Short-Run Forecasting Models of Beef Prices

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This paper reports on the development of autoregressive-integrated-moving-average (ARIMA) forecasting models for selected cattle price series and the nearby live cattle futures price. The ARIMA models are fitted to weekly data by employing the Box-Jenkins time series modeling procedure. Relatively accurate short-run forecasts are obtained with the estimated models, with the Midwest price models performing better than Northwest price models, and the nearby futures model being considerably more accurate for longer forecasting horizons.

A major characteristic of agricultural markets in the past decade is the volatile nature of their prices. Livestock prices have been affected by many diverse factors; for example, cyclical building and depletion of herds, unprecedented changes in feed prices, droughts, blizzards, consumer boycotts, and seasonal factors of supply and demand. Some of these events may occur randomly and only once during a person's lifetime, while others may be cyclical in nature. Regardless of the circumstances, forecasting beef prices, especially on a weekly basis, is not usually an easy process.

However, the importance of price forecasting, especially in times of increased uncertainty, is obvious when one considers the production, investment, and marketing decisions which must be made by producers, processors, and suppliers in the beef trade. Many forecasting methods are discussed in the livestock literature, [Helmers and Held; Nelson and Spreen], but to be effective, the specific techniques must be tailored to fit the requirements and set of resources that are unique to an individual firm, researcher, or both.

The broad range of alternative forecasting methods offers a wide degree of flexibility in determining a particular forecasting system. Some of the more specific criteria to consider in developing a forecasting system include: 1) Choose the simplest, least cost methods available to deliver the degree of accuracy desired. The forecasting system must fit the data and the personnel involved. 2) The planning period needs to be specified before the forecasting technique is chosen. The methods used to project next week's price may be very different from those needed to project next quarter's price. 3) Avoid unnecessary detail. Each specific forecasting purpose will dictate the needed data. 4) Provide a system to check the accuracy of the forecast. This process should reveal any biases in a forecasting technique.

The specific purpose of this paper is to investigate the potential of a relatively new time series analysis technique, namely the Box-Jenkins autoregressive-integrated-moving-average (ARIMA) technique, in the development of weekly forecasting models for various cattle prices. More specific objectives are to develop alternative short-run forecasting models, based exclusively on time

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series for cash-cattle and futures prices, and to test the accuracy of these models for various short-run forecasting horizons.

ARIMA Models

Various techniques have been used to forecast cattle prices. Several researchers have developed econometric models of various livestock markets and then employed these models in forecasting [Hayenga and Hacklander; Langemeier and Thompson; Reutlinger]. Forecasting prices with econometric models requires forecasts of the relevant exogenous and lagged endogenous variables. While forecasts of lagged endogenous and exogenous variables can be obtained in a recursive manner, forecasts of exogenous variables often present problems for econometric model users.

An alternative price-forecasting procedure is the specification and estimation of ARIMA models as presented by Box and Jenkins. ARIMA models may be called self-determining since they are based upon current and past observations of the particular data series in question and no exogenous variables are included. Thus, causal structures implied by economic theory are not included in univariate ARIMA models. For this reason, the authors are not suggesting that ARIMA models should replace traditional econometric models; rather, they should be considered as a supplementary forecasting procedure.

Several authors have recently applied the Box-Jenkins procedure to selected data series. Examples include Leuthold, et. al., to hog prices, Rausser and Oliveira to recreation data and, most recently, Oliveira, Buongiorno and Kmiotek to lumber prices. The findings of these studies suggest the potential benefits of applying this technique to forecasting cattle prices. Before going into the results of this application, however, the basic elements of the ARIMA model will be outlined. More detailed discussions of the ARIMA procedures can be found in Nelson or Box and Jenkins.

The ARIMA model is based exclusively upon the past behavior of the data series of interest and, as the name implies, upon autoregressive (AR) and moving average (MA) models, which are a "powerful" class of stationary time series models useful in describing a wide variety of stationary time series variables.[1] Independently, the AR model is defined as

$$(1) \quad Z_t = \Phi_1 Z_{t-1} + \Phi_2 Z_{t-2} + \cdots + \Phi_p Z_{t-p} + a_t,$$

where Z_t is a finite linear sum of its past values; a_t is a random shock or white noise term assumed to be independently and identically distributed $N(0, \sigma^2)$; Φ_i, $(i = 1, \cdots, p)$ are the parameters of the model; and Z_t is assumed to be stationary.

The MA model is defined as

$$(2) \quad Z_t = \Theta_o + a_t - \Theta_1 a_{t-1} - \ldots - \Theta_q a_{t-q},$$

where Z_t is linearly dependent upon the weighted sum of the current and past values of the random shock series; the Θ_j, $(j = 1, \ldots, q)$ are the moving average parameters; and Θ_o indicates a constant trend pattern within the data. In economic applications Θ_o is often assumed to be zero, thereby preventing forecasts from increasing regardless of the behavior of the series.

AR and MA models may also be extended to analyze nonstationary time series by the use of successive differencing of a suitable degree or by expressing the series in terms of logarithms. For example, if the series Z_t is reduced to stationarity by incorporating a differencing of degree one, i.e., $\Delta Z_t = Z_t - Z_{t-1}$, the AR model (1) can be written in the form

$$(3) \quad \Delta Z_t - \Phi_1 \Delta Z_{t-1} - \ldots - \Phi_p \Delta Z_{t-p} = a_t.$$

[1]A stationary series is said to "have a mean and variance that do not change through time, and the covariance between values of the process at two time points will depend only on the distance between these time points and not on time itself," [Granger and Newbold, p. 4]. In other words, the generating mechanism or filter of a stationary process is time-invariant.

The process of transforming a nonstationary series to a stationary one is signified by the word "integrated" in the ARIMA model.

Combining the AR and MA models, assuming the appropriate degree of differencing is one, and omitting the trend parameters, we may express Z_t in the form of a general ARIMA model as follows:

$$(4) \quad \Delta Z_t - \Phi_1 \Delta Z_{t-1} - \ldots - \Phi_p \Delta Z_{t-p} = a_t - \Theta_1 a_{t-1} - \ldots - \Theta_q a_{t-q}.$$

Conventionally, the ARIMA model is expressed in a more summary fashion using the backward shift operator B, where $B^d Z_t = Z_{t-d}$, $(1-B)Z_t = \Delta Z_t = Z_t - Z_{t-1}$, and $(1-B)^d Z_t = Z_t - Z_{t-d}$. Therefore, assuming the necessary degree of differencing is d, the general ARIMA (p,d,q) model may be expressed as[2]

$$(5) \quad (1 - \Phi_1 B - \Phi_2 B^2 - \ldots - \Phi_p B^p)(1 - B)Z_t = (1 - \Theta_1 B - \Theta_2 B^2 - \ldots - \Theta_q B^q)a_t.$$

In order to "fit" an ARIMA model to a data series, one should have at least 50 and preferably over 100 observations. Given this data requirement, the procedure for modeling a data series with the general ARIMA form consists of a three-step sequence. (1) *Model Identification:* Having duly concluded that time series analysis is appropriate for the sample data, the alternative process (AR, MA, ARMA, or ARIMA) which generates the data series must be identified. Identification entails a comparison of the sample autocorrelation values and sample partial autocorrelation values with the known values for various theoretical ARIMA models. (2) *Parameter Estimation:* From a nonlinear least squares algorithm the maximum likelihood estimates of the parameters are calculated for the tentatively selected model. (3) *Diagnostic Confirmation:* If the original data series has been correctly modeled, the estimated residual series should then be reduced to a "white noise" series as defined in (1). One can employ the sum of the residual autocorrelations in a chi-square test statistic to see if the residual series is "close" to white noise. If the estimated residual series does not appear to be white noise or if some parameters are insignificant, steps (1), (2), and (3) are repeated as needed. After this modeling sequence, the resulting model may then be used for forecasting.

[2]A more general ARIMA model may also contain seasonal differencing, i.e., $(1 - B^s)^D$, where s = order of the season difference and D = the number of seasonal differences.

Cattle Price ARIMA Models

The data set for this study consisted of weekly observations for six cattle cash-market price series and the Chicago Mercantile live-cattle nearby futures price series. Descriptions and sources for the series are given in Table 1. The sample or estimation period for the weekly price series was from January 1972 through December 1976, resulting in 260 observations. The test, or forecast period was January 1977 to August 1977, resulting in 32 post-sample period observations.

The final ARIMA models selected for the various price series are presented in Table 2, along with the approximate standard errors of the estimated coefficients and the standard error of the estimates, σ_a. This latter statistic, which is actually the sample standard deviation for the estimated residual series, is one indication of how well each model "fits" the observations over the sample period. The relative standard error, i.e., σ_a, divided by the sample mean of the price series, gives a comparison of the accuracy of each model relative to the mean price. Another accuracy measure is the sum of squared residuals divided by the degrees of freedom for estimation. Also presented in Table 2 is a chi-square statistic for testing the hypotheses that the residual series of the ARIMA model has been reduced to "white noise."

As one would expect, the Box-Jenkins ARIMA model fitting procedure often results in more than one acceptable model for a given time series. Three criteria were used to select the final models shown in Table 2: (a)

TABLE 1. Identification of Data Series[a]

Abbreviation	Series Title and Description
NW Steer	Northwest steer cash price; weekly average in dollars per 100 pounds (900-1,100 pounds, F.O.B. feedlot, 4 percent shrink, average of Washington, Oregon, and Idaho). SOURCE: Federal-State Market News Service, Livestock Division, USDA.
NW Heifer	Northwest heifer cash price; weekly average in dollars per 100 pounds (900-1,100 pounds, F.O.B. feedlot, 4 percent shrink, average of Washington, Oregon, and Idaho). SOURCE: Federal-State Market News Service, Livestock Division, USDA.
NW Feeder	Northwest feeder cash price; weekly average in dollars per 100 pounds (600-700 pounds, Portland auction market). SOURCE: USDA Agricultural Marketing Service, Livestock Division.
Omaha Steer	Omaha steer cash price; weekly average in dollars per 100 pounds (F.O.B. Omaha, Choice, 2-4 yield, 900-1,100 pounds). SOURCE: Livestock-Meat-Wool Market News, Weekly Summary and Statistics, USDA.
Omaha Heifer	Omaha heifer cash price; weekly average in dollars per 100 pounds (F.O.B. Omaha, Choice, 2-4 yield, 900-1,100 pounds). SOURCE: Livestock-Meat-Wool Market News, Weekly Summary and Statistics, USDA.
K.C. Feeder	Kansas City feeder cash price; weekly average in dollars per 100 pounds (F.O.B. Kansas City, Choice, 600-700 pounds). SOURCE: Livestock-Meat-Wool Market News, Weekly Summary and Statistics, USDA.
Near Futures	Nearby fat cattle futures price; weekly closing price in dollars per 100 pounds, nearby live futures contract, Chicago Mercantile Exchange. SOURCE: Chicago Mercantile Exchange Yearbook, Market News Department, Chicago.

[a]The estimation data consisted of weekly observations for the period Jan. 8, 1972 - Dec. 25, 1976. The forecasting (or post sample) data was for the period Jan. 1, 1977 - Aug. 6, 1977.

low standard error of the estimates implying a good fit over the sample period, (b) significance, in terms of an approximate t-test, of most coefficients at the 95 percent confidence interval, and (c) as few coefficients as possible ("parsimony" rule). In many cases, some relatively less parsimonious models were maintained to test if gains in forecasting accuracy could be obtained with these "larger" models.

If one employs σ_a or the relative standard error as a criterion for choosing between models, it is evident from Table 2 that larger models (in terms of the number and order of parameters) do not necessarily perform better. For instance, Model 2 for the Kansas City Feeder price gives the best fit of the four models listed. The addition of 2nd and 29th order AR terms in Model 4 did not result in a smaller relative sum of squared errors or a smaller σ_a. For other price series, however, the addition of higher order terms did result in a better fit, but the decrease in σ_a was usually not large.

During the initial stages of this analysis it was anticipated that the ARIMA models for comparable price series would be somewhat similar. For example, *a priori* it was expected that the ARIMA model for NW Feeder would be similar, in terms of order and estimated coefficients, to the resulting model for Kansas City Feeder. Obviously the models presented in Table 2 do not support these prior expectations. Apparently the Midwest cattle price series are characterized by different time series patterns than those for their Northwest counterparts.[3]

Forecasting Analysis

Post-sample period forecasts were made for forecasting horizons of 1, 4, 6, 8, 12, 16, 20, and 24 weeks. Forecasting origins, de-

[3]In order to explain these structural differences in time series, one would need to introduce explanatory variables and extend the analysis to dynamic regression (transfer function) models. For example, see Pierce.

fined as the point in time from which a forecast is made, were spaced at approximately monthly intervals throughout the post-sample period, resulting in eight forecasting origins. For example, from forecasting origin 3, which was observation 269 on February 26, 1977, 1-week, 4-week, · · ·, 24-week forecasts were made for each price series by employing the appropriate ARIMA model. As an illustration, the 95 percent forecast confidence limits for two forecast origins, along with the actual price series, are shown for Model Omaha Heifer.1 in Figure 1. The forecasting accuracy of each model was evaluated by computing the percentage error for different forecasting horizons. Then the mean absolute percentage errors for each model and forecast horizon were computed by averaging across the various origins. The mean absolute percentage errors for selected forecasting horizons are presented in Table 3.

The results presented in Table 3 indicate that more accurate forecasts were obtained with the Midwest price models. In other words, lower mean absolute percentage errors were obtained for all forecast horizons with the "best" Midwest price models. These results suggest a more consistent time series pattern in the Midwest price series relative to the Northwest series. One possible explanation is that the Pacific Northwest is a deficit fed-beef market, and a relatively small market for feeder calves relative to the Midwest.

It is also interesting to note that, compared to the cash series forecasts, the nearby futures forecasts were less accurate for very short-run horizons, but much more accurate for longer term horizons. Again, this result may suggest a more stationary and predictive nature of the nearby futures price series relative to the cash series. A tentative explanation for our findings is that the futures market may reflect a national market for live cattle rather than localized supply and demand conditions.

In order to assess the relative accuracy of the ARIMA models, forecasts were also computed for each series by using the following simple naive or no change model [Chisholm and Whitaker, Chapter 2]:

$$Z_{f,\, t+\ell} = Z_t, \tag{6}$$

where $Z_{f,\, t+\ell}$ is the forecast price for ℓ weeks ahead, and Z_t is the actual price for week t. In actuality, the ARIMA forecasts also may be called naive since they are based solely on historical values of variables to be forecast. Dent and Swanson have, in fact, labeled ARIMA models as being "super-sophisticated naive." Nevertheless, we consider model (6) to be relatively simple and naive compared to those models in Table 2. Model (6) requires no statistical analysis and assumes a constant time relationship across all lags. The forecasts obtained from (6) could also be obtained from a random walk model, which is defined as $Z_t - Z_{t-1} = a_t$ [Leuthold]. The mean absolute percentage forecasting errors for model (6) are shown in Table 3 for each series.

As indicated by Table 3, the forecasting ability of the naive model is as good as, and often superior to, that of the ARIMA models for the shorter forecasting horizons, i.e., 1-8 weeks.[4] For the 16- and 20-week forecast horizons, the ARIMA models are slightly more accurate in terms of mean absolute percentage errors. Obviously, a practitioner would need to weigh the cost of estimating the ARIMA models versus their small gain in accuracy over a simple naive model.

The potential usefulness of short-run time series forecasting models is illustrated with two examples. First, consider a feedlot owner facing a buying decision. He may forward contract for feeders now or speculate on the cash price two months (8 weeks) from now. Feedlot operators making 8-week forecasts with the above ARIMA models would have expected absolute errors of five and six percent for the Midwest and Northwest, respectively.

[4]In the opinion of the authors, these results should not be considered as evidence of random walks in cattle prices as discussed by Leuthold. Certainly the random walk model was not sufficient in terms of "fitting" the data series over the sample period. It appears, however, that the ARIMA models need to be altered for the post-sample period data.

TABLE 2. Estimated Univariate ARIMA Models

Series	Model[a]	χ^2(d.o.f.)[b]	$\sum a_t^2$/d.o.f.[c]	σ_a[d]	σ_a/μ[e]
NW Steer.1	$(1-B)Z_t = (1+.473B) + .344B^2)a_t$ (.06) (.06)	60.6 (38)	1.365	1.166	.028
NW Steer.2	$(1-.161B^{11})(1-B)Z_t = (1+.496B + .372B^2)a_t$ (.06) (.06) (.06)	54.4 (37)	1.394	1.176	.028
NW Steer.3	$(1 + .131B^6 - .167B^{11})(1-B)Z_t = (1+.490B + .346B^2)a_t$ (.06) (.06) (.06) (.06)	45.7 (26)	1.376	1.164	.028
NW Heifer.1	$(1 - .332B + .123B^3)(1 - B)Z_t = a_t$ (.06) (.06)	41.4 (38)	1.865	1.363	.034
NW Heifer.2	$(1-.322B)(1-B)Z_t = (1+.211B^{28})a_t$ (.06) (.06)	35.8 (38)	1.818	1.346	.033
NW Feeder.1	$(1-.141B)(1-B)Z_t = a_t$ (.06)	48.7 (39)	1.852	1.361	.039
NW Feeder.2	$(1-.127B + .132B^8)(1-B)Z_t = (1+.176B^{12})a_t$ (.06) (.06) (.07)	28.3 (37)	1.826	1.346	.039
NW Feeder.3	$(1+.151B^8 - .172B^{12})(1-B)Z_t = (1+.135B)a_t$ (.06) (.06) (.06)	26.7 (37)	1.847	1.353	.039
Omaha Steer.1	$(1-.949B)(Z_t-41.61) = (1+.182B^2)a_t$ (.02) (1.9) (.06)	32.7 (37)	1.751	1.318	.032
Omaha Steer.2	$(1-.169B^2)(1-B)Z_t = a_t$ (.06)	24.4 (29)	1.794	1.337	.032
Omaha Steer.3	$(1-B)Z_t = (1+.165B^2)a_t$ (.06)	24.6 (29)	1.785	1.333	.032
Omaha Heifer.1	$(1-.942B)(Z_t-40.28) = (1+.279B + .176B^2)a_t$ (.02) (1.9) (.06)	39.9 (37)	1.267	1.120	.028
Omaha Heifer.2	$(1-.300B)(1-B)Z_t = a_t$ (.06)	38.9 (39)	1.304	1.142	.029
Omaha Heifer.3	$(1-.296B + .170B^{15})(1-B)Z_t = a_t$ (.06) (.06)	32.6 (38)	1.322	1.148	.029
Omaha Heifer.4	$(1-.287B)(1-B)Z_t = (1-.169B^{15})a_t$ (.06) (.06)	34.0 (38)	1.275	1.127	.028

Continued

TABLE 2. Continued

Series	Model[a]	χ^2(d.o.f.)[b]	$\sum a_t^2$/d.o.f.[c]	σ_a[d]	σ_a/μ[e]
K.C. Feeder.1	$(1-.524B + .303B^2)(1-B)Z_t = a_t$ (.06) (.06)	51.0 (38)	1.006	1.001	.024
K.C. Feeder.2	$(1-B)Z_t = (1+.581B)a_t$ (.05)	48.7 (39)	0.990	0.995	.024
K.C. Feeder.3	$(1+.190B^{29})(1-B)Z_t = (1+.618B)a_t$ (.07) (.05)	28.7 (38)	1.028	1.012	.025
K.C. Feeder.4	$(1-.534B + .292B^2 + .162B^{29})(1-B)Z_t = a_t$ (.06) (.06) (.06)	34.62 (37)	1.047	1.018	.025
Near Futures.1	$(1-.95B)(Z_t - 42.5) = (1-.230B^5)a_t$ (.02) (1.7) (.06)	44.61 (37)	3.196	1.781	.042
Near Futures.2	$(1+.181B^{15})(1-B)Z_t = (1-.274B^5)a_t$ (.06) (.06)	31.74 (38)	3.319	1.818	.043
Near Futures.3	$(1-B)Z_t = (1-.257B^5)a_t$ (.06)	45.40 (39)	3.261	1.805	.043

[a]The numbers in parentheses below the coefficient estimates are the approximate standard errors.
[b]Chi-square statistics with the degrees of freedom given in parentheses.
[c]Sum of squared residuals divided by the degrees of freedom.
[d]Standard deviation of the estimated residual series.
[e]Standard deviation of the estimated residuals divided by the sample mean of Z_t.

TABLE 3. Mean Absolute Percentage Forecasting Errors for Selected Forecast Horizons[a]

	Forecast Horizon (weeks)				
Series & Model	1	4	8	16	20
NW Steer.1	1.24 (1.79)	3.99 (2.97)	5.03 (3.99)	7.95 (2.79)	10.41 (1.97)
NW Steer.2	1.13 (0.76)	4.69 (2.87)	5.85 (3.69)	7.77 (3.83)	10.24 (2.60)
NW Steer.3	1.16 (0.67)	4.72 (2.63)	5.54 (3.55)	7.77 (3.68)	10.09 (2.59)
NW Steer.N[b]	1.22 (1.00)	3.45 (2.58)	4.73 (3.70)	7.97 (3.45)	10.29 (1.48)
NW Heifer.1	1.50 (0.76)	4.51 (3.85)	5.82 (5.46)	9.24 (1.56)	8.69 (4.66)
NW Heifer.2	1.58 (0.98)	4.59 (4.91)	6.33 (6.89)	10.88 (4.64)	9.70 (5.51)
NW Heifer.N	1.47 (0.83)	4.15 (3.79)	5.62 (5.52)	9.27 (1.10)	9.00 (4.19)
NW Feeder.1	1.58 (1.23)	5.27 (4.22)	7.28 (4.65)	10.86 (1.36)	13.50 (0.76)
NW Feeder.2	1.89 (1.18)	5.25 (4.14)	5.93 (5.40)	9.76 (1.30)	12.17 (1.66)
NW Feeder.3	1.79 (1.18)	5.47 (4.11)	5.97 (5.63)	9.84 (1.45)	12.31 (1.75)
NW Feeder.N	1.59 (1.22)	5.37 (4.24)	7.23 (4.59)	10.87 (0.94)	13.35 (0.44)
Omaha Steer.1	1.31 (0.85)	4.42 (2.54)	5.02 (1.94)	3.11 (1.36)	2.52 (0.29)
Omaha Steer.2	1.21 (0.97)	3.20 (3.18)	5.42 (3.92)	6.07 (4.10)	6.20 (2.37)
Omaha Steer.3	1.20 (0.96)	3.17 (3.13)	5.40 (3.78)	6.03 (4.07)	6.15 (2.40)
Omaha Steer.N	1.22 (0.89)	3.24 (3.02)	5.35 (3.523)	5.98 (4.00)	5.89 (2.43)
Omaha Heifer.1	1.01 (0.73)	3.24 (2.24)	4.31 (1.74)	2.47 (1.78)	1.46 (0.96)
Omaha Heifer.2	0.97 (0.56)	2.98 (2.71)	4.78 (3.25)	6.22 (3.06)	6.49 (1.51)
Omaha Heifer.3	1.02 (0.54)	3.19 (2.82)	4.77 (2.90)	5.27 (3.50)	6.56 (0.84)
Omaha Heifer.4	1.00 (0.61)	3.12 (2.63)	4.58 (3.10)	5.57 (3.15)	6.42 (1.19)
Omaha Heifer.N	1.06 (0.66)	2.52 (2.68)	4.33 (3.20)	6.28 (3.15)	6.44 (1.23)

K.C. Feeder.1	1.01 (0.79)	4.11 (2.17)	6.07 (3.59)	6.81 (6.22)	7.89 (6.10)
K.C. Feeder.2	1.19 (0.88)	4.07 (2.54)	6.04 (3.76)	6.71 (6.25)	7.69 (6.52)
K.C. Feeder.3	1.31 (0.81)	3.41 (1.72)	4.74 (3.97)	5.10 (4.37)	5.42 (5.40)
K.C. Feeder.4	1.18 (0.68)	3.44 (1.76)	4.93 (3.34)	5.27 (4.32)	5.59 (5.30)
K.C. Feeder.N	1.35 (1.08)	4.54 (1.86)	6.21 (3.85)	6.84 (6.47)	8.14 (6.11)
Near Futures.1	3.39 (3.31)	5.86 (4.77)	6.37 (3.59)	2.13 (0.93)	3.58 (0.27)
Near Futures.2	2.00 (1.46)	5.73 (5.26)	6.18 (5.27)	3.60 (2.15)	3.87 (2.34)
Near Futures.3	1.58 (1.08)	5.88 (5.32)	6.97 (5.44)	4.21 (2.71)	4.27 (1.76)
Near Futures.N	1.55 (1.01)	5.67 (5.62)	7.70 (5.31)	4.58 (3.75)	4.88 (0.53)

[a]The numbers in parentheses are the sample standard deviations of the respective absolute percentage errors.
[b]The naive model for each series is denoted by an upper case N.

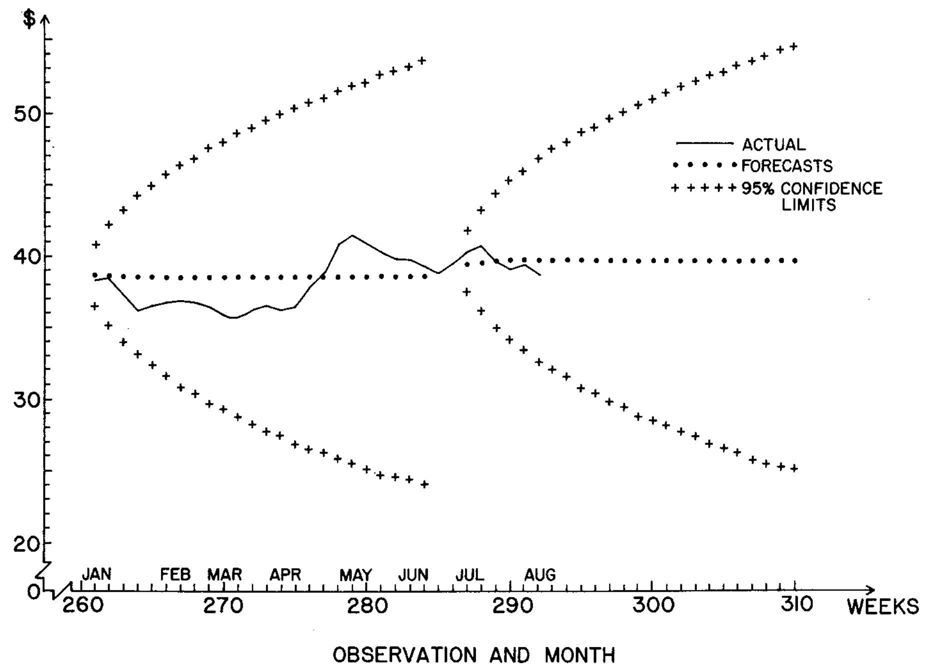

Figure 1. Omaha heifer cash series: Actual 1977 values and 24-week forecasts for selected forecast origins, December 25, 1976 and May 14, 1977.

Another example is a cow-calf operator choosing whether to sell a 400 pound feeder now or feed it five more months for sale at 600 pounds. If this feeder is in the Midwest, an ARIMA price forecast could be made with an expected absolute error of 5.5 to 7.5 percent. Alternatively, a Northwest feeder could expect a 12 percent absolute error. These two examples illustrate that the potential for error increases greatly as the forecast horizon increases, and that ARIMA models may differ in accuracy among regions. In reality, each decision-maker would also employ other information in making short-run forecasts and sale decisions. Thus, an obvious extension of these univariate models would be the development of mulitvariate time series, (i.e., transfer function) models for short-term price forecasting [Pierce].

Summary

Various ARIMA models were used to forecast prices for alternative forecasting periods. In general, the models for cash prices were relatively more accurate for shorter time horizons, and the forecasts for commodity future prices were more accurate for longer time horizons. In addition, there appeared to be little gain in accuracy from developing ARIMA models with more parameters or from using an ARIMA model instead of a naive model.

This analysis is based on data from 1972-1976 and forecasts for 1977. The primary data period (1972-1976) experienced several exogenous shocks, which included the impact of the Russian Grain Deal on prices and supplies of feed grain, and a significant adjustment of the national cow herd, creating a major shift in production and the beginning of a new cattle cycle. In addition, the validation portion of this analysis utilized eight monthly origins for forecasts. Weekly origins likely would have provided more accurate forecasts, but the management of such a system was too expensive for this analysis. Potential users of this forecasting technique should evaluate the results of this report in light of these conditions and their specific research needs and resources.

In light of the above analysis, what are the conclusions regarding ARIMA forecasting models? Once one has become familiar with the notation and model building procedure, ARIMA models are relatively easy to produce. Given the current availability of time series software at most major universities, an experienced practitioner can "fit" an ARIMA model within six computer "runs" for most series. As illustrated above, however, the models produced may not always forecast well. Thus, one is not advised to solely rely upon ARIMA model forecasts, but perhaps to combine these forecasts with those from an econometric model, as discussed by Rausser and Oliveira.

Since an econometric model was not employed in this paper, we cannot directly compare the forecasting abilities of our ARIMA models with those of a weekly beef econometric model. This type of comparison has been presented in detail for other data sets by Naylor, et. al., and Leuthold, et. al.[5] There is no clear consensus on the best forecasting technique. An appropriate conclusion is perhaps best obtained by quoting from Naylor, et. al., (p. 136):

> Of course, the forecasting and computational advantages of Box-Jenkins methods have to be weighed against their inherent shortcomings: (1) they are void of explanatory power; (2) they are not based on economic theory; and (3) they are essentially sophisticated smoothing techniques and not economic models.
>
> In summary, if one is primarily interested in forecasting, the Box-Jenkins methods may have considerable appeal. But there is some risk with Box-Jenkins methods. If they yield poor forecasts, we may be at a complete loss to explain "Why?", since they have no underpinnings in economic theory. Furthermore, if our goal is to "explain" the behavior of an economic system and not merely to grind out forecasts, then Box-

[5]Econometric and ARIMA forecasting models have also been compared by Nelson, Bechter and Rutner, Rausser and Oliveira, and Oliveira and Rausser. The latter two studies, however, do not present a true test of the econometric models since actual values of the exogenous variables were employed for the forecasts.

Jenkins methods may be totally unacceptable. Since they are void of economic theory, they cannot be used to test hypotheses and establish confidence intervals for complex economic phenomena.

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