ECONOMETRIC AND ARIMA MODELS
IN PREDICTING CATTLE AND HOG
PRICES: AN EVALUATION

by

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A Research Paper (Plan B)

Submitted to
Michigan State University
in Partial Fulfillment of the Requirements
for the Degree of

MASTER OF SCIENCE

Department of Agricultural Economics

1983
ACKNOWLEDGEMENT

I gratefully acknowledge the guidance, support, and encouragement which Warren H. Vincent gave me throughout my stay at Michigan State University as my major professor. His suggestions and sound advice were very useful in solving and overcoming the difficulties in most of my work as a student.

The generous help and support of John Ferris as my research supervisor is also acknowledged with grateful appreciation. His suggestions, directions and advice made the preparation of this paper a challenging one and a very useful learning experience.

The useful advice and help of Robert Gustafson, as a member of my research committee, and also the useful suggestions and advice of Lester Manderscheid, James Stapleton, Stanley Thompson and Jim Hilker are gratefully acknowledged.

To the scholarship committee and staff of the Integrated Agricultural Production and Marketing Project (KSU-AID) and the Philippine government, I extend deep appreciation for providing the necessary financial support for my 2-year training at Michigan State University.

The computer programming assistance of Chris Wolf and John Ross are also gratefully acknowledged. I also extend my appreciation to Sherry Rich for her patience in typing the draft of this paper.

And finally, to my family and friends who provided useful guidance and encouragement, and to Him who has been my guide and strength, I dedicate this piece of work.
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CHAPTER I

INTRODUCTION

Forecasting has been very important in decision making at all levels and sectors of the economy. In agriculture, where the decision environment is characterized by risks and uncertainty largely due to uncertain yields and relatively low price elasticities of demand of most commodities, decision makers require some information about the future and the likelihood of the possible future outcomes.

Forecast information serves many users. Farmer's production and marketing decisions, for instance, are often based on some perspective of the likely pattern of price movements over the coming year. Likewise, production prospects for the season are used by market intermediaries in coordinating their resources. Outlook information about production and consumption are also important in developing government price support programs.

Along with the variety of forecast users, there exists a wide range of available forecasting techniques. They range from a very simple trend extrapolation to a very complex system of structural equations and simulation models. Very often, these alternative approaches provide different forecasts of the same event. The forecast user, then must determine which of the set of forecasts to use, given his/her decision environment. After a choice has been made, the other forecasts are often discarded.

If the decision maker is offered alternative forecasts, an important question arises: What makes one forecast better than another? The answer to this question largely depends on the
definition of performance being used, the decision environment and the performance criteria which the forecast user chooses to employ. Empirical tests that evaluate the performance of alternative forecasting techniques in terms of accuracy measures provide different conclusions. For some specific commodity and time intervals, one approach may provide more accurate forecasts than another; while for some other commodities and a different time period, an opposite outcome results. (Bessler and Brandt, 1979 and Bourke, 1979.)

Jones (1980) suggests a principal criterion not based on accuracy but on usefulness of the forecasts for wise decision making. He asserts that the "worth of a forecast depends significantly on the extent to which it both manifests and evokes creative imagination in ways that enlarge planners' and decision makers' feasible options." Jones defines a better forecast to be one that contains new information that determines which responses are more appropriate than others. Further, a forecast based on "faulty data, untenable assumptions and dubious inferences" although it may be proven correct is considered inferior to an incorrect one but derived from better data, well-reasoned assumptions and inferences. A useful forecast is, therefore, one based on the best available data and theoretical information.

This paper aims to test the hypothesis that forecast performance is proportional to the information contained in the forecasting method. This is carried out through the evaluation of a forecasting approach which is a combination of annual and quarterly ratio econometric
models for cattle and hog prices.\textsuperscript{1} Such a combination is done to draw from the advantages of both annual models in estimating structural parameters and quarterly models which provide needed information for decision making.

Key Questions for the Study

1. How does a combination of annual and quarterly ratio econometric models perform in predicting cattle and hog prices?

2. How does the alternative forecasting models, namely: standard quarterly econometric models and autoregressive integrated moving average processes perform compared with the combined model in predicting the prices for the same period?

The Specific Objectives are as follows:

1. To generate quarterly ex-post price forecasts for cattle and hogs using combined annual-quarterly ratio econometric models.

2. To evaluate the price forecasts derived in (1) based on alternative performance criteria and compare it with forecasts based on other forecasting models such as:
   a. standard quarterly econometric model
   b. Box-Jenkins autoregressive integrated moving average processes (ARIMA models).

\textsuperscript{1}The basic procedure was initially developed by Geuze and Ferris (1979).
The organization of this paper is as follows: The relevant information about the different forecasting methods are reviewed in Chapter II. This includes the discussion of the estimation procedures, theoretical justifications and the limitations and advantages of each approach. Chapter III presents a review of related studies and a brief discussion about the theory of forecast evaluation. The model structure, specification and estimation results are then discussed in Chapter IV. Chapter V presents the results of the analysis and evaluation of the alternative forecasts. The final chapter gives the summary and conclusion as well as some recommendations for future research.
CHAPTER II

Review of Relevant Literature about the Selected Forecasting Methods: Theoretical Justification and Estimation Procedure

General Classification of Forecasts

Bessler and Brandt (1979) present four general types of forecasting models which are useful in commodity forecasting. They are based on two general classification schemes, namely: "structural or non-structural and mechanical or non-mechanical models". Price forecasts based on structural models reflect the knowledge about the demand and supply factors affecting the market for the commodity. On the other hand, non-structural forecasts are described as "purely empirical" which reflect the historical movements of the variable being forecast.

Forecasts derived from mechanical models are defined as those which do not contain "human intervention or judgement" while non-mechanical forecasts are the ones, which once derived, are adjusted based on the beliefs of the forecaster.

Based on this classification, the four types of forecasting models are: structural-mechanical; non-structural-mechanical; structural-non-mechanical; and non-structural-non-mechanical.

In practice, however, actual forecasts can fall into two or more of these classifications. Bessler and Brandt observe that often, forecasts derived from mechanical models are adjusted to reflect the beliefs and judgement of the forecaster. Further, the development of structural forecasts often involves the use of non-structural/mechanical forecasts of the exogeneous variables.
More complex forecasting approaches, however, may include structural forecasts of the exogeneous variables. Another classification of forecasts considers the value of the explanatory variables and other exogeneous variables. Under this classification, a forecast may either be an ex-post forecast or an ex-ante forecast. An ex-post forecast is derived by using actual values of both the endogeneous and exogeneous variables. Hence, it can be checked against existing data and provide a way to evaluate a forecasting model. An ex-ante forecast, on the other hand, is considered to be a "true forecast" because it is made before the event occurs. Hence, the values of the exogeneous variables included in the forecasting model are based on the forecaster's assumptions or other predictive functions.

Intriligator (1978) considers the usefulness of ex-post forecasts in situations where the analyst focuses on the explicitly estimated elements of the forecasts such as the estimated coefficients of the structural parameters. Further, errors due to faulty assumptions about the values of the exogeneous variables are eliminated in the development of ex-post forecasts. McKnees (1975) argues however, that the "subjective adjustment of ex-ante forecasts lends more to accuracy than ignorance of the actual values of the exogeneous variables detracts." Hence, they are more appropriate for descriptive forecast evaluation.

Although the above classifications do not provide clear cut boundaries among types of forecasts, they give a useful framework in classifying the forecasts to be analyzed in this study.
Specifically, "structural/mechanical" forecasts derived from the combined annual-quarterly econometric model and "non-structural/mechanical" forecasts from the autoregressive-integrated moving average processes of cattle and hog prices will be analyzed and evaluated. The structural/mechanical price forecasts are ex-post forecasts.

B. Selected Forecasting Methods

Econometric Approach

The econometric approach to forecasting involves the application of a theoretical framework based on the knowledge of economic theory and of the underlying relationships that hold for the commodity under consideration. Representations of these relationships are usually called econometric models or structural models. Price forecasts derived from these models reflect the supply and demand factors relevant to the commodity.

In specifying the model, the analyst determines whether a particular set of relationships can be identified and whether a set of equations is required to derive valid estimates. Similarly, the analyst determines whether equally reliable results can be derived using a single-equation approach. For prediction purposes, a set of simultaneous equations is usually transformed to the "reduced form".

Whether or not a single-equation method is sufficient and appropriate depends on the purpose of the analysis. If the analyst is mainly interested in generating price forecasts given the values of such variables as size of crop and consumer income, satisfactory estimates are usually obtained by least-squares regression with price dependent and other variables independent. The same equation may not, however, provide an unbiased estimate
of the elasticity of demand. An unbiased estimate of structural parameters from single equation models are only possible if and only if the explanatory variables are not measurably influenced by the price of the commodity during the marketing season. If this situation is not satisfied, a set of simultaneous equations is required to derive valid estimates of the structural parameters (Fox 1953).

After model formulation and estimation, another important step in economic forecasting involves the use of the researcher's subjective judgement, experience, and intuition. Interaction with other researchers and with persons who possess working knowledge of the relevant industry is suggested (Ferris, 1974). Forecasts based on econometric models are then adjusted to take account of new information. Models are also updated to include the most recent data in the analysis.

Another aspect of model formulation which is important in the present study relates to the time unit of analysis. Most analysis of factors that affect the price or consumption of a given commodity are based on annual data for either a calendar or crop year. Such an approach is considered to be relatively satisfactory if the conditions that prevailed within the period are sufficiently homogeneous (Foote, 1958). It is suggested that conditions in the shorter periods (quarterly or monthly)

---

2 This procedure leads to non-mechanical forecasts which, for evaluation purposes are not included in this study. More discussion on this will be given in Chapter III.
tend to be more homogeneous than the conditions for longer time units. Irregular and nonmeasurable factors, however, may offset the advantage of homogeneity. Foote (1958) generalizes in choosing the time-unit of analysis by taking one which is long enough such that irregular and nonmeasurable effects are averaged out and short enough so that the prevailing conditions in the period are relatively homogeneous. Since some of the influence on price variations in shorter run situations cannot be isolated in an annual time series analysis, price analyses using quarterly data are common.

While there is a valid argument embodied in each type of time-unit of analysis, it will be useful to explore the possibility of combining the information provided by these two types of analyses in order to better understand the situation being studied.

For estimation of structural parameters, an annual model is usually preferred because there are fewer problems of serial correlation in the residuals. For instance, a change in income in a given quarter can be argued to have a minimal immediate effect on demand for a product, but a year-to-year change in income may be significant in determining demand on an annual basis.

While forecasts of annual averages may prove sufficient for a broad range of managerial decisions, there is an extensive demand for forecasts relating to shorter intervals. This is evident from the large number of econometric models which are on a quarterly basis. Farmers' decisions in timing sales require some perspective on the likely pattern of price movement over the coming year. Supporters of the "intertemporal disaggregation" claim that price
analyses which involve data on a less than a year basis will contain less error due to bias and incorrect specification about causal directions.

Compared to annual models, however, standard quarterly models have inherent estimation and statistical problems, one of which relates to their relatively greater serial correlation in the residuals.

In order to draw from the advantages of both annual models in estimating structural parameters and quarterly models which provide needed information for decision making, the two types of models will be combined in forming a forecasting model for cattle and hog prices.

A simple yet quite adequate representation of the market structure for hogs and beef is given by Bessler and Brandt (1979). The theoretical model suggested incorporates three market levels: consumer demand at retail; marketing groups' supply for retail and demand at retail; marketing groups' supply for retail and demand for raw products and producers' supply at the farm level. The economic relationships are summarized in six equations as follows.³

\[
\begin{align*}
(1) \quad & (Q_d, P_r, Y, \bar{P}_r, Z_1) = 0 \\
(2) \quad & (Q_s, P_r, P_f, Z_2) = 0 \\
(3) \quad & (Q_f, P_r, P_f, Z_2) = 0 \\
(4) \quad & (Q_f, P_f, Z_3) = 0 \\
(5) \quad & Q_d = Q_s + CS - CS_{+1} \\
(6) \quad & Q_s = Q_f
\end{align*}
\]

where \( Q_d \), \( Q_s \), \( Q_f \) represent retail demand, retail supply and production at the farm level respectively; \( P_r \) and \( P_f \) are farm and retail prices.

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³Bessler and Brandt, Composite Forecasting of Livestock Prices: An Analysis of Combining Alternative Forecasting Methods, Station Bulletin No. 265, Purdue University, 1979.
prices; $Y$ represent per capita disposable income; $\bar{P}_r$, stands for the vector of prices of substitutes or complements; CS represents cold storage while $Z_1$, $Z_2$, $Z_3$ are exogeneous factors which influence demand behavior of the marketing agents and farm supply, respectively.

Equation (1) describes the set of factors affecting demand at retail level while equation (2) and (3) represent the relations that characterize the supply for retail provided by the marketing group, and the latter's demand for raw input, respectively. Equation (4), on the other hand, describes the set of factors affecting farm supply of the product. An identity relation between retail demand and supply and inventories is represented by equation (5). Finally, supply at the farm level is equated with demand for slaughter in equation (6).

Based on the above theoretical relationships, consumer demand is a function of major factors such as disposable income level, prices of related commodities and consumers preferences. Marketing intermediaries (e.g., packers, processors, and handlers) serve various functions such as moving the product through the market system and creating form and place utilities. Further, they reflect the consumer demand in the market through "price signals". For analyzing aggregate supply and demand factors affecting farm prices (current and future), the marketing firm is taken at the macro level where aggregate data is considered to represent average behavior of all firms.4

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4 Individual marketing firms are considered to be facing a single production function and maximizing under perfect competition.
For predictive purposes, the theoretical relationships shown in equations (1) to (6) are described in a single equation with the farm price ($P_f$) as a function of all endogenous and exogenous factors affecting demand for or supply of the product.

The present study focuses on the development and evaluation of quarterly demand forecasting models for cattle and hog prices. The theoretical models are based on the fundamental relationships describing the demand of these commodities. Since a complete analysis of demand for each commodity in terms of major end products is not feasible for purposes of the present study, aggregate measurements are employed. For instance, all beef is lumped together with the price variable measured in terms of USDA's cattle average farm price. Since the domestic production of beef and pork in any given year is largely predetermined by earlier decisions and since imports have been a function of largely predetermined factors such as world supplies of the commodity and government trade policies, the forecasting model developed using an econometric approach is formed in a single-equation demand relationship with price dependent. A more detailed description of the structural demand model is given in Chapter IV.

Box-Jenkins Methodology

Autoregressive Integrated Moving Average Processes (ARIMA)

Another approach to forecasting which has been applied recently in agriculture involves the formation of non-structural

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A simultaneous estimation is suggested by other authors for behavioral analyses and estimation of structural parameters. (Bessler and Brandt, Hayenga and Hacklander, Foote and others.)
mechanical forecasts based on Box and Jenkins ARIMA processes.\(^6\) Nelson (1973) provides a simple discussion on the theory behind the Box and Jenkins procedure to forecasting.

The primary concept\(^7\) in the analysis of time series involves the basic tools of probability theory. That is, the time series observations \(y_1, \ldots, y_N\) which are observed in discrete and equal time intervals \(1, \ldots, N\) are considered to be a set of random variables which are generated from a joint probability distribution \(P_1, \ldots, N(y_1, \ldots, y_N)\) where \(P(\cdot)\) defines the probability density function.

The information provided by the joint probability distribution is then used to formulate statements about the future values of the time series being analyzed. If the joint probability distribution for a time series consisting of \(N = T + 1\) values is known (that is, \(P_1, \ldots, T_1, y_1, \ldots, y_T\) is known) and the set of values \(y_1, \ldots, y_N\) have been observed, a "conditional distribution function" for the future value \(y_{T+1}\) denoted by \(P_{T+1}(\cdot, \ldots, y_T)\) can be formulated. The information given by the joint probability distribution about the relationship between \(y_1, \ldots, y_N\) and \(y_{T+1}\) is used to infer about the likelihood of occurrence of \(y_{T+1}\) after \(y_1, \ldots, y_N\) have been observed. Hence, the stochastic relationships describing the series \(y_1, \ldots, y_N\) is used to generate future values of the variable \(y\).

---


\(^7\) The notations used in this study follow those from Nelson (1973).
The concept of stationarity\(^8\) of the time series is important to operationalize the analysis in the forecasting exercise. With the condition of stationarity, certain simplifications about the joint probability distribution and the relationships describing the time series are achieved.

The joint probability distribution of a stationary time series is represented by \(P(Y_t, ... Y_{t+i}) = P(Y_{t+r}, ... Y_{t+i+r})\) where \(t\) defines the position of the observation in time, and \(i\) and \(r\) are any integers. The condition of stationarity has, therefore, simplified the joint probability distribution function as indicated by dropping the subscripts in the function.

If \(i\) is equal to zero, the distribution function then becomes \(P(Y_t) = P(Y_{t+r})\) which implies that the "marginal distribution function" for any two values in the series are equal. Given this condition, it can also be shown that the expected values and variances of any two observations in the series are the same.

If \(i\) is equal to 1, the joint probability distribution function can be written as

\[
P(Y_t, Y_{t+1}) = P(Y_{t+r}, Y_{t+r+1}).
\]

This implies that the covariances between \(Y_t\) and \(Y_{t+1}\) and between \(Y_{t+r}\) and \(Y_{t+r+1}\) are equal. These covariances are expressed as

\[
C(Y_t, Y_{t+1}) = C(Y_{t+r}, Y_{t+r+1}) = \gamma_1.
\]

---

\(^8\)A time series is considered to be stationary if the observations in the series fluctuate around a constant mean (\(\mu\)). In a strict sense, stationarity requires the joint probability distribution to be invariant with time. (Nelson, 1973 and Bowerman, 1979).
Likewise, for any two values separated by \( j \) periods, the probability distribution function is expressed as

\[
P(Y_t, Y_{t+j}) = P(Y_{t+r+j})
\]

The covariances of this is given as

\[
C(Y_t, Y_{t+j}) = C(Y_{t+r+j}) = \gamma_j
\]

It is indicated, therefore, that the covariances between any two observations in the time series which are separated by \( j \) periods depend only on \( j \) value. The value of \( \gamma_j \) is referred in the literature as "autocovariance at lag \( j \)"; that is, the covariance between any pair of observations in one time series.

As mentioned, the condition of stationarity involves certain implications about the behavior of the observations in the time series. The condition of stationarity which implies that the values in the series fluctuate around a constant mean over time helps identify or locate the observation in space around the mean value. Although the values in the series will fluctuate away from the mean, it will repeatedly be around or at the mean value over the entire time period.

The "stationary stochastic process" describing the time series is considered to evolve over time and the best guess about the value of the series at \( Y_{t+1} \) will be in the neighborhood of its expectation or the mean value \( \mu \). Further, if the probability distribution \( P(Y_1, \ldots, Y_N) \) follows a normal distribution, one could construct a confidence interval for the forecast value as \( \mu \pm 1.96 \frac{\sqrt{\gamma_1}}{\sqrt{\gamma_1}} \), where \( \sqrt{\gamma_1} \) is the standard deviation of \( Y_{t+1} \). This indicates that there is only 0.05 probability that the value of \( Y_{t+1} \) will fall outside the interval.
The condition of stationarity implies that the time series can be located within an interval of values and departures from this region will occur at a very small probability.

As defined earlier, the autocovariance between any pair of values in the stationary time series is only dependent upon the number of time lags between them. The autocovariance is further defined in terms of expectations, that is:

\[ \gamma_j = C(Y_t, Y_{t+j}) \]
\[ \gamma_j = E[(Y_t - EY_t) (Y_{t+j} - EY_{t+j})] \]
\[ = E[(Y_t - \mu) (Y_{t+j} - \mu)] \]

This definition represents the covariance between the values \( Y_t \) and \( Y_{t+j} \) as the expected value of the product of the deviation of \( Y_t \) and \( Y_{t+j} \) from the mean. This indicates that a positive autocovariance exists when an observation which is above the mean value is usually followed by another observation which is also higher than the average. On the other hand, a negative autocovariance occurs when an observation which is lower than the mean value tends to be followed by another which is higher than the average.

The argument described above has a significant role in forecasting time series. The information provided by the autocovariances tells something about the behavior of the stationary time series and that such behavior will be the same regardless of the time period. It also means that although the "realization" of value \( Y_1, \ldots, Y_N \) and \( Y_{N+r}, \ldots, Y_{N+r+j} \) will not be exactly equal, their general pattern will be similar. That is, the pattern of behavior of the time series can be determined given the pattern and levels of the covariances. To allow for comparison and to standardize the dispersion of values, the "autocovariances" are further redefined.
in terms of "autocorrelations". This is done by dividing the
autocovariances \( \gamma_0, \gamma_1, \ldots \), by \( \gamma_0 \).

The determination of the joint probability distribution of the
value of stationary time series and the corresponding mean and co-
variances of the distribution involve the calculation of \( N+1 \) par-


ters. The determination of these values is clearly not possible
because we only have \( N \) observations. This problem is solved by
imposing further simplifications so that the statistical analysis
only involves the determination of a few basic parameters.

The simplifying postulate used in the Box-Jenkins methodology involves
the concept of "discrete linear stochastic process"\(^9\) which could
be in the form of "autoregressive, moving-average or mixed auto-
regressive-moving-average." It is argued that these forms of
linear stochastic processes can take account of a wide variety
of autocorrelation patterns. Hence, they can be used to describe
the behavior of a stationary time series.

**Moving-Average Processes**

If the weights in the linear stochastic process is equal
to zero for \( i > q \), a moving average process is expressed as

\[
Y_t = \mu + \epsilon_t - \theta_1 \epsilon_{t-1} - \cdots - \theta_q \epsilon_{t-q}.
\]

This is considered to be a moving-average process of order \( q \) since the values of the time series is expressed in terms of
moving averages of the disturbances going back for \( q \) periods.

A moving average process of order 1, denoted by MA(1) is,
therefore, expressed as

\[
Y_t = \mu + \epsilon_t - \theta_1 \epsilon_{t-1}.
\]

\(^9\)A discrete linear stochastic process exists if each observation
\( Y_t \) can be expressed as \( Y_t = \mu + \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \ldots \) where \( \mu \) and \( \theta \) are fixed
parameters and the time series \( (\epsilon_{t-1}, \epsilon_{t-2}, \ldots) \) is a set of identically
and independently distributed random variables with mean 0 and variance
\( \sigma^2 \) (Nelson, 1973).
The autocorrelation function of this process "cuts-off" or becomes zero after lag 1. This implies that any observation, say \( Y_{20} \) is correlated with \( Y_{19} \) and \( Y_{21} \) and uncorrelated with any other observations in the time series since the moving average contain only the previous disturbance. This implies further that \( e_{19} \) is shared by \( Y_{19} \) and \( Y_{20} \) while \( e_{20} \) is shared by \( Y_{20} \) and \( Y_{21} \), with no other random disturbance shared by any other two observations in \( Y_t \).

**Autoregressive Processes**

The "autoregressive process" denoted by AR(1) describes a certain observation of the time series \( Y_t \) as a function of the current disturbance and past observations. An AR(1) process is expressed as

\[
Y_t = \theta Y_{t-1} + \delta + \epsilon_t
\]

The autocorrelation function for the AR(1) process defines the association (or correlation) between the values of the time series. It can be shown that the theoretical autocorrelation function declines slowly as the number of lag periods increases. The pattern of positive autocorrelation describe a set of observations where higher-than-average values tend to be followed by another observation higher than the mean, not only in the next time period but also in the succeeding few periods.

The characteristic of these two processes can be combined to form a mixed autoregressive-moving-average model.

**Seasonal Time Series Models**

Seasonality is commonly observed in economic time series. A certain pattern of behavior in the observation tends to be repeated
over a seasonal period, generally one year. High serial correlation at the "seasonal lags"\textsuperscript{10} characterize a seasonal time series.

There exists some modelling techniques that seek to take account of seasonality in the time series. Most of these techniques follow a modelling procedure which incorporates the seasonal variation in a "deterministic"\textsuperscript{11} fashion. Such deterministic representation of seasonality is argued to be limited since the seasonality of most economic time series are observed in a non-deterministic way. This is brought about by certain changes or shifts in the degree and pattern of the seasonal variation over time.

To overcome this limitation, an alternative approach is considered by Box and Jenkins in modelling time series with seasonal variation.

The basic feature of the approach is the use of linear stochastic processes to represent patterns of seasonality.

The Seasonal Moving Average Process

A seasonal moving-average process is represented as:

\[ Y_t = \varepsilon_t - \theta_1 \varepsilon_{t-s} - \cdots - \theta_q \varepsilon_{t-Q_s} \]

\textsuperscript{10} For quarterly data, seasonal lags at defined at lag 4, 8, 12, ...

\textsuperscript{11} The "deterministic representation" of seasonality can be done using dummy variables or by a periodic function with a random component. (Nelson, 1973) p. 169.
where $s$ is the number of observation in a seasonal period, $Q$ is the biggest multiple of $s$. The process represented is of the order $Q$. The autocorrelation function for this process will not be zero at lags $s, 2s, \ldots, Qs$.

A seasonal moving-average process of order 1 is described by an autocorrelation function with a non-zero value at lag 1. For a quarterly time series, this means that any given value in the series is correlated only with the observation following and preceding by 4 periods. It is also indicated that the seasonal correlation takes effect only for one seasonal period.

To generalize, a seasonal MA process of order $Q$ describes a correlation pattern which is effective for $Q$ seasonal periods. The correlation of values cuts off after one seasonal period under the first-order seasonal moving-average process.

**Seasonal Autoregressive Process**

The autoregressive process for seasonal time series is represented in the form:

$$Y_t = \phi_{t,s} Y_{t-s} + \cdots + \phi_{t,P_s} Y_{t-P_s} + \epsilon_t$$

where $P$ is the largest multiple of $s$, the number of observation in one seasonal period. Such a model is referred to as seasonal autoregressive process of order $P$.

Under the first-order seasonal autoregressive process (i.e., $P=1$), the correlation of values corresponding to the seasonal lag declines slowly. The series of first-quarter observations is independent of the series of the second quarter observations.

A multiplicative seasonal model is proposed by Box and Jenkins when there is serial correlation in the disturbances in the seasonal ARIMA processes.
The multiplicative formulation of the model is derived
from the argument that the observation is a result of "successive

**Steps in the Box-Jenkins Approach to Forecasting**

The procedure for Box-Jenkins methods involve four general
steps, namely: model identification, model estimation, diagnostic
checking, and use of the fitted model to forecast future values.
The first three steps are repeated until an adequate and satisfac-
tory model is formed.

The identification of the model involves the comparison of
sample autocorrelation ($r_k$) and partial autocorrelation ($r_{kk}$)
functions derived from the stationary\(^{12}\) time series being analyzed
with the theoretical autocorrelation\(^{13}\) ($\rho_k$) and partial autocorre-
lation\(^{14}\) ($\rho_{kk}$) functions of known ARIMA processes.

\(^{12}\) A time series is stationary if the expected value of each obser-
vation is the same for all the period under study that is:
$E(Z_t) = \mu$.
This implies that the statistical properties of the time series do not
vary with time or "that it is unaffected by the time origin". (Bowerman & O'Connel).

\(^{13}\) $\rho_k$ measures the relationships between any two values in
the time series separated by a lag of $k$ time periods. Its
values range from -1 to +1 and $\rho_k = \rho_{-k}$. A value of $\rho_k$ near to
1 implies that the values separated by a lag of $k$ time periods
have a strong linear relationship. An estimator of $\rho_k$ is given by:

$$
\begin{align*}
\rho_k &= \frac{1}{n} \sum_{t=a}^{n-k} (Z_t - \bar{Z})(Z_{t+k} - \bar{Z}) \\
\bar{Z} &= \frac{1}{n} \sum_{t=a}^{n-a+1} Z_t
\end{align*}
$$

\(^{14}\) $\rho_{kk}$ is the partial autocorrelation of any two values separ-
ated by $K$ time units excluding the effects of the values in be-
tween the periods. It is estimated by the statistic:

$$r_{kk} = \begin{cases} 
    r_k & \text{if } K = 1 \\
    r_k - \sum_{j=1}^{k-1} r_{k-1,j} r_{k-j} & \text{if } K = 2, 3, \ldots \\
    1 - \sum_{j=1}^{k-1} r_{k-1,j} r_j & \text{if } K = 1,
\end{cases}
$$

where:

$$
\begin{align*}
    r_{k,j} &= r_{k-1,j} - r_{kk} r_{k-1, k-j}
\end{align*}
$$
The behavior of the theoretical autocorrelation and theoretical partial autocorrelation functions of the general ARIMA models are summarized in Table 1.

**TABLE 1**

General Models of Autoregressive Integrated Moving Average Processes

<table>
<thead>
<tr>
<th>Models</th>
<th>Theoretical Partial Autocorrelation Function</th>
</tr>
</thead>
<tbody>
<tr>
<td>Moving Average of order q</td>
<td>Dieds Down</td>
</tr>
<tr>
<td>[ Z_t = \nu + \varepsilon_t + \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \ldots - \theta_q \varepsilon_{t-q} ]</td>
<td>Cuts-off after lag q (Infinite) (Finite)</td>
</tr>
<tr>
<td>Autoregressive of order p</td>
<td></td>
</tr>
<tr>
<td>[ Z_t = \delta + \phi_1 Z_{t-1} + \phi_2 Z_{t-2} + \ldots + \phi_p Z_{t-p} + \varepsilon_t ]</td>
<td>Cuts-off after lag p (Finite) (Infinite)</td>
</tr>
<tr>
<td>Mixed Autoregressive-Moving average of order (p,q)</td>
<td>Dies Down</td>
</tr>
<tr>
<td>[ Z_t = \delta + \phi_1 Z_{t-1} + \phi_2 Z_{t-2} + \ldots + \phi_p Z_{t-p} - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \ldots - \theta_q \varepsilon_{t-q} + \varepsilon_t ]</td>
<td>Dies Down</td>
</tr>
</tbody>
</table>

Bowerman and O'Connel (1979) consider the theoretical autocorrelation function to "cut-off" after a certain lag \( k=q \) if \( r_k \) is equal to zero for \( k>q \). Sampling variations, however, may cause \( r_k \) to be small but not equal to zero. A simple "rule of thumb" to determine whether \( r_k \) is equal to zero for \( k>q \) is given. That is, if:

\[
(7) \quad |r_k| \leq 2 \frac{1}{(n-a+1)^{\frac{1}{2}}} (1+2 \sum_{j=1}^{q} r_j^2)^{\frac{1}{2}} \quad \text{for } K > q.
\]

Likewise, the theoretical partial autocorrelation function is said to "cut-off" if \( P_{kk} \) is equal to zero for \( k>q \). That is, if:

\[
(8) \quad |r_{kk}| \leq 2 \frac{1}{(n-a+1)^{\frac{1}{2}}} \quad \text{for } K > q.
\]

After a tentative model is identified, the model is fitted to the data by non-linear least squares and its parameters are estimated. The adequacy of the estimated model is then checked by analyzing the autocorrelation of the residuals. The quantity called "Box-Pierce Chi-Square Statistic" denoted by \( Q \) is used to effectively measure the overall adequacy of the model. The \( Q \) statistic is given as:

\[
(9) \quad Q = (n-d) \sum_{k=1}^{k} r_k^2
\]

where \( n \) is the sample size of the original series; \( d \) is the degree of differencing used to achieve stationarity and \( r_k^2 \) is the square of the sample autocorrelation of the residuals at lag \( 1 \).

The estimated model has adequately captured the relationships between the observations in the time series if the residuals are uncorrelated, i.e., \( r_k(\varepsilon) \) is small. Thus the \( Q \) statistic should be small.
The estimated model is adequate if $Q$ is less than the value of the Chi-Square distribution at the $K-n_p$ degrees of freedom at the 95 percent confidence level where $n_p$ is the number of parameters estimated in the model and $K$ is the number of residual autocorrelation used to solve for the $Q$ statistic.

Another measure used to test the adequacy of the models is given by the statistic:

$(10) \quad S = \sqrt{\frac{SSE}{n-n_p}}$

which defines the overall fit of the model.
CHAPTER III

REVIEW OF RELATED STUDIES AND THE METHODOLOGY OF FORECAST EVALUATION

A. Related Studies

The main focus of the present analysis concerns the application and evaluation of a forecasting approach which was initially developed by Geuze and Ferris (1979).\textsuperscript{15} The approach was applied in generating ex-post price forecasts for cattle and hogs for the period 1969 to 1978. Based on comparisons of statistical measures such as $R^2$, sum of squared residuals and turning point errors, Geuze and Ferris favored a combination of annual and quarterly ratio models over a standard quarterly model in predicting the hog prices. The two models, however, performed the same in predicting the cattle price series.

Other studies dealing with cattle and hog price forecasting have used econometric models (Hayenga and Hacklander, 1970; Myers, \textit{et al.}, 1970; Bain, 1977). This is attributed to the primary interest of economists to investigate the factors influencing supply and demand by obtaining estimates of structural parameters such as elasticity and flexibility estimates (Bourke, 1979).

A majority of these studies evaluated the econometric model by using a very simple descriptive performance measure which relates the model with a naive no-change approach. Evaluation

based on this measure tends to favor econometric models over the no-change model.

Tiegen (1973) concluded, however, that simple naive forecasting methods provided more accurate results than more sophisticated methods in forecasting beef prices. Based on absolute accuracy measures and mean square error decomposition, Tiegen obtained more accurate price forecasts from futures markets compared to those derived from econometric models.

Recognizing the limitations of the evaluation measures used in the previous studies, Bourke (1979) expands the analysis of the beef forecasting model by applying both Box-Jenkins methodology and econometric techniques in generating forecasts and by analyzing turning point errors. Bourke's study indicated that for the period 1966 to 1975, more accurate quarterly and monthly price forecasts can be obtained using the Box-Jenkins approach than those derived from econometric methods. Evaluation based on root mean squared error (RMSE), however, implied small differences with both approaches providing more accurate results than a no-change model. Turning points analysis of quarterly price forecasts indicated slightly more accurate results from the Box-Jenkins models. The reverse was found, however, for monthly models.

The overall comparison of methods conducted by Bourke indicated that Box-Jenkins models perform only marginally better than the econometric models. He asserts, however, that Box-Jenkins models are clearly superior to econometric models on the grounds that forecasts derived from the latter are formulated under
optimal conditions by using known values of the explanatory variables. In actual practice, however, such values have to be forecast, thus bigger forecasting errors may actually result.

Nevertheless, Bourke indicated an important point in that forecasts derived from both models are usually adjusted in actual practice to account for the knowledge and experience of the forecaster (as is done to derive nonmechanical forecasts). It is therefore difficult to objectively evaluate the performance of non-mechanical forecasts based on traditional performance measures. That is, forecast performance has to be clearly evaluated and analyzed both in terms of the ability of the forecasting method and the knowledge of the forecaster. Since such adjustments of forecasts could not be explicitly described, appropriate statistical measures could not be employed and as McKness (1975) pointed out, continuity is not assured. Therefore, evaluation of forecast performance for comparative purposes are based on the models' ex-post predictions. Such an approach will allow the analyst to define "pure model" error as opposed to errors due to incorrect assumptions about the values of the exogenous variables.

Another recent attempt to compare alternative forecasting methods (e.g., econometric, ARIMA, and expert opinion) was carried out by Bessler and Brandt (1979). Based on mean square error criterion and tracking performance, no specific forecasting method was found to be superior over the other methods. The ARIMA models, however, were found to perform best in predicting cattle and hog prices from the first quarter of 1976 to the
second quarter of 1979, but were found to be the poorest (based on mean square error) for broiler prices during the same period.

B. Methodological Considerations in Forecast Evaluation

The formulation of a forecasting model or technique and generation of forecasts do not only require a great deal of time and effort but usually entail relatively large expense. Furthermore, a certain amount of loss is borne by the forecast user when predictions happened to be significantly different from realized values, a situation which can undoubtedly happen in an uncertain world. It is, therefore, inevitable and necessary to test the predictive power of the techniques by assessing the quality of the forecasts or predictions generated from the forecasting exercise.

McKeees (1975) argues that an appropriate methodology for forecast evaluation is necessarily a function of the nature or purpose of the investigation. He presented three basic purposes for forecast evaluation, namely: "prescriptive, descriptive and comparative" evaluations.

"Prescriptive" evaluation is conducted primarily to find areas where the forecasting model or technique could be improved. This is done by identifying and examining the possible sources of forecast errors and by attempting to separate the error into various parts or elements. Prescriptive evaluation is typically

---

16 Teigen (1979) argues for an economic criterion regarding attempts to improve forecasts, i.e., "forecast should be improved only to the extent where the welfare gain equals the social marginal cost of improving them." He concludes, therefore, that an "optimal" forecast is not necessarily the "statistically best" one.
carried out for forecasts generated from econometric models which are specified on the basis of economic theory and estimated using current data.

The set of information derived from the analysis of forecast errors are then used in the reformulation process of the forecasting model, and adjustments of future forecasts. For prescriptive purposes, the analysis of ex-post forecasts as opposed to ex-ante forecasts is considered to be most typical. This is argued to be so because the errors associated with ex-post forecasts can be clearly accounted for by "pure model errors" instead of errors due to incorrect assumptions about the values of the explanatory variables.

"Descriptive" evaluation of forecasts is primarily conducted for historical analysis, i.e., examinations of forecasts made available in the past and how they perform given the realized values of the variables predicted. McKee's argues that ex-ante forecasts are more appropriate for descriptive evaluation of forecasts since they are the ones actually used by decision makers.

Evaluation of forecasting performance for comparative purposes, on the other hand, involves the analysis of forecasts made by different forecasters. The forecast user aims to find out who among the forecasters has been most accurate, considering the performance of forecasts they made in the past. The information generated from the comparison is then used to make inferences about the future performance of forecasters' predictions.

17 "Pure model errors" are associated with errors due to estimation and poor specification.
A "controversial question" has been raised on this area of forecast evaluation; that is, whether the forecast user should be concerned about finding the "best forecasting technique" or the "best forecaster." The argument for an evaluation exercise concerning the comparison of an alternative forecasting technique or model is seen to be strongly favored. This is due to the existence of an explicit formulation of the forecasting model(s) which lend itself to statistical inference.  

Furthermore, the analysis of past predictive power of models provides information about their future performance, given that the structure of the system being modeled has not changed.

The question obviously becomes less important when a forecaster usually tends to have an explicit or specific formulation of the procedure by which forecasts are derived.

Dhrymes, et al., (1972) present a framework for a systematic evaluation of econometric models. The evaluation process was divided between two areas) namely: "parametric and non-parametric" evaluations.

Relying primarily on statistical inference and the stochastic properties assumed to characterize the model, "parametric" examination of models involves the following aspects: "model selection, parameter estimation, pseudo-forecasts and structural stability tests."

---

18 This argument is weakened by the absence of sufficient information about the statistical characteristics or properties of differences among standard errors of forecasts, thereby making rigorous statistical analysis of forecast errors not feasible (Mcknees, 1975).
Evaluation of models in a "non-parametric" sense involves the computation of "descriptive performance measures" such as forecast error, turning point errors and separation of forecast errors into components.

Because the probability characteristics of such descriptive measures is unknown, they do not lend themselves to the formal tools of statistical theory.

Included in the "parametric" evaluation aspect are those carried out after the model has been released. This includes the analysis of residuals when more current data become available, and re-estimation of the model to include the new information set.

Dhrymes, et al. (1975), warn the analyst when evaluating the performance of models based on a small new data set. A particular model could not be clearly rejected when the evaluation conducted is based on a small data set, even if such evaluation resulted to a failure to pass certain performance tests. It is argued that new data sets could have been largely influenced by some "unique" events which were not captured in the specified structure in the model. Although each failure may indicate a limitation of the specified model, it does not necessarily imply that the relationships represented in the model's structure are not adequately identified.

Instead of giving primary emphasis on strict identification and specification of model's structure, "non-parametric" evaluation of models concerns itself with the various uses of the econometric model giving particular emphasis on validation,
i.e., to test the reliability of models for their intended purpose. The validation exercise requires that errors associated with the model be identified and the utility function of the forecast user be known.

Econometric models intended for decision making are, hence, evaluated in terms of how much the forecast information helps in minimizing the frequency of wrong decisions and the losses associated with them. Likewise, the model's usefulness in forecasting is argued to be a function of forecast's accuracy.

Given the wide variety of preferences and needs of model users and the inherent complexity of the decision environment, however, it is very difficult to specify the set of minimum requirements to be used in a particular model evaluation.

Spivey (1979) in a review of econometric models for forecast evaluation noted the inadequacies and limitations in the evaluation procedure employed in most studies. Foremost is the evaluation of model performance solely on the basis of descriptive measures (e.g., root mean square error or similar statistics) which only apply to the particular variables studied and time period used. Failure to analyze and examine the model's performance in terms of predicting turning points and changes lead to inadequate analysis and inconclusive rankings of forecasting models.

Another important concern relates to the difficulty of conducting statistical inference in model evaluation which is deemed necessary in order to formulate general statements of confidence about the model's future performance. The difficulty
arises due to the existence of large correlations structure among forecast errors and the fact that only small data sets containing comparable information about forecasts errors are presently available for analysis. Unfortunately, exact and formal inference procedures for analyzing correlated time series using small sample sizes are not currently available. Spivey further argues that studies dealing with evaluation of models which employ performance criteria such as root mean square error or mean absolute deviation calculated from errors which are highly correlated could only be interpreted for descriptive analysis which only relates to specific data sets and time periods. As such, the analysis do not provide a basis for statistical inference for comparisons of forecasting models' performance. 16

16 Spivey (1975) proposed a possible approach to handle the correlation among errors by assuming that such forecast errors are "covariance stationary process." He then proposed two ways to estimate the covariance structure of the process by:

1. "Use of standard asymptotic results associated with autocorrelations and cross-correlation structure either for time or for forecasting domain."

2. "Use of Wold decomposition and model the forecast errors as multivariate moving average processes through appropriate large sample methods."

He noted, however, that these procedures are not usually due to the limitations posed by small sample sizes of forecast errors.
Another important aspect of model evaluation that needs to be addressed relates to the choice of the time period to be used in the evaluation process. Bourke (1979) considers it ideal to carry out the evaluation exercise on data outside the period of model development in order to properly evaluate the forecasting ability of the model as opposed to its "explanatory" ability. To satisfy this, the researcher should either postpone the evaluation until the events forecasted have actually occurred (i.e., actual data on forecasted events are made available) or estimate the specified model using less current information.

The evaluation procedure followed in the present study are more of a validation of the models' predictive ability for the period covering model development. Further tests outside the sample period (first two quarters of 1982) are also conducted. The criteria used to evaluate the models' performance are both "parametric" and "non-parametric."

The models could be reformulated and adjusted to incorporate new information as more current data sets are made available.

C. Forecast Evaluation Measures

The results of the price forecasts generated from the combined annual-quarterly ratio models, straight quarterly models and autoregressive moving average processes were evaluated using different measures of performance.

Except for the mean absolute forecast error, the performance criteria employed in the analyses have been shown to be simple transformations of a quadratic loss function (Teigen, 1979). While the evaluation criteria other than those included
is suggested (Dhrymes, et al., 1972; Granger, 1973), these performance tests will provide an initial basis for assessing the predictive ability of the forecasting models.

The absolute and relative accuracy evaluation procedures have been the two major approaches used in forecast evaluation. Absolute accuracy of forecasts is evaluated using statistical measures describing the differences between the predicted and actual realized values. Relative accuracy evaluation, on the other hand, involves the comparison of forecast errors associated with alternative forecasting techniques. While the Theil Inequality Coefficient \( U_2 \)\(^{20}\) compares a particular forecast with a naive "no-change" approach, Mincer and Zarnowitz (1969) attempted to make forecast comparisons against an "optimal benchmark extrapolation" which were formulated through linear autoregressive processes. Forecasts derived from these processes are considered "optimal" in the sense that the estimation of parameter weights to be applied to past values of the series for forecasting future values is carried out by minimizing the forecasting errors.

**Absolute Accuracy Performance Measures**

Among the simplest statistical measure under the absolute accuracy analysis is the statistic, mean squared error (MSE), defined as \( E(A-F)^2 \). Alternatively, \( \text{MSE} = \frac{1}{n} \sum (a_i - f_i)^2 \), where \( a_i \) and \( f_i \) are the \( i \)th actual and forecast values, respectively. Also called the average squared error of the forecast, MSE is

\[ \text{MSE} = \frac{1}{n} \sum (a_i - f_i)^2 \]

\[^{20}\text{See Theil, H. (1965).}\]
considered as a "non-parametric" statistic that indicates the size of the individual forecast errors from actual values (Bessler and Brandt, 1979). Since deviations of forecasts from actual values are squared, larger errors reflect a significant decline in model performance, and results in larger costs to the forecast user than do smaller errors.

The square root of MSE, called the root mean squared error (RMSE) represents the mean size of forecast error, measured in the same units as the actual values.

Two other measures of absolute accuracy are the mean forecast error (ME) and the mean absolute forecast error (MAE). The mean forecast error indicates whether the average of the forecasted series is above or below the mean of the actual values. To get the absolute size of the errors (i.e., forecast which are above and under the actual value do not cancel each other), the mean absolute forecast error is used.

Further analysis to determine absolute accuracy of forecasts can be done by regressing the actual values on predictions. Mincer and Zarnowitz (1969) defines the "line of perfect forecast" as the 45° line from the origin on a "prediction-realization" diagram where forecasts exactly coincide with realizations. The hypothesized line of perfect prediction can be shows graphically as in Figure 1.

A measure of variation around the line of perfect prediction determines the accuracy of the forecast. One of these
Figure 1. Regression of Actual Values on Predictions

LPP - line of perfect prediction
\( \bar{A} \) - avg of actual values
\( \bar{P} \) - avg of predictions
RL - regression line
\( \bar{P}^c \) - adjusted average of prediction
E = \([\bar{A}, \bar{P}]\)
\( E^c \) - adjusted average

measures is the MSE. Forecasts are considered to be more accurate the smaller the amount of variation (MSE) around the hypothesized line. The regression line between actual and predicted values should coincide with the line of perfect prediction.

The analysis of the results from the regression of actual values on predictions can be extended to determine the bias and efficiency of the forecasts. Mincer and Zarnowitz consider the forecasts to be unbiased if the expected values of "realizations" and predictions are equal. The difference being the size of the bias.

A positive or negative bias indicates that forecasts are, on the average, below or over the levels of actual values, respectively.

On the other hand, forecasts are considered "efficient" if the slope of the regression line is not significantly different from unity. Under this situation, the "residual variance of the regression" and "the variance of the forecast errors" are equal to each other.

---

21 The mean square error is often used as a measure of forecast accuracy because it can easily be handled statistically and mathematically (Mincer and Zarnowitz, 1969).

22 It is noted that unbiased forecasts may have higher mean square error than biased ones. Hence, unbiasedness alone does not determine accuracy of forecasts.

23 Given the identity: \( A_t = \alpha + \beta F_t + U_t \) and the regression: \( A_t = \alpha + \beta F_t + U_t \), the "residual variance in the regression" and "variance of the forecast errors" are denoted by \( \sigma^2(U_t) \) and \( \sigma^2(U) \), respectively (Mincer and Zarnowitz, 1969, pg. 9).
If the intercept of the regression (α) is significantly different from zero and/or the slope (β) is significantly different from unity, the regression line of natural values on predictions will not coincide with the "line of perfect forecast." Hypothesis tests for unbiasedness and efficiency could easily be conducted by comparing the values of the intercept and slope coefficient with their respective standard errors to determine the significance of the t-values.

Although tests of unbiasedness and efficiency are conducted in the present study, no attempt is done to adjust the forecasts to take account of any possible bias. Given that the size of the bias can be determined, Bates and Granger argue that forecasts should be appropriately corrected.

Further extension of the above analysis leads to the decomposition of the mean squared error of the forecast into various components. MSE is alternatively defined as:

\[
\text{MSE} = (\bar{a} - \bar{f})^2 + (1 - b_1)\sigma_f^2 + \sigma_U^2
\]

\[
= (\bar{a} - \bar{f})^2 + (1 - b_1)\sigma_f^2 + (1 - r_{fa}^2) \sigma_a^2
\]

where \(\sigma_f^2, \sigma_a^2, \sigma_U^2\) are the variances of predict, actual values and error terms, respectively. \(p_{af}^2\) is the square of the correlation between predicted and actual values.

---

24 These tests are generally called "Mincer/Zarnowitz forecast efficiency tests." Problems associated with these tests are discussed in Granger and Newbold (1977, p. 40).


26 Granger and Newbold (1973) have shown the problems associated with MSE error decomposition. The basic problem lies on the fact that most practical work involves limited samples, hence, resulting to MSE estimates subject to sampling variations (Gellatly, 1979).
This definition breaks the mean squared error into various components: error due to bias, slope component and forecast correlation component.

Turning Points Analysis

A good forecasting model should correctly anticipate turning points. With this in mind, another performance test would be to determine the number of turning points missed or incorrectly predicted (Bessler and Brandt, 1979). Although turning point errors do not tell the forecast user which model or method best predicts the true values, they are useful in knowing whether reversals from the current pattern of the series being forecasted are likely to happen.

Bourke (1979) classified turning points into two categories, namely: "statistical turning point" and "cyclical turning point." While the statistical turning point indicates a "situation where an error relates to any forecast direction of movement," a cyclical turning point reflects the "economic sense of a reversal of current trend."

Evaluation of cyclical turning points involves the following types of errors (Bourke, 1979):

1. Type I error - "turning point incorrectly predicted"
2. Type II error - "none predicted when one actually occurs"
Table 2. Types of Turning Point Errors

<table>
<thead>
<tr>
<th></th>
<th>Prediction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Turn</td>
<td>No Turn</td>
</tr>
<tr>
<td>A</td>
<td>b</td>
</tr>
<tr>
<td>C</td>
<td>c (Type II)</td>
</tr>
<tr>
<td>T</td>
<td>d</td>
</tr>
</tbody>
</table>

Source: Bourke, 1979, p. 102.

The quantitative error measures are:

\[ f_1 = b/a+b; \quad f_2 = c/c+d \]

where \( b \) includes prediction of a turning point in a false direction. Based on these measures, smaller values of \( f_1 \) and \( f_2 \) indicates good forecast performance.

**Relative Accuracy Measures and Other Tests**

A simple relative accuracy measure is the Theil Inequality Coefficient \( U_2 \) defined as:

\[ U_2 = \frac{1}{n} \sum_{i=1}^{n} (a_i - f_i)^2 \]

This measure compares forecasts with "naive" no-change extrapolation, under which \( U_2 \) will be unity. Rankings of forecasted series based on \( U_2 \) is

---

27 Market situation at the time of forecast and activity of the forecast user are the two factors considered to determine which of the two types of errors are more serious in practical work (Bourke, 1979).

28 See Gellatly, 1979 and Deutshold, \( U_2 \) is preferred to \( U_1 = \frac{\Sigma(F_t - A_t)^2}{\Sigma F_t^2 + \Sigma A_t^2} \). This is because two forecast models for the same variable may results to the same \( U_1 \) but different mean squared error (Teigen, 1973).
expected to be consistent with the rankings based on mean squared error. Values of $U_2$ which are less than one indicate better performance of the predictions compared to a no-change extrapolation.

Another measure of relative accuracy involves the comparison of two mean square errors expressed as a ratio. The relative mean squared error (RVMSE) is defined as $\frac{\text{MSE}_F}{\text{MSE}_E}$ where $\text{MSE}_F$ is the mean squared error of prediction and $\text{MSE}_E$ is the mean squared error of extrapolation. Mincer and Zarnowitz (1969, pp. 20-21) explain that "the ratio measures the relative reduction in forecasting error. RVMSE ranks the quality of performance in a similar way as a rate of return index, where the return (numerator) is inversely proportional to the MSE of forecast and the cost (denominator) is inversely proportional to the MSE of extrapolation, the latter indicating the difficulties encountered in forecasting a particular series." A value of the prediction compared to the extrapolation assumed to be obtained at a relatively smaller cost.

Further indication of the relative merits of the price predictions is given by the simple correlation between the actual values and predicted values ($r_{ap}^2$). Obviously, preferred values of $r_{ap}^2$ will be those closest to unity. Given that trends exist in most economic data, it is generally expected that $r_{ap}^2$ will be always close to one without necessarily indicating that the price prediction is an accurate forecast.

Other tests of performance of forecasting models include the "goodness-of-fit" criteria. These include $R^2$, sign of the coefficients and standard errors of the parameter estimates.
Although these tests do not provide a clear indication of how well the model will perform in the forecast period (outside the time span of the observation), they will indicate possible areas of improvement in the model specification and may provide useful information about what could be expected given the same range of values of the variables being forecast (Bessler and Brandt, 1979).

It is important to note that the descriptive measures described above have a number of limitations. Foremost is the limited application of rankings of models (based on the descriptive measures) to only the specific time period of the data set used in the analysis (Spivey, 1979).
CHAPTER IV
MODEL STRUCTURE, ESTIMATION PROCEDURE AND ESTIMATION RESULTS

A. Econometric Model

Model Structure

The equations for each model are specified as follows:

Annual Model

1. $PSR = f(CBFC, CNBMRC, DICD, CPI, DVD, DVD1)$
2. $PBG = f(CPKC, CNPKRM, CPMC, DICD, CPI, DVD)$

Quarterly Model

1. $PSRQ_i = f(DVQ_2, DVQ_3, DVQ_4, CBFCQ_1, CBFCQ_2, CBFCQ_3, CBFCQ_4, CNBMRC, DICD, CPI, DVD, DVD1)$
2. $PBGQ_i = f(DVQ_2, DVQ_3, DVQ_4, CPKCQ_1, CPKCQ_2, CPKCQ_3, CPKCQ_4, CNPKRM, CPMC, DICD, CPI, DVD)$

Quarterly Ratio Model

1. $\frac{PSRQ_i}{PSR_a} = f(\frac{CNBMRCQ_i}{CNBMRC_a}, \frac{CBFCQ_i}{CBFC_a})$
2. $\frac{PBGQ_i}{PBG_a} = f(\frac{CNPKMCQ_i}{CNPKMC_a}, \frac{CPKCQ_i}{CPKC_a})$

where:

PSR = Price of choice steers at Omaha, average all weights through 1972, for 1973 and later, 900-1100 pounds (dollars per hundred-weight).

PBG = Price of barrows and gilts, 7-8 markets (dollars per hundred-weight).

DICD = Personal disposable income per capita (deflated) (dollars).

CPI = Consumer price index, urban beginning in 1978 (1967=1.00).

CBFC = Domestic civilian consumption of beef per capita, retail weight (pounds).

CPKC = Domestic civilian consumption of pork per capita retail weight (pounds).
\(\text{CNPKRM}C = \text{Domestic civilian consumption of non-pork red meat, retail weight, per capita (pounds)}.\)

\(\text{CPMC} = \text{Domestic civilian consumption of poultry meat, per capita (broilers + other chicken + turkeys), ready-to-cook basis (pounds)}.\)


\(\text{DVD1} = \text{Dummy Variable, 1977 = 1, 0 otherwise (to account for aberration)}.\)

\(\text{Qi} = \text{Quarter}\)

\(\text{a} = \text{Annual}\)

The annual model establishes the price forecast for the year and a quarterly "ratio" model derives the pattern of prices around this average. The quarterly "ratio" model includes only key variables thought to have a differential impact by quarter.

The annual demand models were standard types with hog and cattle prices dependent. This formulation is adequate since the domestic production of beef and competing meats for a given year is largely predetermined. Likewise, beef imports and government trade policies affecting the beef market are also largely known in advance.

The annual average price of choice steers at Omaha was used to represent the general level of fed cattle prices. This is justified among others by the relative importance of the Omaha market, relative consistency of the behavior of price differentials and the availability of the time series (Ferris, 1974).

The independent variables included per capita consumption of the respective meats and their substitutes, consumer income and the Consumer Price Index. The quarterly "ratio" models were separate for each of the four quarters and included the ratio of the quarterly price to the annual price as a dependent variable.
Only two independent variables were included, namely: (1) ratio of the quarterly consumption of the respective meat to annual consumption and (2) ratio of the quarterly consumption of the substitute meat to the annual consumption. These two variables were believed to have significant differential effects by quarters. Income and the Consumer Price Index were excluded because their quarterly influence was believed to be minimal and adequately captured in the annual model.

Model Estimation Procedure

The first step in the formulation of the combined model is the estimation of a quarterly ratio model. Estimated separately from the annual model, the ratio model measured the effect the following variables had on price:

(1) Per capita production (assumed to be equal to consumption) of the commodity in question

(2) Per capita production (assumed to equal to consumption) of respective substitutes

(3) Other factors related to the quarter of the year, i.e., temperature, holidays, etc., as captured by the constant term of the equation.

The quarterly "ratio" model predicts the ratio of the quarterly price to the annual price. A separate equation for each quarter is estimated in which the explanatory variables are the shares of annual consumption of the product and its substitute.

To predict quarterly prices, the calculation is as follows: First, the annual price is predicted by the annual model; Second, the quarterly/annual ratios are calculated from the ratio model; and finally, the predicted quarterly price is
derived by multiplying the predicted quarterly/annual ratio by the predicted annual price.

Model Estimation Results

The statistics presented include the standard error of the coefficients (in parentheses), number of observations \( n \), \( R^2 \), \( F^2 \), sum of squared residuals (SSR), average residual, regardless of sign \( |\bar{e}| \) and turning point errors (TPE).

A. Annual Model

\[
\begin{align*}
\text{PSR} & = 27.407 - 0.9829 \text{CBFC} - 0.1539 \text{CNBMRC} + 0.0284 \text{DICD} \\
& \quad \quad (12.419) (0.1495) (0.1014) (0.0046) \\
& \quad + 15.3063 \text{CPI} - 3.7472 \text{DVD1} + 3.2378 \text{DVD} \\
& \quad \quad (2.1163) (2.5263) (1.9441)
\end{align*}
\]

SSR = 74.288 \quad F = 146.68

\[
\begin{align*}
R^2 & = 0.9832 \\
\text{D.W.} & = 1.7357 \quad |\bar{e}| = 1.404 \\
\text{TPE} & = 4/21 \\
n & = 22
\end{align*}
\]

\[
\begin{align*}
\text{PBG} & = 46.8225 - 0.8975 \text{CPKC} - 0.312 \text{CNPKRMCL} - 1.1581 \text{CPMC} \\
& \quad \quad (10.077) (0.1021) (0.0965) (0.2541) \\
& \quad + 0.0314 \text{DICD} + 18.177 \text{CPI} + 2.520 \text{DVD} \\
& \quad \quad (0.0039) (2.3140) (1.4186)
\end{align*}
\]

SSR = 35.194 \quad F = 217.969

\[
\begin{align*}
R^2 & = 0.9886 \\
\text{D.W.} & = 2.485 \quad |\bar{e}| = 1.03 \\
\text{TPE} & = 5/21 \\
n & = 22
\end{align*}
\]

B. Quarterly Model

Turning point errors indicate both missed and incorrectly predicted turning points.
\[ \text{PSRQ}_1 = 5.3202 + 1.2048 \text{DVQ}_2 + 3.1338 \text{DVQ}_3 - 2.4137 \text{DVQ}_4 \\
\quad (6.341) (7.773) (7.606) (7.450) \\
- 3.3501 \text{CBFCQ}_1 - 3.3982 \text{CBFCQ}_2 - 3.4032 \text{CBFCQ}_3 \\
\quad (0.359) (0.422) (0.385) \\
- 3.4046 \text{CBFCQ}_4 + 0.3627 \text{CNBMRC} + 0.0222 \text{DICD} \\
\quad (0.400) (0.124) (0.002) \\
+ 15.9824 \text{CPI} + 2.8058 \text{DVD} - 3.5425 \text{DVD}_1 \\
\quad (1.140) (1.146) (1.469) \]

\[ \text{SSR} = 516.169 \quad F = 211.081 \]

\[ R^2 = 0.9712 \quad \text{D.W.} = 1.0486 \quad |\bar{e}| = 1.79 \]

\[ \text{TPE} = 27/87 \quad n = 88 \]

\[ \text{PBGQ}_1 = 71.4155 + 1.571 \text{DVQ}_2 + 3.662 \text{DVQ}_3 + 4.712 \text{DVQ}_4 \\
\quad (10.130) (9.603) (9.482) (9.762) \\
- 4.836 \text{CPKCQ}_1 - 5.2477 \text{CPKCQ}_2 - 5.2957 \text{CPKCQ}_3 \\
\quad (0.494) (0.461) (0.455) \\
- 4.952 \text{CPKCQ}_4 - 1.0937 \text{CNPKRM} + 0.1642 \text{CPMC} \\
\quad (0.438) (0.289) (0.139) \\
+ 0.0115 \text{DICD} + 11.653 \text{CPI} + 5.996 \text{DVD} \\
\quad (0.002) (1.106) (1.140) \]

\[ \text{SSR} = 494.043 \quad F = 167.48 \]

\[ R^2 = 0.964 \quad \text{D.W.} = 1.182 \quad |\bar{e}| = 1.89 \]

\[ \text{TPE} = 14/87 \quad n = 88 \]

C. Quarterly Ratio Model

Choice Steers:

\[ Q_1: \frac{\text{PSRQ}_1}{\text{PSR}_{\text{a}}} = 3.396 - 7.2342 \frac{\text{CNBMRCQ}_1}{\text{CNBMRC}_{\text{a}}} - 2.6185 \frac{\text{CBFCQ}_1}{\text{CBFC}_{\text{a}}} \]

\[ \text{SSR} = 0.0602 \quad F = 6.4718 \]

\[ R^2 = 0.4052 \quad \text{D.W.} = 1.9526 \quad |\bar{e}| = 0.041 \]

\[ \text{TPE} = 1/21 \quad n = 22 \]
\[ Q_2: \frac{\text{PSRQ}_2}{\text{PSR}_a} = 2.8628 - 6.605 \frac{\text{CNBMRCQ}_2}{\text{CNBMRC}_a} - 0.932 \frac{\text{CBFCQ}_2}{\text{CBFC}_a} \]

SSR = 0.0196 \quad F = 9.083

\[ R^2 = 0.49 \quad \text{D.W.} = 1.686 \quad |\bar{e}| = 0.025 \]

TPE = 2/21 \quad n = 22

\[ Q_3: \frac{\text{PSRQ}_3}{\text{PSR}_a} = 2.924 - 2.558 \frac{\text{CNBMRCQ}_3}{\text{CNBMRC}_a} - 5.093 \frac{\text{CBFCQ}_3}{\text{CBFC}_a} \]

SSR = 0.0147 \quad F = 9.528

\[ R^2 = 0.50 \quad \text{D.W.} = 1.458 \quad |\bar{e}| = 0.022 \]

TPE = 2/21 \quad n = 22

\[ Q_4: \frac{\text{PSRQ}_4}{\text{PSR}_a} = 2.4815 - 5.5976 \frac{\text{CNBMRCQ}_4}{\text{CNBMRC}_a} - 0.278 \frac{\text{CBFCQ}_4}{\text{CBFC}_a} \]

SSR = 0.037 \quad F = 3.343

\[ R^2 = 0.26 \quad \text{D.W.} = 1.967 \quad |\bar{e}| = 0.041 \]

TPE = 7/21

Barrows and Gilts:

\[ Q_1: \frac{\text{PBGQ}_1}{\text{PBG}_a} = 4.792 - 8.771 \frac{\text{CNPKMCQ}_1}{\text{CNPKMC}_a} - 6.334 \frac{\text{CPKCQ}_1}{\text{CPKC}_a} \]

SSR = 0.09518 \quad F = 20.766

\[ R^2 = 0.686 \quad \text{D.W.} = 1.879 \quad |\bar{e}| = 0.053 \]

TPE = 3/21 \quad n = 22

\[ Q_2: \frac{\text{PBGQ}_2}{\text{PBG}_a} = 4.574 - 7.423 \frac{\text{CNPKMCQ}_2}{\text{CNPKMC}_a} - 7.3099 \frac{\text{CPKCQ}_2}{\text{CPKC}_a} \]

SSR = 0.0465 \quad F = 17.543

\[ R^2 = 0.65 \quad \text{D.W.} = 1.98 \quad |\bar{e}| = 0.033 \]

TPE = 4/21 \quad n = 22
\[
Q_3: \frac{\text{PBG}_3}{\text{CPK}_3} = 3.758 - 7.875 \frac{\text{CNPKMC}_3}{(0.6037)(1.2724)} - 3.1927 \frac{\text{CNPKMC}_3}{(1.6675)}
\]

\[
Q_4: \frac{\text{PBG}_4}{\text{CPK}_4} = 4.053 - 6.945 \frac{\text{CNPKMC}_4}{(1.0474)(1.2692)} - 4.739 \frac{\text{CPK}_4}{(3.1051)}
\]

\[
\text{SSR} = 0.0326 \quad F = 19.244
\]

\[
\text{R}^2 = 0.669 \quad \text{D.W.} = 2.185 \quad |\bar{e}| = 0.031
\]

\[
\text{TPE} = 5/21 \quad n = 22
\]

\[
\text{SSR} = 0.075 \quad F = 20.203
\]

\[
\text{R}^2 = 0.68 \quad \text{D.W.} = 2.005 \quad |\bar{e}| = 0.045
\]

\[
\text{TPE} = 1/21 \quad n = 22
\]

The estimation results indicate that the single-equation annual demand models have performed very well in explaining the movements of prices for both cattle and hogs over the 22-year period ending 1981. In the cattle equation, coefficients have the correct sign and are highly significant with respect to their standard errors. Further, R\(^2\) indicates that over the 22-year period, 98 percent of the variation in cattle prices is accounted for by the explanatory variables. Three turning point errors for the 22-year period is shown in the cattle series.

The coefficients of the hogs annual demand equation are of the expected sign and are highly significant relative to their standard errors. The equation has a very good fit with R\(^2\) of about 99 percent, i.e., about 99 per cent of the variations in hog prices for the 22-year period is explained by the independent variables. The Durbin-Watson statistics calculated from the annual regressions do not indicate strong autocorrelation in the residuals.

The quarterly-ratio single equation models, although they did not perform well in explaining the variations in quarterly
prices as ratio to the annual prices, have coefficients with correct signs. Further, the key explanatory variable in the quarterly-ratio equation are highly significant for most quarters.

B. Autoregressive Integrated Moving Averages (ARIMA)

The autoregressive moving average processes were identified, estimated and tested for cattle and hogs quarterly price series. The price forecasts derived from these models are "non-structural-mechanical" forecasts, i.e., no particular economic theory is employed in the model specification/identification phase of model development and the price forecasts were not adjusted to account for certain judgements of the researcher about the economic events being forecasted.

An important assumption implied in the analysis involves the continuity of the particular historical price relationships, i.e., the processes in the estimated price model is assumed to hold into the future.

The estimated autocorrelation function and partial autocorrelation function of each price series are shown in Table 3. The sample autocorrelation function of the original time series indicate non-stationarity; that is, they die down very slowly. The estimated autocorrelation and partial autocorrelation of the first differences of the hog price series indicate stationarity. First order regular and seasonal differencing have to be applied to the cattle price series before an adequate model was identified.
Table 3 Sample Autocorrelation and Partial Autocorrelation Functions for Cattle and Hogs Quarterly Prices 1960-1981

<table>
<thead>
<tr>
<th>Lags</th>
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<tr>
<td>Hogs:</td>
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<tr>
<td>Auto $PB_{G_t}$</td>
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<td>.86</td>
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<td>.75</td>
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<td>.60</td>
<td>.55</td>
<td>.50</td>
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<td>.38</td>
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<tr>
<td>Partial Auto $PB_{G_t}$</td>
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<td>.03</td>
<td>.04</td>
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<td>.40</td>
<td>.10</td>
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<td>-.04</td>
<td>.02</td>
<td>-.11</td>
<td>-.00</td>
<td>-.08</td>
<td>-.11</td>
<td>-.17</td>
<td>-.03</td>
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<tr>
<td>Auto $(PB_{G_t} - PB_{G_{t-1}})$</td>
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<td>-.02</td>
<td>-.06</td>
<td>.14</td>
<td>-.54</td>
<td>.01</td>
<td>-.05</td>
<td>.14</td>
<td>-.18</td>
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<td>.08</td>
<td>-.03</td>
<td>.23</td>
<td>-.18</td>
<td>.02</td>
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<tr>
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<td>-.03</td>
<td>-.07</td>
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<td>-.53</td>
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<tr>
<td>Auto $PS_{R_t}$</td>
<td>.95</td>
<td>.91</td>
<td>.86</td>
<td>.82</td>
<td>.77</td>
<td>.70</td>
<td>.65</td>
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<tr>
<td>Partial Auto $PS_{R_t}$</td>
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<tr>
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<td>.05</td>
<td>-.04</td>
<td>.17</td>
<td>-.03</td>
<td>-.09</td>
<td>-.03</td>
<td>-.06</td>
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<td>-.06</td>
<td>-.05</td>
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<td>-.12</td>
<td>.12</td>
<td>-.01</td>
</tr>
<tr>
<td>Partial Auto $(PS_{R_t} - PS_{R_{t-1}})$</td>
<td>-.29</td>
<td>-.03</td>
<td>-.04</td>
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<td>-.10</td>
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<td>-.16</td>
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</table>

52
Some difficulties in the model identification phase were encountered as there were apparent possibilities. Under this situation, it is suggested by Box-Jenkins to estimate the most appropriate models and select the best one based on the analysis of results.

Hence, the model identification phase can be difficult. A more practical approach to identify an adequate seasonal model which is followed in this study is somewhat intuitive and involves an iterative technique in the modelling process. At each iteration, the sample autocorrelation function and sample partial autocorrelation function were calculated to determine which components were obviously present in the time series being modelled. After a particular form of the model is identified and fitted, the estimated residuals were analyzed in order to determine the adequacy of the tentative model.^{30} Statistical measures such as sum of squares residuals, mean square error and standard errors of estimates are also used to compare tentative models.

The constant term $\delta$ included to account for the trend in the undifferenced series $Y_t$. If $U = 1$ (first order difference) and $\delta$ is positive, the series is considered to trend upward, with a positive average change.

In order to identify the particular form of the model with seasonal component, one has to determine which of the operators to include and in what order would they adequately fit

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^{30} The Q statistic described in Chapter II was employed to determine the adequacy of the model.
the time series. The methodology for identification of models which is presented by Box and Jenkins involves the comparison of the sample autocorrelation function and sample partial autocorrelation function calculated from the series with the theoretical autocorrelation and partial autocorrelation functions of known ARIMA processes.

In practical work, however, such comparison does not usually provide clear indications as to which are the appropriate operators to include.

The notation which is generally used to represent seasonal models is as follows:

The general multiplicative seasonal autoregressive integrated moving average (ARIMA) model for a seasonal time series $Y_t, t=1,2, \ldots, T$ with a known seasonal period $S$ can be written as

$$
\phi_p(B) \phi_p(B^S) (1-B)^d (1-B^S)^D Y_t = \delta + \phi_q(B) \theta_q(B^S) \varepsilon_t,
$$

where

$\varepsilon_t$ is a random disturbance assumed to be normally distributed;

$B$ is the backshift operator such that $BY_t = Y_{t-1}$ and $B^S Y_t = Y_{t-S}$;

$\phi_p(B)$ is the non-seasonal autoregressive operator of order $p$, i.e., $\phi_p(B) = (1-\phi_1B-\phi_2B^2-\ldots-\phi_pB^p)$; $\phi_p(B^S)$ is the seasonal autoregressive operator of order $P$, i.e., $\phi_p(B^S) = (1-\phi_1^SB-\ldots-\phi^SB^p)$; $d$ is the number of regular differences; $D$ is the number of seasonal differences; $\theta_q(B)$ is the nonseasonal moving average operator of order $q$, i.e., $\theta_q(B) = (1-\theta_1B-\ldots-\theta q B^q)$; $\theta_q(B^S)$ is the seasonal moving-average operator of order $Q$.

It is indicated in Table 3 that the estimated partial autocorrelation of the first difference of hog prices at
lag five is significantly different from zero. Partial autocorrelation values at all other lags indicate no significant magnitudes. It is also apparent that the autocorrelation function exhibits similar pattern, that is, the autocorrelation is significantly different from zero at lag 5, with all other lag periods showing no significant values.

Under this situation, both the autoregressive and moving average processes seem appropriate. The estimation and diagnostic checking procedures indicated that the most adequate model (given the number of observations) include an autoregressive process of order five, and a first-order seasonal autoregressive component.

The final form of the ARIMA model selected for barrows and gilts is as follows:

\[(1 - \phi_1 B - \phi_2 B - \phi_3 B - \phi_4 B^4 - \phi_5 B^5) (1 - \phi_1 B^4) Z_t = \delta\]

where

\[Z_t = (1-B)^1 \text{PBG}_t\]

\[= \text{PBG}_t - \text{PBG}_{t-1}\]

The fitted model yield the following estimates:

\[\phi_1 = -0.0096 \ (0.0952) \quad \text{SS} = 1012.98\]
\[\phi_2 = -0.0974 \ (0.0929) \quad \text{MS} = 12.66\]
\[\phi_3 = -0.038 \ (0.0979)\]
\[\phi_4 = -0.2949 \ (0.1482)\]
\[\phi_5 = -0.5731 \ (0.1038)\]
\[\phi = .6238 \ (0.3816)\]

The figures in parentheses are the standard error of the estimates.
This model involves a regular autoregressive element of order five and a seasonal autoregressive element of order 1.

The first 16 autocorrelations of the residuals of the estimated hog model are listed in Table 4. As shown, no autocorrelation values of the residuals is significant. The performance of the hog model is considered adequate based on the Q statistic which is less than the critical chi-square level. The hypothesis that the autocorrelations are based on a white noise series was therefore accepted.

To achieve the condition of stationarity of the cattle price series, first-order regular and seasonal differencing were applied. The estimated autocorrelation and partial autocorrelations of the differenced series is significantly different from zero at lag 1; with other values indicating no significant magnitudes.

The most adequate model chosen to describe the cattle series consists of a regular first order moving-average and a seasonal moving average of order 1. The model can be expressed as

\[(1-B^4)^1 (1-B)^1 PSR_t = \delta + (1-\theta_1 B) (1-\theta_{1,4} B^4) \epsilon_t\]

The estimates of the parameters with the corresponding standard error in parentheses are:

\[\theta_1 = 0.2940 (.1093) \quad SS = 1046.30\]
\[\theta_{1,4} = 0.9142 (.0681) \quad MS = 13.08\]
\[\delta = 0.0504 (.03708)\]

No recognizable pattern is indicated by the autocorrelation functions of the estimated residuals from the fitted model. Individual autocorrelation values at all lags is small and is insignificant. The Q-statistic is also below the critical chi-square
Table 4  Sample Autocorrelations of the Residuals of the Estimated ARIMA models

1960-1981 Quarterly Cattle Prices:

<table>
<thead>
<tr>
<th>Lags</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
<th>13</th>
<th>14</th>
<th>15</th>
<th>16</th>
</tr>
</thead>
<tbody>
<tr>
<td>Auto $\hat{e}_t$</td>
<td>-.03</td>
<td>.13</td>
<td>.00</td>
<td>.07</td>
<td>-.05</td>
<td>-.07</td>
<td>-.10</td>
<td>-.17</td>
<td>.09</td>
<td>-.14</td>
<td>-.15</td>
<td>-.16</td>
<td>-.06</td>
<td>-.07</td>
<td>-.10</td>
<td>-.03</td>
</tr>
<tr>
<td>Q</td>
<td></td>
<td></td>
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<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>13.95</td>
</tr>
<tr>
<td>Critical $X^2$ Level</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>22.36</td>
</tr>
</tbody>
</table>

1960-1981 Quarterly Hog Prices

<table>
<thead>
<tr>
<th>Lags</th>
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<th>2</th>
<th>3</th>
<th>4</th>
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<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
<th>13</th>
<th>14</th>
<th>15</th>
<th>16</th>
</tr>
</thead>
<tbody>
<tr>
<td>Auto $\hat{e}_t$</td>
<td>-.03</td>
<td>-.02</td>
<td>.01</td>
<td>.02</td>
<td>.00</td>
<td>-.10</td>
<td>-.01</td>
<td>.08</td>
<td>-.10</td>
<td>.04</td>
<td>.04</td>
<td>.02</td>
<td>.09</td>
<td>-.05</td>
<td>.02</td>
<td>.02</td>
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<tr>
<td>Q</td>
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<td>3.886</td>
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<tr>
<td>Critical $X^2$ Level</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td>16.92</td>
</tr>
</tbody>
</table>
level. This test accepts the hypothesis that the residuals exhibit a white noise process. Hence, the processes included in the model adequately describe the cattle price series.

The $s$ statistic defined earlier as $\sqrt{\frac{SSE}{n-n_p}}$, where $n$ is the number of the original observation and $n_p$ is the number of estimated parameters, indicates the overall fit of the model. The calculated $s$ statistic are 0.023 and 0.045 for hogs and cattle, respectively. Since these values are small, the overall fit of the model were considered satisfactory. Small values of $s$ will provide shorter confidence interval forecasts.
CHAPTER V

EVALUATION OF THE PRICE PREDICTIONS FROM
ALTERNATIVE FORECASTING MODELS

Some Considerations and Evaluation Results

It was mentioned earlier that the evaluation of forecasting accuracy should ideally be conducted on data outside the sample period used to formulate the model. Bourke (1979) argues for such an approach in order to properly assess the models' forecasting ability as opposed to its ability to explain the variables under consideration.

The quarterly forecasting models developed in this study were evaluated on the period 1960-1981, and also on the first two quarters of the following year. The attempt to develop the models based on more current data prevented the researcher to carry out an evaluation for a longer forecasting period. As new data become available, however, further evaluation about the forecasting ability of the developed models can be carried out. The ex-post nature of the analysis provides the benefit of certainty of values of the explanatory variables, hence, a better performance is ensured compared to a true forecasting situation.

It should be remembered that the price predictions derived from the models are only "mechanical estimates." In practice, these price predictions are usually adjusted to account for the "beliefs and judgments" of the forecaster.

It should also be noted that ranking of models based on the evaluation exercise is not assured to continue into the
future. That is, the quality of the price predictions obtained from the present analysis only apply to the specific time period used, and that an opposite conclusion may be obtained for another time period. This reminds us of the limitations of the descriptive evaluation measures used in the analysis, although they are the ones usually applied in a practical model evaluation exercise such as this.

Table 5 presents a summary of the accuracy statistics associated with the price predictions for cattle and hogs derived from the alternative models. Part A includes the mean and standard deviations of the actual and predicted values together with the mean squared error (MSE) and its decomposition expressed as a percentage. The results of the regression of actual price values on predictions are shown on Part B. The test statistics for the hypotheses of "unbiasedness" and "efficiency" are also included.

Comparison of the mean squared error of the price predictions derived from the forecasting methods indicates that for the sample 1960 to 1981, the econometric models provided more accurate quarterly price predictions for cattle and hogs than the Box-Jenkins' autoregressive-moving average processes.

Between the two econometric models, the combined annual quarterly ratio model performed relatively better than the straight quarterly model in predicting the hog prices for the same period. Based on RMSE values, the two econometric models showed relatively similar performance in predicting cattle prices.
### Table 5.

#### Accuracy Statistics of Price Predictions for Cattle and

**Hogs from Alternative Forecasting Models**

<table>
<thead>
<tr>
<th>Model</th>
<th>Mean ($/ct)</th>
<th>Standard Deviation</th>
<th>Bias (Residuals)</th>
<th>Mean Squared Errors</th>
<th>Correlation Coefficient</th>
<th>Accuracy Measures</th>
</tr>
</thead>
<tbody>
<tr>
<td>Combined Model (88)</td>
<td>29.29 29.32</td>
<td>12.56 12.42</td>
<td>2.06</td>
<td>4.2</td>
<td>0.06</td>
<td>.906</td>
</tr>
<tr>
<td>Straight-Q Model (88)</td>
<td>29.29 29.32</td>
<td>12.56 12.34</td>
<td>2.37</td>
<td>5.62</td>
<td>0.06</td>
<td>100.00</td>
</tr>
<tr>
<td>ADMA Model (87)</td>
<td>29.47 29.47</td>
<td>12.53 12.33</td>
<td>3.41</td>
<td>11.64</td>
<td>0.06</td>
<td>59.4</td>
</tr>
</tbody>
</table>

---CHOICE STEERS---

<table>
<thead>
<tr>
<th>Model</th>
<th>Mean ($/ct)</th>
<th>Standard Deviation</th>
<th>Bias (Residuals)</th>
<th>Mean Squared Errors</th>
<th>Correlation Coefficient</th>
<th>Accuracy Measures</th>
</tr>
</thead>
<tbody>
<tr>
<td>Combined Model (88)</td>
<td>37.01 37.34</td>
<td>14.36 14.33</td>
<td>2.41</td>
<td>5.8</td>
<td>0.1</td>
<td>59.3</td>
</tr>
<tr>
<td>Straight-Q Model (88)</td>
<td>37.01 37.01</td>
<td>14.36 14.20</td>
<td>2.42</td>
<td>5.67</td>
<td>0.06</td>
<td>100.00</td>
</tr>
<tr>
<td>ADMA Model (87)</td>
<td>37.66 37.73</td>
<td>14.52 14.51</td>
<td>3.52</td>
<td>12.39</td>
<td>0.05</td>
<td>1.36</td>
</tr>
</tbody>
</table>

*Less than .001

*b* was reduced due to differencing.

1The price predictions are for the period 1960-1981. The number of quarters covered are in parentheses.

*Significant at the 25 percent level.*
Both the econometric and Box-Jenkins forecasting methods were considerably more accurate than a "naive no-change" extrapolation as shown by the value of the Theil Inequality Coefficient ($U_2$). As another test of forecast performance, the turning points of the forecasted series were compared with those of the actual values. The ability of the forecasting models in tracking the actual price movements from period to period is indicated in Table 6. The table shows cross-comparisons of what actually prevailed and the predictions of the price series. The prices for the two commodities either decreased or increased. A change in price movement is indicated when prices decreased in one period, then increased in the next. No reversal in the price movement, on the other hand, is indicated by the same price directions in two periods (i.e., an increase in one period is followed by an increase in the next period). Either a turn or a no-turn in the prices actually happened and this is compared with the predicted turn or no-turn. The upper left hand number (a) is incremented when an actual turn is correctly predicted. The lower righthand element (d), on the other hand, indicates correct predictions of a no-turn. High values of diagonal elements (a) and (d) indicates good performance of the forecasting model.

As indicated in the values of cyclical and statistical errors (Tables 6 and 7), the two econometric models out-performed the Box-Jenkins autoregressive-moving average processes in predicting turning points in the quarterly price series for both commodities.
Table 6. Turning Points Analysis of Forecasts from Alternative Models for Cattle and Hogs -- 1960-1981

<table>
<thead>
<tr>
<th></th>
<th>Combined Annual Quarterly Ratio Model</th>
<th>Standard Quarterly Model</th>
<th>ARIMA Model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Prediction</td>
<td>Prediction</td>
<td>Prediction</td>
</tr>
<tr>
<td>Turn</td>
<td>No Turn</td>
<td>Turn</td>
<td>No Turn</td>
</tr>
<tr>
<td>A C Turn</td>
<td>35 (a)</td>
<td>10 (c)</td>
<td>33</td>
</tr>
<tr>
<td>T</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>U No A Turn</td>
<td>17 (b)</td>
<td>25 (d)</td>
<td>16</td>
</tr>
<tr>
<td>L</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

BARROWS AND GILTS

CATTLE

<p>| | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>A C Turn</td>
<td>31</td>
<td>16</td>
<td>26</td>
</tr>
<tr>
<td>T</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>U No A Turn</td>
<td>17</td>
<td>23</td>
<td>20</td>
</tr>
<tr>
<td>L</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 7. Turning Point Errors

<table>
<thead>
<tr>
<th></th>
<th>Cyclical Errors</th>
<th>Statistical Errors</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Type I Error $f_1$ (percent)</td>
<td>Type II Error $f_2$ (percent)</td>
</tr>
<tr>
<td>Barrows and Gilts</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Combined Model</td>
<td>32.69</td>
<td>28.57</td>
</tr>
<tr>
<td>Straight-Q Model</td>
<td>32.65</td>
<td>28.95</td>
</tr>
<tr>
<td>ARIMA Model</td>
<td>46.51</td>
<td>51.16</td>
</tr>
<tr>
<td>Cattle</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Combined Model</td>
<td>35.42</td>
<td>41.02</td>
</tr>
<tr>
<td>Straight-Q Model</td>
<td>43.48</td>
<td>51.02</td>
</tr>
<tr>
<td>ARIMA Model</td>
<td>53.66</td>
<td>62.50</td>
</tr>
</tbody>
</table>

Type I error: Turning point incorrectly predicted.

Type II error: Turning point missed.

TPE: All direction of change in the predicted series which are not the same as those in the actual series.
While the combined model and straight quarterly model failed to predict turning points for hog prices (Type II error) for 10 (or 28.57%) and 11 (or 28.97%) periods, respectively, the hog's ARIMA model missed 22 (or 51.16%) turning points. Likewise, both the econometric models incorrectly predicted a turning point for fewer periods in the hog price series than was the case for the ARIMA models (i.e., 17 (or 32.6%) and 16 (or 32.65%) periods for combined model and straight quarterly model, respectively, versus the reported 20 (or 46.51%) periods associated with the ARIMA model).

For cattle, Type I and Type II errors associated with the two econometric models are both smaller than those associated with the ARIMA models.

Between the two hogs econometric models, the results of the turning points analysis (TPE) indicate that the hogs straight quarterly and combined models performed relatively the same in tracking the movements of the hog price series.

While the combined model for hogs correctly predicted a turning point in 35 periods, the quarterly model only predicted 33. The quarterly model, however, correctly predicted a "no turn" in 27 periods while the combined model predicted 25.

Given that a turning point incorrectly predicted (Type I error) is as serious as a turning point missed (Type I error), the off-diagonal elements indicate relatively the same level of performance of the two forecasting models for barrows and gilts. The combined model, however, has a higher number of statistical turning points (i.e., 16 periods) than that associated with the quarterly model (i.e., 14 periods).
For the cattle series, the combined annual quarterly ratio model was more consistent in predicting turning points than the straight quarterly model. While the combined model for cattle correctly predicted a turning point in 31 periods, the quarterly model correctly predicted only 26 turning points. Moreover, the number of turning points missed by the combined model (i.e., 16 periods) is significantly less than those missed by the quarterly model (i.e., 21 periods). The turning points incorrectly predicted by cattle combined model is, likewise, smaller (17 periods) than those associated with the cattle quarterly model (20 periods).

It is interesting to note that the Type II errors are more serious than the Type I errors for all the cattle forecasting models; that is, the turning points incorrectly predicted (in percent) are less than the turning points missed in all the cattle forecasting models.

Except for the hog's ARIMA model, an opposite situation is observed in the two econometric models for barrows and gilts.

Comparisons based on total turning points errors (TPE) across commodities indicate that all forecasting models performed relatively better in tracking the movements of the hog price series than in the cattle series. This can be partly explained by the relatively greater variation in the cattle quarterly prices than in hogs over the 1960-1981 period (see Table 7).

Analysis of Regression Between Actual Values and Predictions

For barrows and gilts, the statistical tests of the hypotheses for "unbiasedness" and "efficiency" for all hog models is
accepted except for the ARIMA model which shows the regression coefficient to be significantly different from unity at the 25 percent level. The degree of inefficiency can be considered to be relatively minor as the value of the regression slope is still close to unity (Table 5, Part B).

For cattle, the statistical tests rejected the hypothesis of unbiasedness of forecasts derived from the combined annual quarterly ratio model and ARIMA model. The bias is due to the slight overestimation of the cattle prices. However, the test statistic indicates unbiased quarterly price predictions from the straight quarterly cattle model.

Likewise, the tests accepted the hypothesis of efficiency of the cattle price predictions derived from both the combined and the straight quarterly model. The hypothesis of efficiency of predictions for cattle prices from the ARIMA model is, however, rejected at the 25 percent level.

The $r^2_{AP}$ statistic indicates large and positive correlation between predictions and actual price levels for all models. These are generally expected due to the presence of strong trends in the price data. It should be noted that the correlation coefficient between predictions and actual values does not provide any indication of the absolute accuracy of the price predictions. They are included in the present analysis for the sake of completeness. The coefficient of determination, however, can provide some information about the relative accuracy of the predictions (Mincer and Zarnowitz, 1969).

The results of the MSE error decomposition as shown in Part A of Table 5 indicate that the fraction of error due to
forecast correlation ($P_{AF} \neq 1$) is the most important component of the mean square error. The proportion of error due to forecast slope ($8 \neq 1$) is negligible. Price predictions for hogs from all models are unbiased. While both the straight quarterly model and ARIMA model provided unbiased price predictions for cattle, a very slight bias is associated with the predictions derived from the combined model. It was mentioned earlier that unbiasedness does not imply anything about forecast accuracy.

**Evaluation of Short-Run Forecasts**

Short-run mechanical price forecasts for the first two quarters of 1982 were derived from both the straight quarterly models and ARIMA models for cattle and hogs. Based on the values of MSE and RMSE, the econometric straight quarterly model performed better than the ARIMA model in forecasting hog prices for the period considered.

The ARIMA model, however, out-performed the straight quarterly model in forecasting the cattle prices for the same period.

No valid conclusion can be drawn concerning the turning points of the quarterly forecasts because too few data points are considered.

Greater inaccuracy is associated in all the forecasting models when forecasting (ex-post) outside the sample period as indicated by the significant increase in the RMSE values (Table 8). Only the straight quarterly econometric model developed for hogs gave more accurate mechanical price forecasts than a no-change extrapolation for the 2-quarter period as indicated by the values of the $U_2$ statistics.
In summary, the evaluation of models based on the absolute and relative accuracy measures indicate that the combined annual quarterly ratio model out-performed both the straight quarterly model and ARIMA model in predicting the prices of barrows and gilts for the period 1960-1981. Likewise, both econometric models performed better than the ARIMA model in predicting the hog prices for the same period.

For cattle, similar descriptive evaluation measures indicate only a slightly different performance between the combined and quarterly model (i.e., the combined model is only marginally superior to the straight quarterly model); but a highly superior predictive performance of both cattle econometric models (i.e., combined and straight quarterly models) compared with the cattle ARIMA model is indicated.

The turning points analyses, however, clearly indicated a superior performance of both econometric models over the ARIMA models in tracking the cattle and hog price movements over the 22 year period (Tables 6 and 7).

Between the two econometric models, the tracking ability test indicated a relatively better performance of the cattle combined model over the straight quarterly model in tracking the cattle prices. On the other hand, the straight quarterly models showed a slightly better performance than the combined model in tracking the hog price series.

Evaluation of the short-run forecasts for the two-quarter period indicated that the straight quarterly econometric model
Table 8. Short-Run Forecasts of Cattle and Hog Prices from Alternative Models* ($/cwt)

<table>
<thead>
<tr>
<th>Period</th>
<th>Actual Prices</th>
<th>Econometric Quarterly Model</th>
<th>Straight Model</th>
<th>ARIMA Model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Forecast</td>
<td>Squared Error</td>
<td>Forecast</td>
</tr>
<tr>
<td>Barrows and Gilts</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8201</td>
<td>48.17</td>
<td>54.657</td>
<td>42.081</td>
<td>42.312</td>
</tr>
<tr>
<td>8202</td>
<td>56.46</td>
<td>54.287</td>
<td>4.722</td>
<td>45.992</td>
</tr>
<tr>
<td>MSE</td>
<td></td>
<td>23.402</td>
<td></td>
<td></td>
</tr>
<tr>
<td>RMSE</td>
<td></td>
<td>4.837</td>
<td></td>
<td></td>
</tr>
<tr>
<td>U₂</td>
<td></td>
<td>0.686</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cattle</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8201</td>
<td>63.36</td>
<td>73.231</td>
<td>97.437</td>
<td>61.513</td>
</tr>
<tr>
<td>8202</td>
<td>70.46</td>
<td>74.669</td>
<td>27.716</td>
<td>62.18</td>
</tr>
<tr>
<td>MSE</td>
<td></td>
<td>57.576</td>
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<td></td>
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<tr>
<td>RMSE</td>
<td></td>
<td>7.588</td>
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<td></td>
</tr>
<tr>
<td>U₂</td>
<td></td>
<td>1.3786</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*Short-run ex-post forecasts from the combined econometric model could not possibly be derived because the actual 1982 annual price is not yet available at the time of the analysis.
for hog prices gave more accurate forecasts than the ARIMA model. An opposite conclusion is, however, indicated about the performance of models in forecasting the cattle prices.
CHAPTER VI

Conclusions, Implications and Recommendations for Future Research

The need for accurate price forecasts is indeed overwhelming as decision makers face commonly violent fluctuations in commodity prices. Livestock producers and market intermediaries require more accurate and useful forecasts in order to minimize the costs of wrong decisions.

The evaluation and analysis of forecasting performance of alternative forecasting models (or techniques) can be useful to the forecast user and the forecaster by providing some measure of confidence about the forecasts. Alternative performance criteria can be employed to assess the predictive ability of the forecasting models.

As is done in the present study, these performance criteria provided the basis for ranking the forecasting models. The results of the comparative analysis can be further compared with those provided by other similar studies.

The main objective of this research involves the evaluation of the forecasting performance of a forecasting model which involves the combination of annual and quarterly-ratio models in predicting cattle and hog prices. It was hypothesized that the forecast performance is proportional to the information contained in the forecasting method.

To test this hypothesis, a sophisticated extrapolation technique was also applied to formulate ARIMA forecasting models for both commodities. The ARIMA models were constructed using only
the information provided by the historical time series of the variable being forecast; hence the amount of information required to develop these models was considered to be less than those employed in formulating the econometric structure models. Likewise, the costs involved in developing the econometric forecasting models were considered to be more than the cost associated in developing extrapolative models.

Based on the absolute and relative accuracy tests of ex-post forecasts for the period 1960-1981, the performance of the combined annual quarterly ratio model in predicting hog prices is clearly superior to the performance of both the straight-quarterly hog model and the ARIMA model. (With the price predictions from the straight-quarterly model still more accurate than the price predictions derived from the ARIMA model.)

Both econometric models showed about the same forecasting accuracy in predicting cattle prices for the same period. The ARIMA model for cattle provided inferior price predictions to the two econometric models.

It should be remembered, however, that the econometric price predictions were derived under optimal conditions. That is, the values of the explanatory variables used to generate the forecasts are the known actual values; whereas they would have to be forecast in a true forecasting situation thereby introducing another source of forecast error.

It is difficult to conclude about the adequacy of the forecasts derived from the alternative models, since it largely depends on the particular use to which the price predictions are to be employed.
It is also important to consider the results of the turning points analysis in order to decide which forecasting method to use.

As is indicated in the analysis, the ranking of models based on the absolute and relative accuracy performance measures only apply to the specific time period used. Evaluation of the short-run price forecasts for the first two quarters of 1982 indicated a better performance of the ARIMA model (in terms of MSE) than the straight-quarterly model in predicting the cattle prices. The latter performed better, however, than the ARIMA model in forecasting the hog prices. The period of forecasts is, nevertheless, too short to provide valid conclusions about the relative future performance of the two models.

The accuracy of more currently used methods will undoubtedly determine whether the forecasting techniques considered in this study are sufficiently accurate and adequate enough in a more practical forecasting work. As noted earlier, the forecasts generated from these models are usually adjusted and modified in order to take account of other factors not considered in the model. The knowledge and beliefs of the forecaster regarding relevant changes in the market are accounted for in arriving at a final forecast. This is necessary in order to improve the accuracy of the forecasts derived from the methods considered here.

Implications

A major finding in this study is that there is no specific forecasting method which exhibited universal or general superiority in terms of performance as indicated by the evaluation criteria.
employed in the analysis. Although the combined econometric model performed best in predicting hog prices for the 22-year period, it performed relatively the same as the straight quarterly model in predicting the cattle prices for the same period. A clear superiority of the two econometric models over the ARIMA models in predicting the prices of both commodities is, however, indicated.

Based on the evaluation of the short-run forecasts, the value of the straight quarterly econometric model can subjectively be considered as less than that of the ARIMA model in forecasting cattle prices, in spite of the smaller amount of information required for this simpler extrapolative method.

Further tests on this issue is, however, necessary to arrive at more conclusive results.

Forecast users and researchers should realize that, with the greater information contained in the econometric forecasts, better information about future prices can be derived from the econometric models considered here than from the naive-no-change methods.

Further efforts to improve the development of econometric models for the livestock industry are needed. Likewise, the application of time series analysis models in developing agricultural commodity models can potentially be improved.

A record of forecasting performance of the alternative techniques which are useful in providing outlook information should be maintained. By maintaining accurate information of price forecasts and other information related to the forecasting method, the forecaster can see the potential areas to be improved and need to be updated.
Recommendations for Future Research

Possible refinements that can be done in future work involve two major areas. First, is the extension of the time period used in the evaluation of models. This is necessary in order to better assess the forecasting ability of the models as opposed to their explanatory ability. This is possible as new price information and other required data become available.

An alternative approach to provide a longer evaluation period involves the use of backforecasts; i.e., the models can be assessed as to how they would predict the prices for the earlier years.

The second area involves the potential modification and further refinements in developing both the econometric models and ARIMA models for both commodities.

The straight quarterly econometric model could, for instance, be improved by taking account of the serial correlation in the residuals. Forecasts from this model could also be adjusted to account for the serial correlation. Further, additional key variables could be tested and see how they would affect the quarterly-ratio model.

In order to get more efficient estimates of the structural parameters in the combined annual-quarterly-ratio model, the two equations could be estimated together instead of employing the two-stage procedure. The Zellner's seemingly unrelated regression could potentially be applied. The efficiency of the parameter estimates is improved because the information about the correlation of the error terms is explicitly accounted for. The correlation in the residuals among the four-quarterly ratio models arises due to the restriction that the sum of the ratios is 100 percent or one.
The cost involved in using this procedure should, however, be evaluated in terms of its benefits. As mentioned earlier, the marginal benefits from more accurate forecasts should be compared with the marginal cost incurred in deriving those forecasts.

Potential refinements in the ARIMA models could potentially be explored.
REFERENCES


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APPENDIX