	0.73	0.67	0.68	0.64	0.33	0.48
Structural System Model						
RAF	0.14	0.05	0.30	0.18	0.14	0.05
RWF	0.23	0.52	0.15	0.18	0.38	0.60
RAWF	0.60	0.09	2.00	1.00	0.38	0.08
RIF	0.64	0.43	0.55	0.64	0.48	0.35
RWF+RIF	0.86	0.95	0.70	0.82	0.86	0.95

[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	Feeder Steer Price Forecasts 1	2	3	Alfalfa Hay Price Forecasts 1	2	3
	(Quarters Ahead)			(Quarters Ahead)		
Classical Decomposition						
U^m% [a]	4.01	10.06	26.25	11.67	23.86	23.69
U^s% [b]	12.46	8.42	1.47	0.43	0.44	0.00
U^c% [c]	83.53	81.52	72.28	87.90	75.70	76.31
r [d]	0.57*	0.13	0.18	0.76*	0.62*	0.24
Exponential Smoothing						
U^m%	2.51	3.64	9.07	8.70	17.07	17.88
U^s%	14.04	12.28	6.22	1.39	2.30	0.46
U^c%	83.45	84.08	84.71	89.91	80.64	81.66
r	0.54*	0.14	0.16	0.78*	0.63*	0.27
Univariate Stochastic Model						
U^m%	0.00	0.03	0.02	5.83	17.26	18.86
U^s%	4.10	14.71	22.53	3.05	5.15	18.90
U^c%	95.90	85.26	77.45	91.12	77.59	62.24
r	0.48*	0.23	0.29	0.48*	0.40*	0.34*
Regression Model						
U^m%	4.23	8.75	21.81	18.94	37.18	45.40
U^s%	2.62	3.50	4.08	0.01	0.23	0.02
U^c%	93.15	87.76	74.12	81.04	62.59	54.58
r	0.41*	-0.05	0.18	0.79*	0.58*	0.40*
Bivariate Stochastic Model						
U^m%	11.18	20.68	31.30	1.66	8.90	21.13
U^s%	5.92	13.22	19.54	3.07	9.03	11.17
U^c%	82.90	66.10	49.16	95.27	82.07	67.71
r	0.46*	0.14	0.15	0.72*	0.46*	0.35*
VAR, No Restrictions						
U^m%	31.55	46.68	53.61	0.06	1.18	1.73
U^s%	17.72	19.62	20.73	18.89	40.27	38.35
U^c%	50.73	33.70	25.66	81.05	58.56	59.93
r	0.64*	0.41*	0.30	0.78*	0.69*	0.44*
VAR, With Prior						
U^m%	23.30	37.77	50.99	0.89	4.83	5.77
U^s%	4.53	8.51	13.20	1.54	7.14	10.94
U^c%	72.17	53.72	35.81	97.57	88.03	83.29
r	0.62*	0.33*	0.36*	0.79*	0.67*	0.43*
VAR, Stepwise Selection						
U^m%	31.32	41.75	50.12	3.03	0.01	0.62
U^s%	19.39	20.60	23.82	0.07	0.63	9.63
U^c%	49.30	37.65	26.07	96.90	99.36	89.75
r	0.68*	0.37*	0.35*	0.80*	0.68*	0.40*
Structural System Model						
U^m%	1.84	3.07	0.30	4.12	14.59	23.32
U^s%	0.99	1.08	0.15	0.19	1.10	1.68
U^c%	97.17	95.85	99.54	95.69	84.31	75.00
r	0.42*	-0.10	0.02	0.67*	0.35*	0.21

[a] U^m% = Bias Proportion of Mean Squared Error.
[b] U^s% = Variance Proportion of Mean Squared Error.
[c] U^c% = Covariance Proportion of Mean Squared Error.
[d] r = Correlation coefficient of predicted and actual values. An asterisk (*) indicates r is significant at the 95% confidence level.

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