Alternative Forecasting Techniques: A Case Study for Livestock Prices

by

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Part of the research and extension effort in the Department of Agricultural Economics at the University of Illinois is to generate short-term forecasts on prices of agricultural commodities produced by Illinois farmers. A Price Forecasting and Sales Management (PFSM) team is responsible for these price forecasts.

For about four years the PFSM team has been using single equation demand models to forecast live cattle and live hog prices. However, in early 1980 these models began to overestimate actual prices for cattle and hogs (most noteably, cattle). These unacceptably high forecast errors have prompted the PFSM group to search for alternative forecasting techniques. This paper reports current findings from research that examines alternative techniques available to the PFSM team for forecasting live cattle and hog prices.

The research findings reported herein focus on systematic forecasting techniques for predicting live cattle and hog prices; that is, techniques which when properly used may reveal a certain systematic behavior among variables although real world changes may seem accidental (Chisholm and Whitaker). The systematic approach is implicit in variety of techniques

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including regression (econometric) and Box-Jenkins analysis. In the context of the PFSM team's need to forecast live cattle and hog prices, four alternative forecasting techniques to the single equation regression models currently used are examined. These alternative forecasting techniques are univariate Box-Jenkins, a composite forecast approach, and two methods that integrate Box-Jenkins and econometric approaches: serial correlation regression and multivariate time series analysis. Forecast performance is compared among the two individual, two integrated, and one composite method using two criteria: root mean square error (RMSE), and a measure of directional accuracy, turning points.

The remainder of this paper examines the alternative techniques for forecasting cattle and hog prices and the forecast performance of each. But first, a priori beliefs about which forecast techniques will provide the best forecast(s) are anything but certain. Leuthold, et al. compared autoregressive-integrated-moving average (ARIMA) and econometric models as alternative methods to forecasting daily hog prices. Their results indicated that the econometric model slightly outperformed the ARIMA model over the evaluation period. Brandt and Bessler concluded that among three individual forecasting techniques for predicting quarterly hog prices, econometric, ARIMA, and expert opinion, the ARIMA model performed best while a composite forecast model that combined the forecasts from the three individual forecast techniques outperformed the individual ARIMA technique. Yet, in another study that compared alternative approaches to forecasting, Kulshreshtha et al. discovered that among two individual and three composite forecasting models for predicting Canadian cattle price, the univariate Box-Jenkins, the while in the long-run the econometric and transfer function methods were preferred.

ALTERNATIVE FORECASTING TECHNIQUES

INDIVIDUAL MODELS

Econometric. Equations (1) and (2) are standard price dependent, quarterly demand models. Equation (1) is the PFSM team's cattle model. Using ordinary least squares (OLS) regression over the 56-quarter (calendar quarters) period from first quarter, 1969 (6901) through fourth quarter, 1982 (8204), the results are:

$$PC_t = 85.017 - \underset{(-9.14)}{.0109BP_t} - \underset{(-4.10)}{.0045PP_t} - \underset{(-3.62)}{.0106BRP_t} + \underset{(4.33)}{.0571DPI_t} \qquad (1)$$

where $R^2 = .62$, DW = .86, SER = 2.82, PC is the quarterly farm price of cattle (Omaha choice steers, \$/CWT), BP, PP, and BRP are respectively quarterly beef, pork, and broiler production (millions of pounds carcass weight), and DPI represents annual disposable personal income in billions of dollars (adjusted to a quarterly basis). PC and DPI are deflated to 1972 dollars. The t-values in parentheses indicate that the relationships of the explanatory variables to cattle price are quite reliable and the signs are as expected. The Durbin-Watson test statistic (DW), 0.86, suggests the presence of autoregressive disturbances at the 5 percent significance level. The presence of serial correlation raises doubts about the reliability of equation (1).

Equation (2) is the PFSM team's hog model. The model is estimated over the 72-quarter (hog quarters) period from first quarter, 1965 (6501) through fourth quarter, 1982 (8204). The OLS regression results are:

$$PH_t = \underset{}{52.646} - \underset{(-14.67)}{.0136PP_t} - \underset{(-1.22)}{.0012BP_t} - \underset{(-5.00)}{.0121BRP_t} \tag{2}$$

$$+ \underset{(5.94)}{.0633DPI_t}$$

where PH is the quarterly farm price of hogs (barrows and gilts seven markets, \$/CWT), PP, BP, BRP, and DPI are defined as before, and $R^2 = .81$, DW = 1.51, and SER = 2.78. PH and DPI are deflated to 1972 dollars. Figures in parentheses are t-values of the coefficients. All explanatory variables have t-values greater than two except beef production. Signs are as expected. The test for serial correlation at the 5 percent significance level is inconclusive.

ARIMA. An alternative forecasting technique is to use Box-Jenkins univariate time series analysis. The methods of Box and Jenkins (1968, 1970) decompose a data set into autoregressive (AR), moving average (MA), and trend or integrated (I) components (i.e., a time series is specified as an autoregressive integrated-moving-average, or ARIMA, process). Once the process which generates the observed time series is identified and transformed into a predictive model which meets certain diagnostic checks, forecasts for various lead times can be made. These forecasts take into account past behavior of the time series and current and past errors.

A three-step procedure is involved in identification or selection of a univariate ARIMA model, estimation of the coefficients of such a model, and checking the appropriateness of the estimated model. The selection procedure involves the comparison of estimated autocorrelations and partial autocorrelations of the time series being examined against theoretical autocorrelations and partial autocorrelations of known ARIMA processes. Once a model has been selected, the parameters of the model are estimated using a nonlinear least squares algorithm. After the parameters of the tentative model have been estimated, the fitted model undergoes diagnostic checks to see how adequately it represents the actual series. The check can be carried out several ways. The approach used herein is to test the autocorrelation function of the residuals for randomness applying a Ljung-Box "portmanteau" test.

The above procedures were applied to the quarterly cattle price series and the following ARIMA model was specified:

$$(1 - B)(1 - .2540B^4)PC_t = (1 + .2522B)a_t \tag{3}$$

where B is the backward operator ($B^i PC_t = PC_{t-i}$) and a_t is a white-noise (random) disturbance. The number of quarterly observations is 55.

Box-Jenkins univariate time series analysis also was applied to the quarterly hog price series resulting in the following ARIMA model:

$$(1 - B)\ PH_t = (1 + .5777B^5)a_t \tag{4}$$

Quarterly observations number 71.

COMPOSITE MODEL

Bates and Granger have suggested that performance of individual forecasting methods could be improved by combining the forecasts from individual approaches. Researchers (e.g., Bessler and Brandt), using empirical data, have demonstrated that composite forecasts are likely to outperform forecasts from individual models.

The idea behind composite forecasting is that alternative forecasts of the same identical random variable will likely contain information which is independent of that contained in other forecasts. Therefore, by combining alternative forecasts, forecasters should be able to improve their forecast performance. The objective of the PFSM team and of the research reported herein is to generate the best forecast possible. In this context, a composite forecasting approach that combines the forecasts of the individual models described earlier is considered in the analysis of alternative forecasting techniques for both cattle and hog prices.

A basic problem underlying the generation of composite forecasts is what weight to apply to each individual forecast. Bates and Granger and Granger and Newbold discuss several procedures for determining these weights. These authors suggest when no information is available on the historical performance of each individual method that a composite forecast method that employs a simple average of the current period forecast of each individual method be used. Since we have no historical record for ARIMA model forecasts, we use this procedure of combining equally weighted econometric and ARIMA forecasts in determining cattle and hog quarterly composite predictions.

INTEGRATED MODELS

Several forecasting techniques combine time series analysis and regression analysis into integrated models. Integrated techniques include the mixed forecast technique (Kulshreshtha *et al.*), transfer function noise models [Box and Jenkins, (1970), Granger and Newbold, Newbold, Pindyck and Rubinfeld], and multivatiate time series analysis (Granger and Newbold, Newbold). Our focus will be a special case of the transfer function noise method, serial correlation regression,[1] and a multivariate time series model.

Underlying integrated forecasting models is the idea that by combining time series analysis and regression analysis better forecasts will likely result than if either technique is used alone; the argument being that more useful information is being incorporated into the integrated forecasting model.

Serial Correlation Regression. As mentioned earlier, the DW statistic suggests that the PFSM team's single equation econometric demand model for cattle (equation 1) contains autocorrelated errors. If autocorrelated errors in time series regression equations are ignored, problems arise. One problem, of particular interest here, is that sub-optimal forecasts result when the fitted equation is used to derive forecasts. Therefore, as theory suggests, an integrated regression-time series model that accounts for the structural and nonstructural variation in steer prices likely will outperform not only the econometric forecast model (equation 1) but the ARIMA model (equation 3) as well.

An integrated model (equation 5), combining the structural variables of equation (1) and an ARMA (p,q) model for the residual series "a_t" of equation (1) was estimated using a generalized least squares estimator. Parameters of the structural regression equation and time series model were estimated simultaneously.[2] The ARMA (p,q) error model was determined by subtracting the estimated values of PC_t from the actual values (equation 1), and then applying the principles of univariate model identification discussed earlier to the residual series. Following this procedure, it was found that the errors followed a first order autoregressive process (AR1).[3]

The statistical model estimated was:

$$PC_t = \underset{}{93.31} - \underset{(-7.37)}{.0103BP_t} - \underset{(-3.12)}{.0033PP_t} - \underset{(-0.90)}{.0024BRP_t} \tag{5}$$

$$+ \underset{(1.22)}{.0182DPI_t} + \underset{(7.30)}{.7129RHO1}$$

where PC, BP, PP, BRP, and DPI are defined as before, RHO1 is the first order autoregressive component, $R^2 = .78$, DW = 2.14, and SER = 2.18. Figures in parentheses are t-values of the coefficients. Number of quarterly observations is 55. In contrast to equation (1), note the DW statistic is closer to 2.0, indicative of no serial correlation. Also observe the standard error of the equation is smaller and R^2 higher. Signs remained the same but unlike equation (1), BRP and DPI are not significant.

Although the DW statistic for the PFSM team's single equation econometric demand model for hogs (equation 2) is in the inconclusive region, a serial correlation regression model (equation 6) was constructed by combining the structural variables of equation (2) and an ARMA (p,q) model for the residual series "a_t" of equation (2). The ARMA (p,q) error model was determined by subtracting the estimated values of PH_t from the actual values (equation 2) and then applying univariate Box-Jenkins model identification procedures to the residual series. An MA(2) process was identified for the error series.[4]

Using a generalized least squares estimator, the statistical model estimated was:

$$PH_t = 50.186 + \underset{(.07)}{.0001BP_t} - \underset{(-5.08)}{.0119PP_t} - \underset{(-3.58)}{.0086BRP_t} \tag{6}$$

$$+ \underset{(3.33)}{.0432DPI_t} + \underset{(1.38)}{.4114MA1} + \underset{(4.73)}{.3832MA2}$$

where PH, BP, PP, BRP, DPI, and "t" are defined as before, MA1 and MA2 are first and second order moving average components, respectively, $R^2 = .86$, DW = 1.99, and SER = 2.46. Figures in parentheses are t-values of the coefficients. Number of quarterly observations is 70. In contrast to equation (2), the DW statistic is nearer to 2.0, SER is lower, and R^2 higher. Significant structural variables remained the same, but unlike equation (2), BP changed sign.

Multivariate Time Series. The multivariate time series method extends univariate time series models to the multivariate case. The form of the model is determined by the data alone. Economic theory is used only to suggest possible relevant variables (series). The objective in multivariate time series modeling is to build a model that transforms a vector of time series to a white noise vector. Unlike the transfer function noise method, multivariate time series modeling accommodates the possibility of feedback in the system modeled.

Equation (7) represents a general form of a multivariate, ARMA (p,q), time series model:

$$(I - \Phi_1 B - \ldots - \Phi_p B^p)\, \underset{\sim}{X}_t = (I - \Theta_1 B - \ldots - \Theta_q B^q)\, \underset{\sim}{a}_t \tag{7}$$

where I is the identity matrix, Φ_j and Θ_j are square matrices of autoregressive and moving average coefficients, respectively, $\underset{\sim}{X}_t$ represents "m" stationary time series such that $\underset{\sim}{X}_t = (X_{1,t}, X_{2,t}, \ldots, X_{m,t})$, and $\underset{\sim}{a}_t$ is vector white noise; that is $E(\underset{\sim}{a}_t, \underset{\sim}{a}'_{t-j}) = 0$; $(j \neq 0)$ (Newbold, pp. 109-110).

Implementation of a practical model building cycle for fitting the multiple ARMA process to data again involves a three-step procedure of selection, estimation, and diagnostic checking. The selection step is exceedingly more difficult than the selection procedure used in univariate Box-Jenkins model building. The remaining steps in the multivariate model building cycle are more straightforward.

The ARMA program used in this study required that all data series be deseasonalized. Thus, the first step toward generating a predictive model was to deseasonalize the data. This was done using the U.S. Bureau of the Census's X11 Quarterly Seasonal Adjustment Program. Following deseasonalizing of the data, a three-step procedure of selection, estimation, and diagnostic checking was carried out.

An ad hoc identification procedure was used to select the models. Initially, an AR1 matrix (Φ_1) was assumed for both systems - cattle and hogs. Next, the 25 parameters of each respective AR1 matrix were estimated using a maximum likelihood algorithm. Following the initial estimation step, all AR1 matrix elements whose values were not close to or greater than two standard errors were fixed to be zero. Maximum likelihood estimation was again applied to those parameter values allowed to vary (i.e. those values not set equal to zero). This procedure of estimating and reestimating parameter values that were near to or greater than two standard errors was repeated until all 25 matrix elements were either set equal to zero or had values equal to or greater than two standard errors.

Having completed the estimation step, the representativeness of each fitted model was checked through examination of sample cross-correlation matrices for 12 lags. The AR1 specification seemed to adequately account for the lag structure of both systems - cattle and hogs.

Equation 8 is the estimated predictive multiple time series model for cattle:

$$[I - \Phi_1 B]\underset{\sim}{X}_t = \underset{\sim}{a}_t \tag{8}$$

where $\underset{\sim}{X}_t = (BP_t,\ PP_t,\ BRP_t,\ DPI_t,\ PC_t)$, $N = 48$, and

$$\Phi_1 = \begin{bmatrix} 0 & -.30 & 0 & 0 & 0 \\ & (.11) & & & \\ 0 & 0 & .87 & 0 & 0 \\ & & (.42) & & \\ 0 & -.15 & .30 & 0 & 0 \\ & (.04) & (.12) & & \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}.$$

Values in parentheses are standard errors.

The multiple time series model constructed for hogs is the following:

$$[I - \Phi_1 B]\underset{\sim}{X}_t = \underset{\sim}{a}_t \tag{9}$$

where $\underset{\sim}{X}_t = (PP_t,\ BP_t,\ BRP_t,\ DPI_t,\ PH_t)$, $N = 64$, and

$$\Phi_1 = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & .25 & 0 & 11.2 \\ & & (.11) & & (3.41) \\ 0 & 0 & .04 & 0 & 0 \\ & & (.01) & & \\ -.01 & 0 & 0 & 0 & 0 \\ (.003) & & & & \end{bmatrix} .$$

Standard errors are in parentheses.

The time series (variables) suggested by equations (1) and (2) were used as the initial series in each multivariate model. The forecasts generated by the multivariate cattle and multivariate hog models were seasonalized before being reported in Tables 1 and 3, respectively.

FORECAST RESULTS AND PERFORMANCE EVALUATION

Steer price and hog price forecasts generated by the PFSM team's single equation econometric demand models (equations 1 and 2, respectively) serve as the norm for comparing the alternative forecasting models examined in this study and their respective price forecasts. Five four-period quarterly *ex post* forecasts and their associated RMSEs for live cattle prices (choice steers Omaha, $/CWT) and live hog prices (barrows and gilts, seven states, $/CWT) are reported in Tables 1 and 3 respectively, along with actual steer prices (hog prices) over the eight quarter forecast horizon.[5] Estimates are in constant-value dollars.[6] The first four-quarter forecast sequence reported in Table 1 (Table 3) is for the interval 8101 through 8104. The last four-quarter forecast sequence reported covers quarters 8201 through 8204. After receipt of new quarterly data, each forecasting model was reestimated and a new (updated) four-quarter ex post forecast interval was generated.

The RMSE results (Table 1) indicate that among cattle price forecast techniques examined, the ARMA model performed best over every four-quarter forecast interval. The ARIMA model always performed second best. A comparison of the composite, econometric, and transfer function noise model forecasts reveals that the simple average composite model outperformed both the econometric and the transfer function noise models. Of these two remaining techniques neither clearly outperformed the other, so which technique performs the poorest is inconclusive. For both of these latter two techniques, the forecast error increased each forecast interval.

Table 3 reports RMSE results for the various hog price forecast techniques. The ARIMA model and the composite model each had the lowest RMSE twice. For the forecast interval 8101-8104, the econometric model performed the best. None of the techniques seemed to perform susbtantially worse than any other.

Tables 2 and 4 summarize forecasting performance with respect to directional accuracy; that is, the ability of the forecast models to predict turning points. A turning point occurs if actual prices increase (decrease) one quarter, then decrease (increase) the next. Price increases (decreases) two quarters in a row indicate no change in price direction. Directional accuracy among forecast model choices is compared with each four-quarter forecast interval. Consequently, at a maximum, an actual change in price movement could be forecast correctly only twice within a forecast interval. Each observed price change that is correctly forecast adds an increment to the upper left-hand element of each 2x2 matrix in Table 2 (4). Likewise, if no change is predicted or observed, the lower right-hand element of each 2x2 matrix increases incrementally. High directional performance for each alternative forecasting technique is associated with larger numbers on the positive diagonal of each 2x2 matrix while high off-diagonal numbers suggest poor tracking performance. Examination of Table 2 (cattle prices) reveals that the econometric, composite, and transfer function noise models performed better than the multivariate and ARIMA techniques on average. The ARIMA model performed poorest. The first three techniques performed equally well.

Examination of Table 4 indicates that with respect to hog price forecasts, the ARIMA approach performed best with respect to directional accuracy while the ARMA technique was the poorest predictor of turning points. The three remaining techniques performed nearly equally.

SUMMARY AND CONCLUSIONS

The conclusions that follow are specific to the data used and the time period studied. Therefore, generalization of the conclusions herein to other data, time periods, and forecast horizons is cautioned. The purpose of this study was to compare the performance of the Price Forecasting and Sales Management group's single equation econometric demand models for live cattle and live hogs with alternative models for forecasting these price series. The alternative forecasting methods examined were univariate Box-Jenkins, a composite model approach, and two integrated techniques, serial correlation regression and multivariate time series. Forecast performance was compared among the various techniques by examining the RMSEs and turning point accuracy.

With respect to RMSE and cattle prices, the ARMA and ARIMA methods substantially outperformed the other forecast techniques. Between these two methods, the ARMA model performed best over each forecast interval. In the case of hogs, no technique clearly outperformed all other forecast techniques. When turning point accuracy of each model was evaluated, the models that showed the lowest RMSEs did not necessarily predict turning points best. In the case of hogs, the ARIMA model performed best in predicting turning points, but had the lowest RMSEs over only two forecast intervals. For cattle, the two techniques that forecast prices most accurately, the ARMA and ARIMA methods, performed poorest when predicting turning points.

Several results seem inconsistent, at least in part, with expectations formed from theoretical considerations. Theory suggests that by combining time series analysis and regression analysis, better forecasts will result than if either technique is used alone. In this study, the transfer function noise method that integrated econometric and time series analysis did not perform as well as both individual techniques. This applies to cattle and hogs. The ARIMA models outperformed the transfer function noise models except for one forecast interval. The transfer function noise models and the econometric models performed about equally well. What might explain the performance of the serially correlated econometric models?

For cattle, the PFSM team's single equation demand model likely is misspecified The misspecification could be due to 1) the omission, or 2) the inclusion of irrelevant variables, or 3) autocorrelated residuals. In this study the econometric model was only corrected for autocorrelated errors. It seems possible in light of the poor performance of equation (1) after correction for serial correlation (equation 5) that the PFSM team's structural demand model contains irrelevant variables or omits relevant variables. Some suggest that consumer demand for beef shifted in 1981, and this phenomonon might explain a large part of the poor forecast performance of equations (1) and (5). The question now is whether there will be a return to earlier spending patterns or whether consumer demand will remain depressed or get even worse. In light of these observations, this study could be extended by respecifying the structural demand model. A respecified structural demand model may well forecast better both with and without correction for serial correlation.

When we consider the performance of the serially corrected regression models together, we cannot ignore the computational limitations imposed by the TROLL regression program used to estimate the respective predictive models. As discussed earlier, it was not possible to consider several likely specifications for the respective error processes. Consequently, the serially corrected statistical models reported herein and used as predictive models might not be "truth." A regression routine that retains the property of being able to simultaneously estimate all model parameters and is able to accommodate mixed (ARMA) processes and high order processes could possibly alleviate at least some of the performance problems associated with the serially corrected regression models.

Another result that should be noted is the performance of the composite models. From the theoretical concepts supporting the composite forecasting approach, it would be expected that the performance of individual forecasting methods could be improved by combining the forecasts from individual approaches. The RMSE performance criterion applied in this study is, by and large, not consistent with this hypothesis. The composite models were simple average models that equally weighted the forecasts from the ARIMA and econometric methods. The composite models' forecasts outperformed the econometric models' forecasts over every forecast sequence except one, but only performed better than the ARIMA models over three forecast intervals. When the "equal weights" procedure is considered along with the relatively poor forecast performance of the econometric method, the results are not surprising. For forecasters not constrained by the availability of historical forecasts (as we were here), they might want to consider other composite forecasting methods that use different weighting criteria.

The results of this forecast performance evaluation suggest that for the near-term, the PFSM team should possibly use the ARIMA models for short-term, four-quarter forecasts, particularly in the case of cattle. Unfortunately, the cattle ARIMA model does not forecast turning points well. Although the ARMA models perform relatively well with respect to RMSEs and the other forecasting alternatives, their estimation is computationally burdensome and costly. For this reason, we currently would not suggest their use, particularly in light of how well the ARIMA models perform which are not nearly so computationally burdensome or costly. However, as less costly and cumbersome multivariate time series programs become available, the PFSM team might want to reconsider the ARMA technique.

In the longer-term, the PFSM team might experiment with respecifying the structural component of their single equation demand models, particularly for cattle. After that, the serially corrected regression method or the composite method may hold promise as a forecasting technique.

Table 1. Live Cattle Price Forecasts from Alternative Forecasting Techniques

Period[a]		Actual	Technique				
			Individual		Composite	Integrated	
Year	Quarter	Prices[b]	ECON[c]	ARIMA[d]	SA[e]	SCR[f]	ARMA[g]
			1972 $/CWT				
1981	1	$32.95	$37.49	$35.95	$36.72	$37.72	$36.61
	2	34.90	38.79	35.32	37.06	39.06	35.51
	3	34.01	39.20	35.90	37.55	39.24	33.54
	4	30.08	36.01	34.82	35.42	36.36	31.95
	RMSE[h]		4.95	2.97	3.87	5.17	2.09
1981	2	34.90	38.25	33.24	35.75	38.20	35.98
	3	34.01	38.73	33.82	36.28	38.44	33.40
	4	30.08	35.48	32.74	34.11	35.65	31.91
1982	1	31.11	39.81	31.99	35.90	39.48	30.79
	RMSE		5.88	1.63	3.36	5.74	1.12
1981	3	34.01	38.15	34.72	36.43	38.11	33.58
	4	30.08	35.15	33.64	34.40	35.42	31.85
1982	1	31.11	39.40	32.88	36.14	39.21	30.77
	2	34.21	40.00	33.29	36.65	39.85	33.56
	RMSE		6.02	2.07	3.73	5.98	.98
1981	4	30.08	34.85	33.69	34.27	35.13	31.86
1982	1	31.11	38.98	32.93	35.96	38.84	30.77
	2	34.21	39.26	33.35	36.31	39.40	33.56
	3	30.78	37.08	33.04	35.06	37.04	33.00
	RMSE		6.12	2.36	3.99	6.15	1.47
1982	1	31.11	38.68	30.11	34.40	38.49	31.04
	2	34.21	38.99	30.52	34.76	39.19	33.55
	3	30.78	36.86	30.21	33.54	36.87	32.90
	4	27.98	35.82	29.13	32.48	35.50	28.64
	RMSE		6.68	2.02	3.12	6.57	1.16

a/ Forecasts are reported in four quarter groupings to reflect the Price Forecasting and Sales Management (PFSM) team's procedure of generating a four-quarter forecast and then updating their forecasts each quarter as new data become available.

b/ Average of three monthly prices of choice Omaha steers. USDA Livestock and Meat (Poultry) Outlook and Situation.

c/ Econometric model (equation 1).

d/ Autoregressive-integrated-moving average model (equation 3).

e/ Composite of econometric and ARIMA methods - simple average method.

f/ Serial correlation regression model (equation 5).

g/ Multivariate time series model (equation 8).

h/ $$\text{RMSE} = \left[\frac{1}{n} \sum_{t=1}^{n} (F_t - A_t)^2 \right]^{1/2}$$

where F = forecasted steer price time period "t",
A = actual steer price time period "t",
n = number of quarters simulated (4).

Table 2. Turning Point Errors Within Forecast Intervals for Evaluating Directional Accuracy of Live Cattle Price Model Forecasts[a]

Forecast Interval			Model Choice[c]									
Year/Quarter	Movements[b]		ECON		ARIMA		COMP		SCR		ARMA	
			C	NC	C	NC	C	NC	C	NC	C	NC
(8101 - 8104)	Actual	C	0	1	0	1	0	1	0	1	0	1
		NC	1	0	1	0	1	0	1	0	0	1
			C	NC	C	NC	C	NC	C	NC	C	NC
(8102 - 8201)	Actual	C	1	0	0	1	1	0	1	0	0	1
		NC	1	0	1	0	1	0	1	0	0	1
			C	NC	C	NC	C	NC	C	NC	C	NC
(8103 - 8202)	Actual	C	1	0	0	1	1	0	1	0	0	1
		NC	0	1	1	0	0	1	0	1	1	0
			C	NC	C	NC	C	NC	C	NC	C	NC
(8104 - 8203)	Actual	C	1	0	1	0	1	0	1	0	1	0
		NC	0	1	1	0	0	1	0	1	1	0
			C	NC	C	NC	C	NC	C	NC	C	NC
(8201 - 8204)	Actual	C	1	0	1	0	1	0	1	0	1	0
		NC	0	1	0	1	0	1	0	1	0	1

Note: Table adapted from Brandt and Bessler, p. 138.

[a] A turning point is defined as such: if actual prices increase (decrease) one quarter, then decrease (increase) the next, a turning point (change in direction) is observed. Price increases (decreases) two quarters in a row suggest no change in direction.

[b] The measures indicate a change (C) or no change (NC) in the direction of the price movement. High directional accuracy performance is associated with larger numbers on the positive diagonal of each 2x2 matrix.

[c] See table 1 for model definitions.

Table 3. Live Hog Price Forecasts from Alternative Forecasting Techniques

Period[a/] Year	Quarter	Actual Prices[b/]	Technique: Individual ECON[c/]	ARIMA[d/]	Composite SA[e/]	Integrated SCR[f/]	ARMA[g/]
			1972 $/CWT				
1981	1	$23.15	$25.18	$27.73	$26.46	$24.99	$25.85
	2	21.33	21.19	26.94	24.07	22.18	22.46
	3	25.88	26.42	30.44	28.43	28.45	23.20
	4	23.09	24.00	28.24	26.12	24.33	25.39
	RMSE[h/]		1.15	4.99	2.65	1.75	2.29
1981	2	21.33	21.07	22.35	21.71	21.37	22.19
	3	25.88	26.32	25.85	26.09	28.12	23.15
	4	23.09	23.89	23.65	23.77	23.64	25.34
1982	1	22.38	26.86	23.45	25.16	26.57	22.17
	RMSE		2.29	0.79	1.45	2.39	1.82
1981	3	25.88	26.44	24.83	25.64	27.96	24.43
	4	23.09	23.98	22.63	23.31	23.54	25.17
1982	1	22.38	26.95	22.43	24.69	26.46	22.19
	2	25.96	25.71	25.09	25.40	25.44	21.62
	RMSE		2.35	0.72	1.20	2.32	2.51
1981	4	23.09	22.93	23.68	23.31	23.46	25.04
1982	1	22.38	26.71	23.48	25.10	26.34	22.25
	2	25.96	25.34	26.14	25.74	25.30	21.64
	3	29.35	30.51	26.75	28.63	29.96	28.62
	RMSE		2.26	1.44	1.42	2.04	2.40
1982	1	22.38	26.72	22.89	24.81	26.36	23.35
	2	25.96	25.35	25.55	25.45	25.32	21.38
	3	29.35	30.52	26.16	28.34	29.97	28.62
	4	27.64	30.01	25.57	27.79	29.57	28.70
	RMSE		2.56	1.93	1.34	2.25	2.43

a/ Forecasts are reported in four-quarter groupings to reflect the Price Forecasting and Sales Management (PFSM) team's procedure of generating a four-quarter forecast and then updating their forecasts each quarter as new data become available.

b/ Average of three monthly prices of barrows and gilts, seven states. USDA Livestock and Meat (Poultry) Outlook and Situation.

c/ Econometric model (equation 2).

d/ Autoregressive-integrated-moving average model (equation 4).

e/ Composite of econometric and ARIMA models - simple average method.

f/ Serial correlation regression model (equation 6).

g/ Multivariate time series model (equation 9).

h/ $$\text{RMSE} = [\frac{1}{n}\sum_{t=1}^{n}(F_t - A_t)^2]^{1/2}$$

where F = forecasted hog price time period "t",
A = actual hog price time period "t",
n = number of quarters simulated (4).

Table 4. Turning Point Errors Within Forecast Intervals for Evaluating Directional Accuracy of Live Hog Price Model Forecasts[a]

Forecast Interval Year/Quarter	Movements[b]		ECON		ARIMA		COMP		SCR		ARMA	
			C	NC	C	NC	C	NC	C	NC	C	NC
(8101 - 8104)	Actual	C	2	0	2	0	2	0	2	0	1	1
		NC	0	0	0	0	0	0	0	0	0	0
			C	NC	C	NC	C	NC	C	NC	C	NC
(8102 - 8201)	Actual	C	1	0	1	0	1	0	1	0	0	1
		NC	1	0	0	1	1	0	1	0	1	0
			C	NC	C	NC	C	NC	C	NC	C	NC
(8103 - 8202)	Actual	C	0	1	1	0	0	1	0	1	0	1
		NC	1	0	0	1	1	0	1	0	1	0
			C	NC	C	NC	C	NC	C	NC	C	NC
(8104 - 8203)	Actual	C	0	1	1	0	0	1	0	1	0	1
		NC	1	0	0	1	0	1	1	0	1	0
			C	NC	C	NC	C	NC	C	NC	C	NC
(8201 - 8204)	Actual	C	1	0	1	0	1	0	1	0	0	1
		NC	1	0	0	1	0	1	1	0	1	0

Model Choice[c] spans ECON, ARIMA, COMP, SCR, ARMA.

Note: Table adapted from Brandt and Bessler, p. 138.

[a] A turning point is defined as such: if actual prices increase (decrease) one quarter, then decrease (increase) the next, a turning point (change in direction) is observed. Price increases (decreases) two quarters in a row suggest no change in direction.

[b] The measures indicate a change (C) or no change (NC) in the direction of the price movement. High directional accuracy performance is associated with larger numbers on the positive diagonal of each 2x2 matrix.

[c] See Table 3 for model definitions.

FOOTNOTES

[1]Serial correlation regression is classified as a special case of the transfer function method following the arguments of Pindyck and Rubinfeld (pp. 593-595).

[2]Failure to simultaneously estimate all of the parameters can lead to loss of efficiency. The serial correlation regression program used to simultaneously estimate all model parameters was the regression module, Ordinary Least Squares with Serial Correlation Correction and Optional Distributed Lag Procedures (SCC), which is an appendant to the TROLL applied econometrics computer program. Unfortunately, the time series part of the SCC routine can only accommodate AR or MA processes - not mixed (ARMA) processes. Furthermore, the p or q order cannot be greater than 2. Due to these computational limitations, it was impossible to specify mixed (ARMA) processes for the time series part of the serial correlation regression model or AR (p) or MA (q) processes greater than order 2.

[3]An ARMA (1,1) process also seemed a likely candidate for the error process generated by subtracting the estimated values of PC_t from the actual values (equation 1). However, for the reasons outlined in footnote 2, it was not possible to test the appropriateness of this particular specification. Therefore, the statistical model (equation 5) and the forecasts generated by this model (see Table 1) may not be "truth."

[4]Given the computational limitations of the serial correlation regression package used for model estimation (see footnote 2), the second order moving average process was the best specification among available choices. Again, we caution that the statistical model (equation 6) and the forecasts generated by this model (see Table 3) may not be "truth."

[5]Although the PFSM group generates both _ex ante_ and _ex post_ forecasts, only _ex post_ forecasts are generated and reported herein. _Ex ante_ forecasts require that the forecaster first forecast current exogenous variable values before forecasting the dependent variable. Such a procedure is likely to increase forecast error (which is indeed the experience of the PFSM group). Since this paper focuses on forecasting techniques and forecasting performance, it is assumed that the method providing the best forecast would do so whether explanatory variable values are forecasted or represent actual values. However, this assumption may not always hold (Kulshreshtha, _et al._, p. 56).

[6]Reporting forecasts in constant or nominal dollars does not alter comparative results; only absolute values of forecasts are affected.

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