SHORT TERM HOG PRICE FORECASTING MODELS FOR THE MANITOBA HOG INDUSTRY

by

SHAKIB MBABAALI

A Thesis

Submitted to the Faculty of Graduate Studies
in Partial Fulfilment of the Requirements
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ABSTRACT

The Manitoba hog industry operates under uncertain and changing circumstances. Manitoba Department of Agriculture cites some of the factors responsible for the uncertain and changing environment. Such factors include high costs of new facilities, rising energy costs, variable prices for feed grains and protein supplements, and uncertainties about future hog market prices.

The research reported in this study concentrates on the uncertainties about future hog market prices by identifying the factors responsible for hog price fluctuations both on a weekly and monthly basis. The identified factors are used to generate knowledge about future hog market prices by using univariate time series, econometric and composite models as forecasting tools. The forecasts generated using those models are evaluated against the naive or no change model for their quantitative and qualitative forecasting performance. Evaluation measures used include Mean Squared Error, Mean Absolute Percentage Error and Theil's U_1 inequality coefficient for quantitative evaluation. The qualitative evaluation measures include the Naik and Leuthold 4 x 4 contingency table method and the Henriksson-Merton probability-based method. Under certain circumstances the Naik and Leuthold 4 x 4 contingency table method is shown to be inappropriate and a 9 x 9 contingency table is suggested.

Overall, the models developed do not perform very well quantitatively but the univariate time series model performs well at predicting turning points. The study demonstrates how producers could benefit from the turning point information generated by the univariate time series model.

Keywords: forecasting, time series, econometric model, composite model, naive model, quantitative forecast evaluation, qualitative forecast evaluation.

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Lastly, I would like to express my sincere thanks to my family and friends for being there whenever I needed them.

DEDICATION

to my mother
Hanifah Nakachwa Mbabaali

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Chapter One

INTRODUCTION

Economic analysts attempt to understand and explain social and economic phenomena. Accurate and expedient information about relevant economic variables leads to proper business planning (Sullivan and Claycombe). Almost all business organizations encounter the need to assess current and likely future trends of economic variables. The main objective of such an assessment is to access knowledge about risky events that are quite crucial to the decisions made in the present period with intentions of improving the economic pay-off to such decisions. Decision making in an uncertain environment can be based on information generated by forecasts of random variables in the problem that are relevant to current decisions and future consequences (Lawrence). Forecasting general business and economic behaviour provides a basis for making current decisions but whose effects and outcomes can only be realised in the future.

The use of information generated by good and reliable forecasting methods is becoming a necessity to the survival and prosperity of many business organizations (Sullivan and Claycombe). Hence, forecasts can be utilised to reduce the uncertainty about the future course of events and provide as much information as possible to the decision maker, bearing in mind the fact that "... forecasting is a means to aid decision taking and not an end in itself" (Jenkins, 1982, p.3). The usage of forecasts as essential inputs in most decisions concerning the future of a business setting cannot be overemphasised (McLaughlin).

In reference to hog markets, Luby (1957) observes that future knowledge on both supplies and prices of hogs are essential for an efficient marketing system. More reliable information enables farmers to adjust both production and marketing decisions geared towards profit maximization. Luby (p.1402) states that,

> ...farmers need price forecasts each time they make either a marketing or production decision. A hog producer usually has a period of up to 45 days in which he can market butcher hogs. During some seasons of the year, he will usually net a greater return from marketing at a lower weight while during other periods he will usually gain by feeding to higher weights.

The Manitoba hog industry, like many other industries, changes from time to time. A study by Manitoba Department of Agriculture (MDA) identified some of the factors responsible for the observed changes. Such factors include:

a) high costs of new facilities;

b) rising energy costs;

c) variable prices for feed grains and protein supplements;

d) uncertainties about future hog market prices.

Under such circumstances, it becomes essential for the producers to make use of as much information as they possibly can get to prepare for the likely constraints and at the same time take advantage of possible opportunities. Forecasting of hog prices is one way of providing such information to the producers, particulary as a way of reducing uncertainties about future price levels.

When discussing forecasting as a prerequisite to good decision making, it is important to point out that different business settings may require different forms of forecasts ranging from the simplest and less involved to complex and more cumbersome. For example, consider a local agricultural producer selling only a few products into a small market. Given such circumstances, that producer may acquire a thorough understanding of the circumstances governing the business and thus be able to produce reasonable intuitive forecasts. On the other hand, consider a large scale agricultural producer operating within an international market framework. Forecasts for such a setting require an understanding of the inter-relationships within and between the different market levels. Another important point is that even within a given business setting, different decisions may call for different forecast characteristics. Such characteristics include (Firth):

a) accuracy - some decisions require a higher degree of accuracy while others could tolerate wider margins of error;

b) time horizon - this refers to the time period over which the decision will have an effect. Decisions may be short-term, medium-term, or long-term;

c) speed and regularity - some decision making processes require regular forecasts with a quick response rate to major changes in patterns of the series concerned.

Although different forecasting situations may call for unique requirements, there still exist many elements that are common to a range of situations (Wheelwright and Makridakis). Such elements include:

a) uncertainty - forecasts are designed, primarily, to generate some information about the uncertain future events; and,

b) historical data - all decision-making processes requiring a forecast, directly or indirectly, make use of information embedded in historical data.

Relationship Between Planning and Forecasting

In economics, forecasting is used to predict the possible movements of economic variables in the future, given some specified conditions or assumptions (Wheelwright and Makridakis). Planning comes after forecasting whereby planners make use of information generated by forecasts in making decisions that are best suited for the organizations they represent. In so doing, planners attempt to influence, based on the results of a forecast, the subsequent events in a favourable direction. It is important to point out that as decisions are made, there is a feedback effect in which the decisions impact on the original forecasts. Hence, there is a need to adjust the forecasts so as to incorporate the feedback effect. This prevents the possibility of forecasts becoming misleading since they will no longer represent the circumstances that prevailed at the time of preparation (Wheelwright and Makridakis).

Limits of Forecasting

It is important to point out the limitations of forecasting since the knowledge of such limitations should enable forecast users to think more appropriately around the decision situation and, therefore, make it possible to consider alternative solutions and/or seek for improved techniques (Wheelwright and Makridakis). It is true that economic forecasts are becoming increasingly important for the strategic planning of business organizations, but at the same time there is an increasing sense of frustration rising at the failures of forecasts (McAuley). Naylor partly attributes this to the fact that some economic forecasters have a tendency to over-sell their ability to predict the future. McAuley (p. 389) stresses that "... economic forecasts deal with uncertainty, and so it is prudent and honest to set out the risks that may cause a forecast to err."

Forecasts are bound to have errors irrespective of the degree of sophistication of the method used to generate them. That is, all forecasters make errors since it is impossible to know the future with certainty (Webster). Some of the sources of error include the stochastic nature of the process that generates data used in forecasting, errors in measurement of variables used, and misspecification of functional forms. When using conditional forecasts, there is an added source of possible errors due to the forecasting of exogenous variables. Hence, given such possible sources of error, it would be unrealistic to expect perfect forecasts.

In a world that changes continuously, it is difficult to develop simple and reliable quantitative forecasting techniques to signal the nature and magnitude of the likely future changes. Granger and Newbold (1986, p.265) point out that,

> ... given a world in which the amount of potential information is vast and the number of potential ways of employing it enormous (partly because in many areas economic theory is ill structured, or insufficient data are available to distinguish with any high degree of confidence between competing theories), it makes very little sense to view forecast optimality as a useful working concept.

Forecasts are likely to perform best if the future looks similar to the past, which might not necessarily be the case. Hence, forecast users should examine the assumptions underlying the forecasts together with the maintained hypotheses when making use of forecast results.

Problem Statement

Participants in the hog industry operate under uncertain circumstances. Although some of the factors causing the unpredictable circumstances are quite uncontrollable (weather, for example), the effect of others (like price and quantity movements) can be managed if appropriate information regarding such circumstances can be obtained. However, the extent to which the effect of these factors can be reduced largely depends on the quantity and quality of information available to decision makers. Both, long-run and short-run information is required in order to enable producers to make more accurate and timely decisions regarding the production and marketing of hogs. Hog producers have about 45 days during which they can make marketing decisions (Luby). Hence, they need to determine whether it is more rewarding to sell their hogs at a point in time at the going price or retain them for sale at a later date at an uncertain price. The final decision will be affected by beliefs about the short-run movements of the market variables.

It has been shown that, although absolute price movements and their variations around the means are essential to both hog producers and commercial parkers, they (producers and packers) are more concerned about the future trends of prices and try to determine the possible production or marketing alternatives in an effort to reducing the effects of any unfavourable trends in price movements (Myers and Havlicek). The Manitoba hog industry, like many industries, is a dynamic industry that changes from time to time. Decisions taken by market participants under such uncertain circumstances are believed to be crucial to the wellbeing of the enterprise. Provision of reliable information about possible future movements of the variables concerned is likely to improve the quality of the decisions. Hence, a short-run forecasting model could help generate the knowledge required for short-run profit maximizing marketing decisions.

Scope of the Study

It is intended, in this study, to develop, evaluate and compare short-run price forecasting models for the Manitoba hog economy. Hog producers require information about the short-term movements of market variables to help them make short-term marketing decisions. It is thought that the provision of such information will help improve the hog industry operational efficiency. In developing the forecasting model, the operational structure of the industry in question is considered. All of the slaughter hog trading activities in Manitoba province are conducted through the Manitoba Pork Board which, like many other pork boards in Canada, operates on a weekly price pool basis (Manitoba Pork Press). Given this information, a weekly price forecasting model is formulated for the Manitoba hog economy. Also, since hog producers have up to 45 days during which to market slaughter hogs (Luby), a monthly price forecasting model is formulated for the hog economy. Information generated by these models may be of use to hog producers when determining the number of slaughter hogs to market at a point in time.

A number of analytical procedures are employed to generate forecasts. Specifically, the methods employed include the following:

a) time-series analysis;

b) econometric analysis; and,

c) composite forecasting methods.

A naive model (that is, the previous period's price prevails to the present) is used as a benchmark against which the performance of the three core models (considered to be more complicated and sophisticated) is measured. The important issue here is to determine whether it is beneficial to use elaborate methods (bearing in mind the increased costs in terms of time and money) relative to using the naive but less expensive methods.

Objectives

The following are the specific objectives of the study:

a) identify the factors responsible for weekly and monthly hog price fluctuations in the Manitoba hog market and use them to develop models to generate knowledge about the short-run relevant economic variables for the purpose of hog price forecasting; and,

b) determine which of the developed models does a better forecasting job given Manitoba hog market conditions.

Guide to Choosing the Appropriate Forecasting Technique

Wheelwright and Makridakis suggest four points that can be considered when deciding on a technique to use for a given situation:

a) item to be forecasted - in this case the forecaster should study the characteristics of the situation at hand bearing in mind the purpose of the forecast. The purpose could be to predict the following or a combination of any of them:

i) the continuance of the underlying pattern in the series;

ii) the continuance of the underlying relationship(s) between series; and,

iii) a turning point;

b) relationship(s) between the situation and the characteristics of the available forecasting techniques;

c) quantity and quality of available data; and,

d) time available for preparing the forecast.

Layout of the Study

This study is primarily concerned with three analytical models (univariate time series, econometric and composite forecasting models) and each model is assigned a separate chapter. A brief theoretical framework of each of the three models and forecast evaluation methods are provided in chapter two. For the univariate time series model, the four basic stages are discussed. These stages include identification, estimation, diagnostic checking and forecasting. Econometric modelling, on the other hand, makes use of economic theory and reported applied research in identifying the variables to include in the model. For deriving the weights to use in constructing the composite forecasting model, a regression method is used.

Weekly and monthly time series models are treated in chapter three. Sample autocorrelation and partial autocorrelation functions are used to identify two monthly and four weekly models. All the six tentatively identified models are estimated using data covering the period January, 1986 to August, 1991 for the weekly series and from January, 1986 to December, 1990 for the monthly series. The models are checked for white noise using the Ljung-Box test statistic. A preliminary evaluation of the competing time series models is done in order to choose a monthly time series model to be used as part of the composite model.

Chapter four deals with the econometric model. Demand and supply functions are defined for the Manitoba hog industry. The functions are estimated recursively using the Ordinary Least Squares (OLS) estimation procedure for the period 1986-1990. However, because weekly data on most of the explanatory variables were not available, only a monthly econometric model is estimated. The estimated parameters are used to generate twelve monthly forecasts for the year 1991 (data not used in estimation).

A monthly composite model (comprising the best of the monthly time series models and the monthly econometric model) is presented in chapter five. Various methods of deriving weights of the constituent models have been suggested by different people. A restricted regression method developed by Granger and Ramanathan is used because it accounts for any possible biases that may exist in the constituent model forecasts.

Model evaluation is the subject of chapter six which contains a review of the existing forecast evaluation methods. Formal evaluation techniques are used to compare the performance of the alternative forecasting models. Models are evaluated based on their quantitative and qualitative characteristics. Measures used for quantitative evaluation include Mean Squared Error (MSE), Mean Absolute Percentage Error (MAPE) and Theils' U1 inequality coefficient. For qualitative evaluation the measures used include the

4 x 4 contingency table method developed by Naik and Leuthold and the Henriksson-Merton probability based test.

Finally, a discussion of the results together with the concluding remarks are presented in chapter seven.

Chapter Two

THEORETICAL FRAMEWORK

Time-Series Data

A time-series data set can be described as a series of measurements or values ordered by a time parameter. The order in which the sample is presented is of considerable importance (Granger and Newbold). A time-series can further be categorised as either being a discrete time-series or a continuous time-series. The other characteristic of a time-series is the deterministic nature. The series can be classified as deterministic if it could be represented by a unique and explicit mathematical relationship and as such exact future values of the series could easily be forecasted (Appelbaum). On the other hand, non-deterministic series exhibit random or fluctuating properties and cannot be represented by an explicit mathematical function. Non-deterministic time-series data are considered to be a result of a stochastic process. Hence, forecasting of exact future values for such non-deterministic series is very difficult. Because of the random nature of the series, probability statements are employed to represent the relationships, and different analytical techniques could be employed for investigative purposes. This study deals with non-deterministic time-series data.

Analysts are always in search for new information or better ways of looking at the existing information so as to confirm or change forecast results, and because of that, there are various techniques that can be used in generating forecasts (Webster). This study concentrates on the following methods:

a) univariate time-series;

b) structural or econometric; and

c) composite forecasting.

Following below is a brief discussion of the theoretical underpinning of each method.

Univariate Time-Series Models

Univariate time-series models are often considered to be *ad hoc*, that is, with little or no theoretical basis. A typical univariate time-series model usually relates dependent variables to lagged values of the dependent variables and to variables that describe the random nature of their past behaviour. That is, the model makes use of information obtained from past behaviour of a given economic variable and replicates it in order to forecast future behaviour of the same variable (Pindyck and Rubinfeld). For example, if the observed price series $(P_1,P_2,P_3,\ldots,P_t)$ is regarded as a realisation from the general ARIMA (p,d,q) process and the desire is to forecast a future value P_{t+j}, then the forecast value P_{t+j} $(j\geq 1)$ will be made at time t at which time only $P_t,P_{t-1},\ldots,P_{t-n}$ observations are available. In this case, t is referred to as the origin and j as the lead time and, in probabilistic terms, the forecast value could be viewed as a conditional expectation of P_{t+j}, given $P_t,P_{t-1},\ldots,P_{t-n}$. That is (Mills, p. 104):

$$f_{t,j}=E(P_{t+j}|P_t,P_{t-1},\ldots,P_{t-n})$$

The process of univariate time series forecasting involves four basic stages. These include:

a) identification stage which is concerned with determining the degree of differencing (d) required to induce stationarity in the original data series and determining the orders p and q for the autoregressive and moving average components respectively. In case of seasonal data, the identification stage also involves determining the degree of seasonal differencing (D) and the orders P and Q for the seasonal autoregressive and seasonal moving average components respectively. The major concept used at the identification stage is that of sample autocorrelation function and partial autocorrelation function whose characteristics are data specific (Granger and Newbold). The concepts are defined in detail in the next chapter where they are used extensively;

b) estimation stage which follows the identification stage and is concerned with estimating parameters of the tentatively identified models;

c) diagnostic checking stage which is used as a criterion for model choice (Mills). It is concerned with checking whether a given estimated model is adequate or not and adequacy, in this case, is determined by investigating the residuals. The specific characteristics to be checked include:

    i) the mean of the residuals which should be zero;

    ii) the residual variance which should be approximately constant;

    iii) the residual autocorrelations which should be insignificant;

d) forecasting stage which is the last stage of the process and involves projecting the identified movement patterns of a given series to future periods. The underlying assumption is that some pattern or a combination of them in a given series keep recurring over time (Wheelwright and Makridakis).

Econometric Modelling

Koutsoyiannis distinguishes two major categories of econometric analysis. These include:

a) theoretical econometrics which basically involves the designing of appropriate techniques to measure economic relationships. In designing such techniques, however, the nature of the process to be analyzed is an important consideration. Some economic relationships may exist independently and, therefore, would require single equation techniques, while other relationships may be inter-related and would, therefore, need simultaneous equation techniques. In this study, a recursive system is used which is a special case of simultaneous equations;

b) applied econometrics which makes use of the theoretical econometric tools in analyzing economic phenomena and forecasting economic behaviour.

In econometric analysis, economic theory, reported applied research and knowledge about any peculiar behaviour of the situation under investigation are indicators of what to expect as far as parameter magnitudes and signs are concerned.

Composite Forecasting

The field of composite forecasting has received great attention in empirical and academic literature over the last few years. It is contended, in the literature, that there is a need to combine forecasts from different forecasting techniques for better results.

Various methods for combining forecasts have been suggested for different situations. All the suggested methods are concerned with the derivation of weights for the respective forecasts and these weights have been shown to depend on the variances and covariances of the forecast errors (Holden et al). The regression method with a constant term, suggested by Granger and Ramanathan, is employed in this study largely because of its allowance for any possible biases in the forecasts being combined. The method is explained in detail in Chapter Five.

Forecast Evaluation Methods

Forecast accuracy can be measured in different ways. In this study forecast accuracy is looked at from the quantitative and qualitative perspectives. The quantitative measures are concerned with the size of the forecast error and make use of descriptive statistics to summarise the characteristics of sample evidence. Three of such measures are briefly introduced below:

a) mean squared error (MSE) - this is defined as $\frac{\sum (F_t - A_t)^2}{n}$ (Holden et al., p.14), where F_t refers to the forecast at time t, A_t is the actual realisation at time t and n is the number of forecasts. The lower the MSE the better the method is. Squaring the errors in the formula above gives extra weight to large errors. This, in essence, makes the cost of making positive or negative errors the same (Holden et al.);

b) mean absolute percentage error (MAPE) - it is defined as $\sum \frac{100|A_t - F_t|}{n|A_t|}$

(Holden et al., p. 37). MAPE differs from MSE in that it does not assign extra weight to large errors. Again the lower the MAPE the better the method;

c) Theil's U1 inequality coefficient - it is defined as $\dfrac{\sqrt{\sum \frac{(F_t - A_t)^2}{n}}}{\sqrt{\frac{\sum F_t^2}{n}} + \sqrt{\frac{\sum A_t^2}{n}}}$

(Holden et al. p. 38). The coefficient lies between 0 for perfect forecasts and 1 for the worst forecasts.

Qualitative forecast evaluation, on the other hand, deals with the model's ability to predict turning points. In the 1960s, the method that was commonly used for qualitative forecast evaluation was the directional change measure. It involves noting whether the predicted value is lower or higher than the actual and whether the corresponding movement of the actual variable tallies with the predicted one (Naik and Leuthold). Theil suggested the use of over or under predictions and the turning point method as an alternative. This method uses a 2 x 2 contingency table as will be explained in greater detail in chapter 6. However, Naik and Leuthold found that conclusions made based on this method could be misleading as it fails to account for the direction of the turning or no turning points. They suggested the use of a 4 x 4 contingency table as a means of overcoming this weakness and, therefore, provide more information about the qualitative performance of forecasting methods. The method uses four summary measures to evaluate the performance of forecasts. These measures include:

a) ratio of accurate forecasts (RAF);

b) ratio of worst forecasts (RWF);

c) ratio of accurate to worst forecasts (RAWP);

d) ratio of inaccurate forecasts (RIF).

A closer look at this 4 x 4 contingency table method reveals that it does not, also, tell the whole story. Specifically, the method fails to account for cases where prices stay unchanged for at least two periods. A 9 x 9 contingency table is, therefore, suggested in chapter 6.

Another measure used in this study is that developed by Henriksson and Merton called the H-M method. This is a nonparametric statistic that measures the ability of forecasting methods to predict the direction of change. What distinguishes the Henriksson and Merton measure from all the other measures of qualitative performance is its probability-based scale. All these measures are explained in detail in chapter 6.

Chapter Three

UNIVARIATE TIME SERIES ANALYSIS

Time-series models are part of the major category of quantitative methods widely used in analytical work. The models attempt to identify the underlying pattern in a given series, with time used as reference, and then try to project that pattern in the future for forecasting purposes (Wheelwright and Makridakis). The underlying assumption is that of continuity of the identified pattern to future periods (Newbold, 1983). Time-series models have proved to be quite successful particularly with short-term forecasting (Judge et al.).

Univariate models, like all other forecasting models, are associated with advantages and limitations depending on the situation. Some of these advantages and limitations are listed below.

Advantages of Univariate Models

a) They are simple and straightforward (Moore);

b) have been found to produce good short term forecasts (Judge et al.);

c) they provide an optimal means of forecasting because of their low marginal cost yet with high marginal returns (Holden et al.);

d) model building process allows for flexibility of model choice which is largely dependent on the characteristics embedded in the data being used.

Limitations of Univariate Models

a) Univariate time-series models, like all time-series models are *ad hoc*, especially at the identification stage. They lack the underlying theory to help guide the analyst when choosing between possible models, and therefore success at the identification stage calls for a lot of experience. This leads to the widely held criticism about the necessity of using judgement at the identification stage as opposed to using a deterministic method that leads to a single solution (Newbold);

b) model building process involves extensive pretesting in an effort to specify number of lags to include in the model. This drastically reduces the power of hypothesis tests (Mills);

c) they do not take account of any other factors, other than the present and past values of the series at hand, that could influence the series being forecast (Moore). They are stochastic or probabilistic descriptions of the outcome of a generating process and no information about the inputs of the generating process is provided (McClearly and Hay);

d) for the inexperienced users, the statistics used at the identification stage, (that is, sample autocorrelations and partial autocorrelations) do not provide adequate information to guide the users in choosing a more appropriate model from the possible alternatives (Newbold).

Model Identification

Time-series models are based on the assumption that the sequence of observations making up a given time-series are a result of jointly distributed random variables (Nelson). The underlying stochastic process that generated the data is characterized and approximated by a model which is then estimated using statistical methods. With univariate time-series models (which is the major concern of this chapter) characterization "...is given not in terms of a cause-and effect relationship (as would be the case in a regression model) but in terms of how that randomness is embodied in the process..." (Pindyck and Rubinfeld, p.493). In doing so, it may intuitively appear that available information is being neglected thereby not making best use of the data. Judge et al. (1988) note that this observation would be true if the models employed by economists in describing the data generating processes were precisely the models that prevailed in real life. It is therefore noted that

> ...unfortunately, our information about the underlying sampling mechanism is generally incomplete, and thus economic and econometric models are at best rough approximations to reality. Therefore it should not be surprising that time-series models that use only the information from a set of observations on a single variable have in some instances provided forecasts that are superior to predictions from a large-scale econometric model (Judge et al. p.675).

Granger and Newbold acknowledge that model identification is the most difficult stage of the model building process and they attribute this to the fact that there is no deterministic method of handling the problem. Furthermore, Box and Jenkins (1976) note that the data being used are a function of the behaviour of the physical world whose exact characterization using mathematical tools is very difficult.

The purpose of identification is to choose a model, among the general class of Autoregressive Integrated Moving Average (ARIMA) models (Mills). That is, to provide a reason of selecting one model over another (McClearly and Hay). ARIMA models are generally described as ARIMA(p,d,q,) where, p refers to the number of lagged autoregressive terms; d is the degree of differencing required to induce stationarity; and q is the number of lagged stochastic errors in the moving average component (McAuley). McAuley identifies six possible types of ARIMA models depending on the values assumed by p, q, and d as follows (McAuley, p.114):

a) ARIMA(p,0,0) = a pure autoregressive model having *p* lagged autoregressive terms, that is AR(p);

b) ARIMA(p,d,0) = pure autoregressive model having *p* lagged autoregressive terms of a *d* order differenced time series, that is ARI(p,d);

c) ARIMA(0,0,q) = pure moving average model having *q* lagged stochastic error terms, that is MA(q);

d) ARIMA(0,d,q) = pure moving average model having *q* lagged, *d* order differenced stochastic error terms, that is IMA(d,q);

e) ARIMA(p,0,q) = mixed model having *p* lagged autoregressive terms, *q* lagged stochastic error terms, and undifferenced, that is ARMA(p,q);

f) ARIMA(p,d,q) = mixed p term autoregressive, q term moving average, and d order differenced model.

Generally, nonseasonal ARIMA models are represented as (Mills, p,116):

$$\Phi(B)\nabla^{d}x_{t}=\Psi_{0}+\Psi(B)a_{t}$$

where,

x_t = actual observed series or a transformation of the observed series, and t = 1, 2, ..., T;

∇ = differencing operator;

B = back shift operator;

d = degree of differencing required to achieve stationarity;

Φ, Ψ = $(\phi_1,...,\phi_p)$, $(\psi_0,\psi_1,...,\psi_q)$ are the parameters, and;

a_t = a representation of the white noise error process.

However, with seasonality considerations the model assumes a more general form of the kind presented below (Bowerman and O'Connell, p. 100):

$$\phi_p(B)\phi_P(B^L)Z_t=\delta+\psi_q(B)\psi_Q(B^L)a_t$$

where,

Z_t = actual observed stationary series or a transformation of the observed series to induce stationarity, and t = 1, 2, ..., T;

$\phi_p(B)$ = the nonseasonal autoregressive operator of order p;

$\phi_P(B^L)$ = the seasonal autoregressive operator of order P, and L represents the seasonal span (i.e L=52 for weekly data, and L=12 for monthly data);

ψ_q = the nonseasonal moving average operator of order q;

$\psi_Q(B^L)$ = the seasonal moving average operator of order Q;

δ = constant term whose inclusion in the model depends on certain conditions to be discussed in the estimation section; and,

a_t = representation of the white noise error process.

The problem addressed by the identification process is that of determining the values assumed by $d,p,P,q,$ and Q. Following below is a step-by-step identification process.

Stationarity

In time-series analysis, the very first step of model identification should be to check the series at hand for stationarity (Ali and Thalheimer). It is important to know whether or not the underlying stochastic process that generated a given series is stationary, since the concept of stationarity is crucial in choosing the appropriate model among the general ARIMA family of time-series models (Box and Jenkins, 1976). According to Granger and Newbold (p.4), a series Y_t is said to be stationary if

mean of $Y_t = \mu$, variance of $Y_t = \sigma_y^2 < \infty$, and

$$\text{covariance } Y_t, Y_s = \lambda_{t-s}$$

where, $\sigma_y^2 = \lambda_0$. That is, the process is stationary if its mean and variance are invariant with respect to time and, therefore, the covariance between two data points Y_t and Y_s at two different time periods is determined by the length of the time period separating the two data points, (t-s), and not on time itself.

The method used to test for stationarity is that suggested by Mills (1990), Granger and Newbold (1986), Pindyck and Rubinfeld (1981), and Box and Jenkins (1976). They suggest the use of sample autocorrelation function, which is said to provide a close approximation of the true population autocorrelation if the number of observations in the time series under investigation is large. Granger and Newbold (1986, p.81) and Box and Jenkins (1976, p.33) suggest that in order to ensure reasonable success in the identification process, a lag length of at least 50 observations should be used when computing autocorrelation functions. It is noted that "... we would not be terribly confident of success with much less than 40-50 observations" (Granger and Newbold, 1986, p.81). The method's strength is embedded in its ability to capture the extent to which a given value of the series is correlated with previous values, the lag length and hence, the memory power of the process (Mills, 1990). Sample autocorrelations range from 1 to -1. A sample autocorrelation value that is close to 1 indicates that those observations in a given series with k lags apart tend to move together linearly and with a positive slope; the reverse is true for sample autocorrelations close to -1 (Bowerman and O'Connell). The autocorrelation function with lag k is defined as follows (Mills, p.65; Granger and Newbold, p.78; Pindyck and Rubinfeld, p.499):

$$\rho_k = \frac{\sum_{t=1}^{T-k} (y_t - \bar{y})(y_{t+k} - \bar{y})}{\sum_{t-1}^{T} (y_t - \bar{y})^2}$$

where,

ρ_k	=	autocorrelation function with lag k;
t	=	time period (week or month depending on the model under consideration) and ranges from t=1, 2,...,T.

The usefulness of the autocorrelation function in model identification stems from the fact that any one time series is theoretically characterized by a unique autocorrelation function (McClearly and Hay).

Sample autocorrelations were computed (using the Shazam package) for both weekly and monthly, original undifferenced, data using a lag length of 60. According to Mills, a slow and almost linear decay of the sample autocorrelation function as the lag length increases is a suggestion of nonstationarity. That is, a series is considered stationary if its sample autocorrelation function either cuts off or dies down fairly quickly; on the other hand, a series whose sample autocorrelation function dies down at a slow pace is said to be nonstationary (Bowerman and O'Connell). The cause of the autocorrelation function to remain large even at long lags is the tendency of the series to be on one or the other side of the sample mean of the series for many periods (Nelson). Many researchers and authors acknowledge the fact that the identification process causes difficulty to the analyst because there are no clear-cut guidelines to some aspects of the process, hence differences of opinion are bound to occur amongst analysts. It has been observed by McClearly and Hay (p.94) that

> ambiguity in identification sometimes amounts to differences of opinion or interpretation. One analyst may see two spikes in the estimated ACF whereas some other analyst may see only one spike. The first analyst will then conclude that an ARIMA (0,0,2) model adequately represents the series ... while the second analyst will conclude that an ARIMA (0,0,1) adequately represents the series...

McClearly and Hay suggest, however, that as a means of reducing the ambiguity surrounding the identification process, confidence bands should be placed around the estimated autocorrelation functions (ACF) and partial autocorrelation functions (PACF). The formulas for computing the respective standard errors are given as follows (McClearly and Hay, p.94):

$$SE\rho_k = \sqrt{1/T(1+2\sum_{i=1}^{k}\rho_i^2)}$$

where,

SE ρ_k refers to the standard error associated with autocorrelation for lag k.

Standard errors for the partial autocorrelations are calculated using:

$$SE(\phi_{kk})=\sqrt{1/T}$$

where,

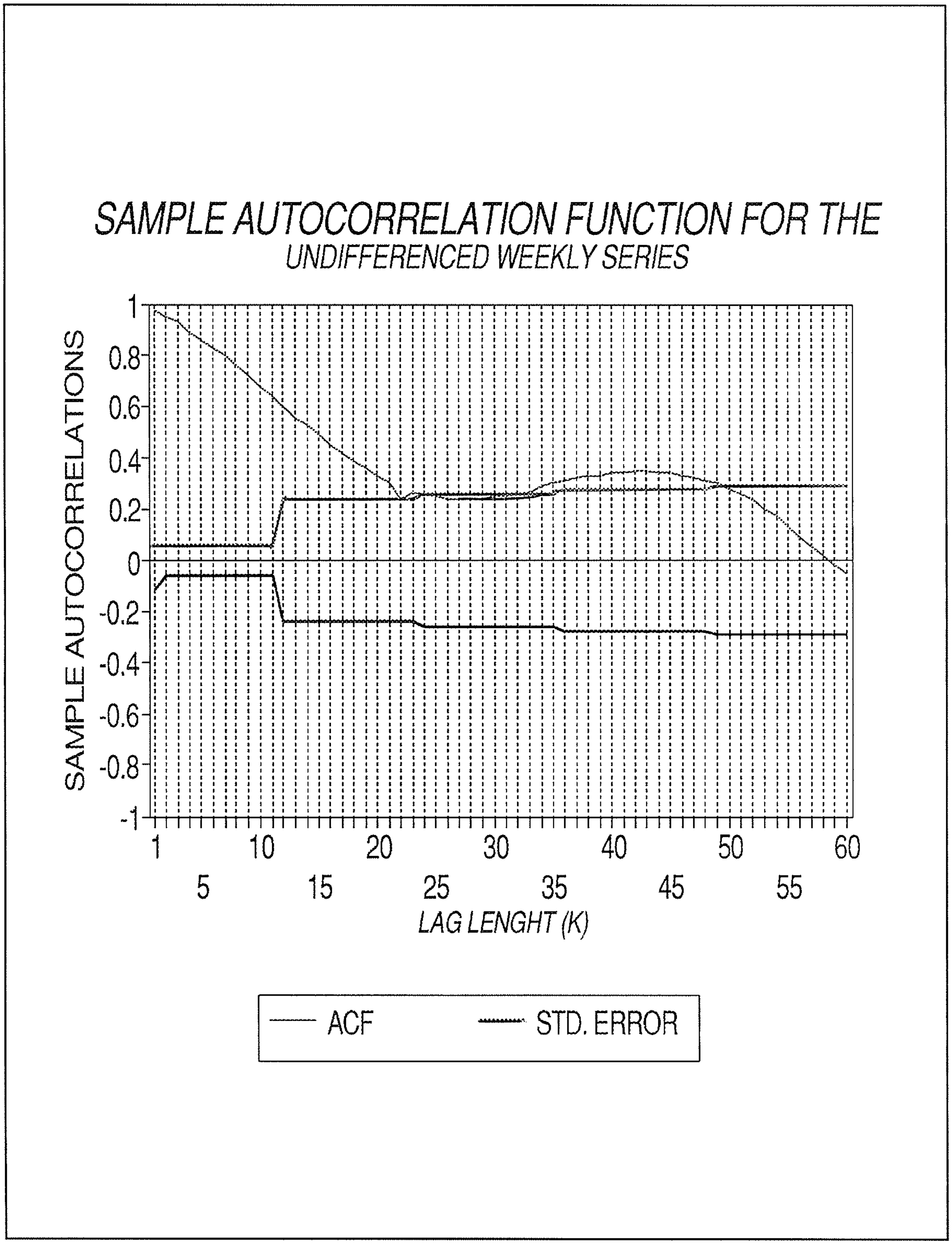
$SE(\phi_{kk})$	=	standard error associated with ϕ_{kk}, the partial autocorrelation for lag k; and
T	=	sample size.

Values of ρ_k and ϕ_{kk} that fall within the interval ±2 SE are considered to be not significantly different from zero at a 95 percent confidence level (McClearly and Hay).

Identifying Degree of Differencing, *d*

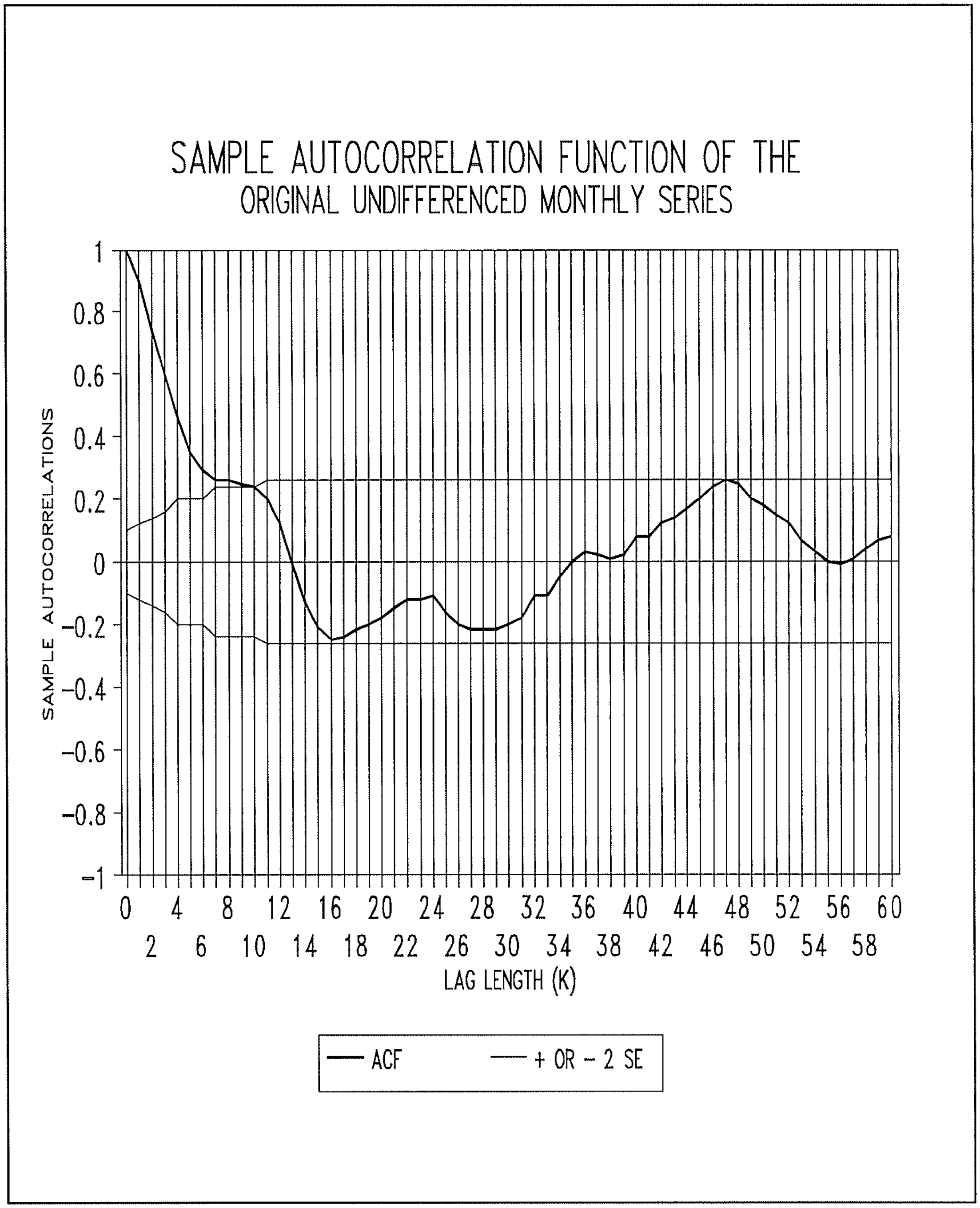
To determine the degree of differencing, sample autocorrelation functions are used as suggested by Granger and Newbold (1986), Nelson (1978), Bowerman and O'Connell (1987) and Pindyck and Rubinfeld (1981). A sample correlogram is a plot of the calculated sample autocorrelations, ρ_k against the lag length, k. Figure 1 below represents sample correlogram for the original undifferenced weekly data. It is observed from figure 1 that sample autocorrelation functions (SAC) die down quite slowly as k increases which is an indication that differencing is required (Pindyck and Rubinfeld).

Figure 1


SAMPLE AUTOCORRELATION FUNCTION FOR THE
UNDIFFERENCED WEEKLY SERIES
SAMPLE AUTOCORRELATIONS
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1
1
10
20
30
40
50
60
5
15
25
35
45
55
LAG LENGHT (K)
ACF
STD. ERROR

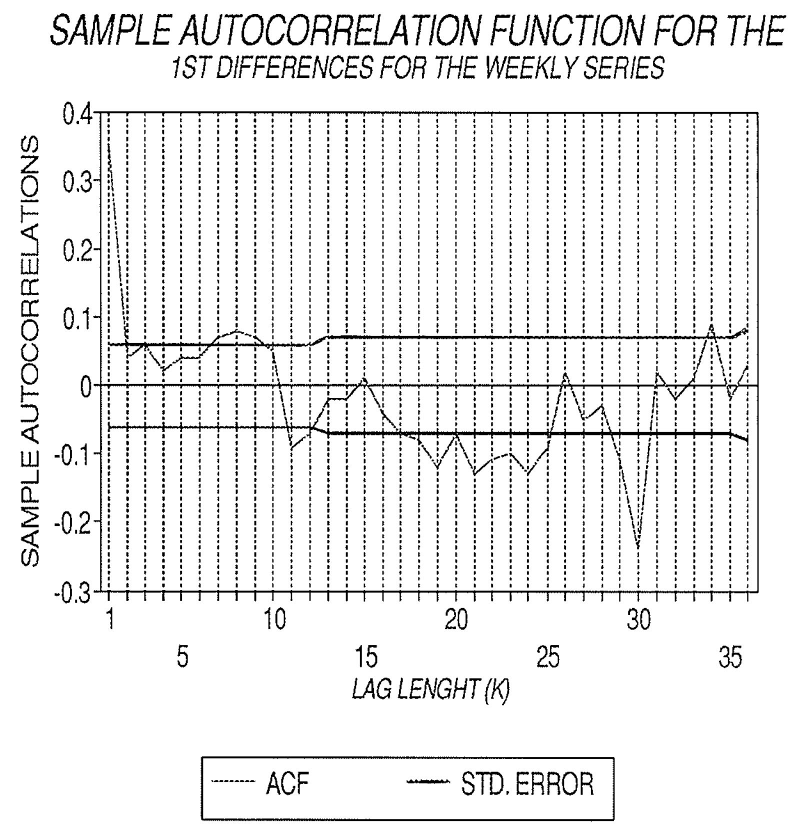
On the other hand, the sample correlogram for the monthly series (figure 2) exhibits a stationary pattern which is manifested by a rapid decline of the SAC at the nonseasonal level.

Figure 2



This is an indication of a stationary series and, therefore, no nonseasonal differencing is required of the monthly series. Next, first differences of the weekly data are computed their autocorrelation functions plotted (see figure 3).

Figure 3



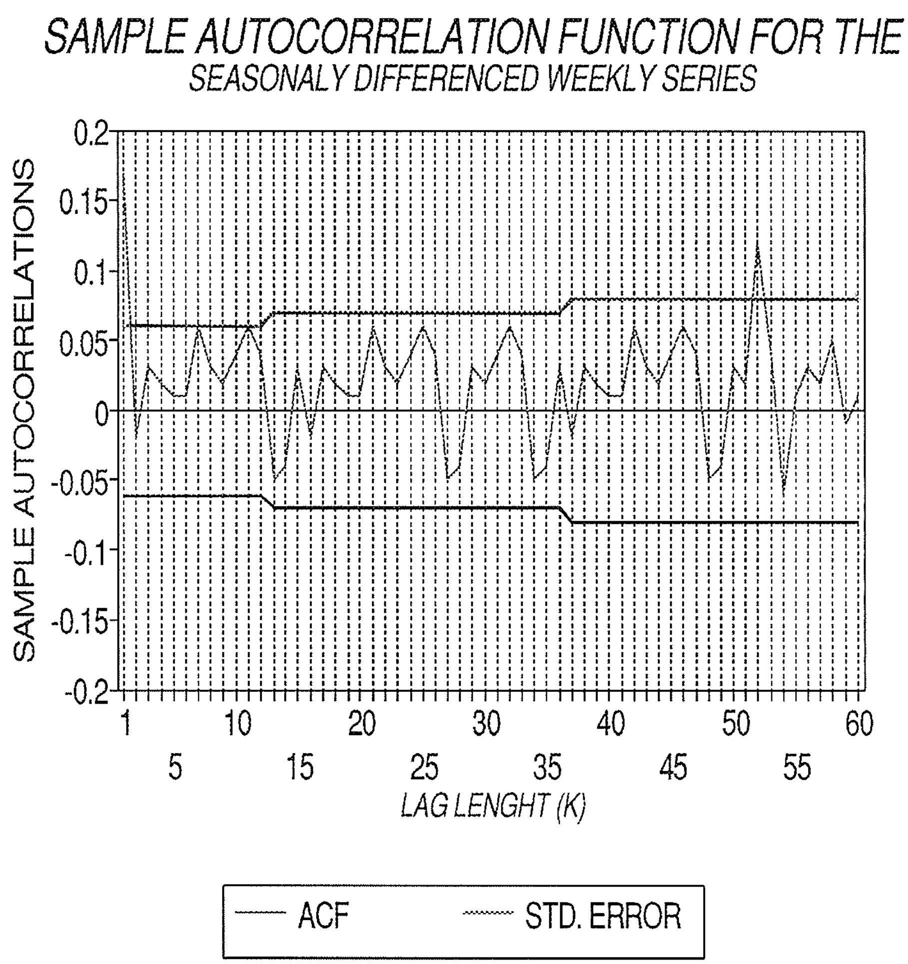
From the graph for the first differences of the data, it is observed that the SAC values seem to fluctuate around a constant mean but with large and repetitive swings across the data period. This is suggestive of seasonal variation which is expected of hog prices. An examination of figures 2 and 3 indicates that, although the series seem to be stationary at the nonseasonal level, there is a need for seasonal differencing to account for the strong seasonal effects being manifested. Figures 4 and 5 below represent sample autocorrelation functions of weekly and monthly data series respectively, with the following values:

$$Z_t=(1-B^L)^D(1-B)^d X_t$$

where,

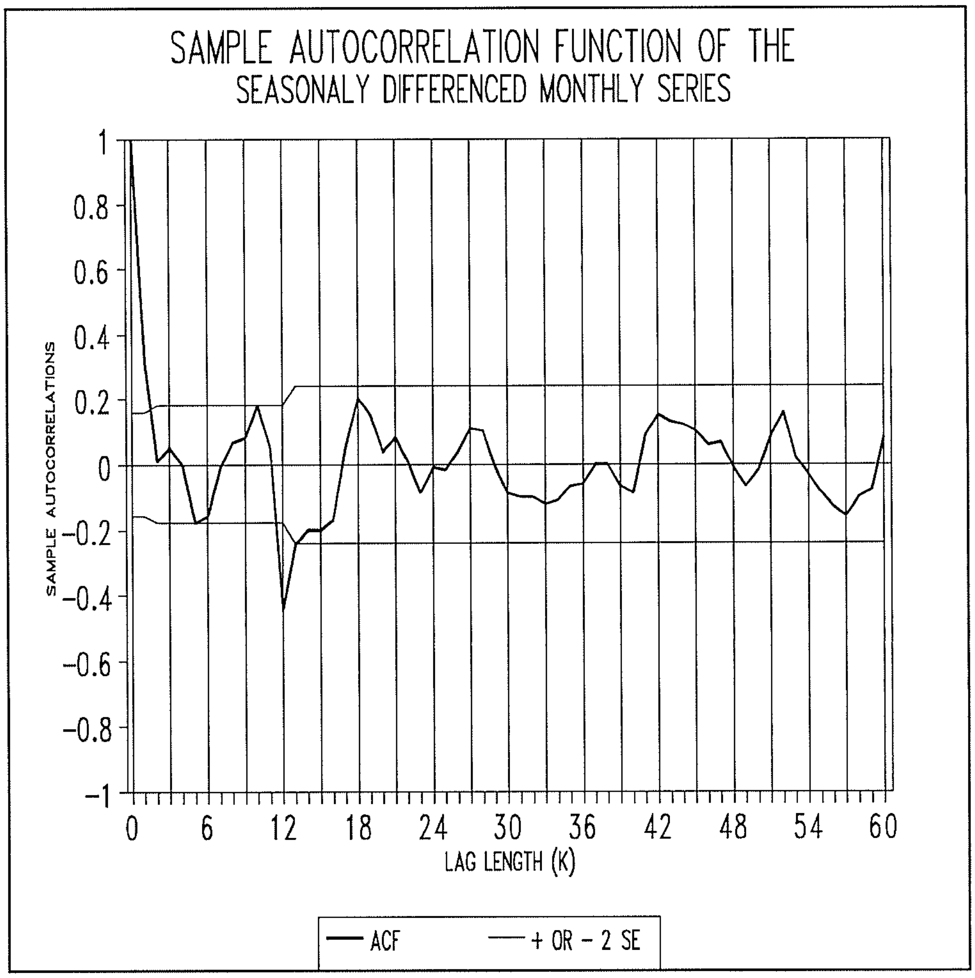
Z_t	=	transformed stationary series with t representing the time unit which is either week or month and t=1, 2, 3, ..., T;
d	=	1 and is the degree of differencing required to induce stationarity at the nonseasonal level;
D	=	1 and is the degree of differencing required to induce stationarity at the seasonal level;
B	=	back shift operator;
L	=	seasonal span which is 52 for weekly series and 12 for monthly series; and,
X_t	=	the original untransformed data series.

Figure 4


SAMPLE AUTOCORRELATION FUNCTION FOR THE
SEASONALY DIFFERENCED WEEKLY SERIES
SAMPLE AUTOCORRELATIONS
0.2
0.15
0.1
0.05
0
-0.05
-0.1
-0.15
-0.2
1
10
20
30
40
50
60
5
15
25
35
45
55
LAG LENGHT (K)
ACF
STD. ERROR

Looking at the sample autocorrelation functions for the seasonally adjusted first differences, it is observed that at the nonseasonal level of the weekly series the SAC has a spike at lag 1 and dies down fairly quickly in a sinusoidal pattern thereafter. At the seasonal level, the SAC has a spike at k=L=52 and cuts off quickly thereafter. With monthly data series (figure 5), a somewhat similar pattern is observed.

Figure 5



From figure 5, the SAC has a spike at lag 1 at the nonseasonal level and cuts off quickly thereafter. At the seasonal level, the SAC has a spike at k=L and dies down quickly thereafter. Hence, the values obtained by using the above transformations are considered to be stationary leading to an ARIMA(p,1,q)(P,1,Q) seasonal model for the weekly series, and ARIMA(p,0,q)(P,1,Q) for the monthly series. The next task then is to identify the values assumed by p, P, q, and Q, the orders of the nonseasonal and seasonal autoregressive and moving average components respectively.

Identification of the Seasonal Models

Identification of a particular form of the general Box-Jenkins model of order (p,P,q,Q) calls for (Bowerman and O'Connell):

a) deciding whether the models should include δ, the constant term;

b) choosing which of the operators $\Phi_p(B)$, $\Phi_P(B^L)$, $\psi_q(B)$, and $\psi_Q(B^L)$ to include in the model together with the orders they assume.

To determine whether to include δ in the model or not, a procedure suggested by Bowerman and O'Connell is adopted. It involves determining whether the mean of the working series (Z_t in this case) is statistically different from zero or not. The decision rule is to include δ if the mean is statistically different from zero and to exclude the term if the mean is not statistically different from zero. The value of δ is given by

$$\delta = \mu\phi_p(B)\phi_P(B^L)$$

and the test statistic is

$$\frac{\bar{Z}}{\frac{S_Z}{\sqrt{T-b+1}}}$$

where S_Z represents the standard deviation of the time-series under consideration and is approximated as follows (Bowerman and O'Connell):

$$S_Z=\sqrt{\frac{\sum_{t=b}^{T}(Z_t-\bar{Z})^2}{(T-b+1)}}$$

where,

b=d=1, and the rest of the notation is defined above.

If the absolute value of S_Z is greater than 2 the implication is that the mean is statistically different from zero and thus to include δ in the model. The reverse is true if the absolute value of S_Z is less than 2. In this particular case the mean was found to be not statistically different from zero and, therefore, the constant term was excluded.

In determining the autoregressive and moving average terms both at the seasonal and nonseasonal levels, the behaviour of sample autocorrelation functions and partial autocorrelation functions is examined. If a process is autoregressive of order p and with no seasonal effects, then the current observation of a given series is a function of a weighted average of past observations lagged p periods plus a random disturbance in the present period (Pindyck and Rubinfeld). That is

$$X_t=\alpha_1 X_{t-1}+\alpha_2 X_{t-2}+\ldots+\alpha_p X_{t-p}+\varepsilon_t$$

where,

X_t = the series under investigation with t = 1, 2, ..., T;

ε_t = random disturbance in the current period.

The random disturbances, ε, are assumed to be independently distributed over time. That is, each ε_t (with t=1, 2, ..., T) is assumed to be a normal random variable with mean 0, variance σ_ε^2, and covariance $\gamma_k = 0$ for $k \neq 0$ (Pindyck and Rubinfeld, p.515). On the other hand, a process is characterized as a moving average process of order q if each observation X_t is determined by a weighted average of random disturbances lagged q periods (Pindyck and Rubinfeld). The process is denoted as MA(q) and represented in an equation form as follows (Granger and Newbold, 1986; Pindyck and Rubinfeld, 1981):

$$X_t=\mu+\varepsilon_t-\psi_1\varepsilon_{t-1}-\ldots-\psi_q\varepsilon_{t-q}$$

where,

X_t = series under investigation and t = 1, 2, ..., T;

ψ_i = are parameters that can be either positive or negative, and i = 1, 2, ..., q;

μ = mean of the moving average process which is equal to $E(X_t)$.

The assumptions regarding the random disturbances are similar to those made for the autoregressive component.

In identifying the autoregressive and moving average components at the nonseasonal levels, that is p and q, the generated sample autocorrelation functions and partial autocorrelation functions are compared to the theoretical properties of various commonly used ARIMA models. Holden et al. (1990, p.57) and Mills (1990, p.130) summarize the theoretical properties as follows in table 1 below:

Table 1

Properties of the Autocorrelation and Partial Autocorrelation functions for Various ARIMA Models

ARIMA Model	ACF	PACF
(1,d,0)	Exponential or oscillatory decay.	$\phi_{kk}=0$ for k>1.
(2,d,0)	Exponential or sine wave decay.	$\phi_{kk}=0$ for k>2.
(p,d,0)	Exponential and/or sine wave decay.	$\phi_{kk}=0$ for k>p.
(0,d,1)	$\rho_k=0$ for k>1.	Dominated by damped exponential.
(0,d,2)	$\rho_k=0$ for k>2.	Dominated by damped exponential or sine wave.
(0,d,q)	$\rho_k=0$ for k>q.	Dominated by linear combinations of damped exponentials and/or sine waves.
(1,d,1)	Tails off. Exponential decay from lag 1.	Tails off. Dominated by exponential decay from lag 1.
(p,d,q)	Tails off after q-p lags. Exponential and/or sine wave decay after q-p lags.	Tails off. Dominated by damped exponentials and/or sine waves after p-q lags.

When determining the order of the underlying autoregressive process, more information is obtained by making use of the partial autocorrelation functions in addition to sample autocorrelation functions (Pindyck and Rubinfeld). Pindyck and Rubinfeld define partial autocorrelation function of lag k, PACF(k), as a measure of correlation between time-series observations k units apart after the correlation at intermediate lags has been controlled; that is, removing the effects of all other lags except the appropriate ones. Essentially, the identification process for the autoregressive process is concerned with choosing AR(p) such that (Judge et al. p.685)

$$\phi_{kk} \neq 0 \, for \, k = p ; \phi_{kk} = 0 \, for \, k > p.$$

However, estimating partial autocorrelation functions for a series is difficult. Mills, (1990), Granger and Newbold (1986), Pindyck and Rubinfeld (1981), Box and Jenkins (1976), and Nelson (1973) recommend using the Yule-Walker equations, which linearly relate sample autocorrelation functions to partial autocorrelation functions. However, solving the Yule-walker equations requires knowledge about the order of the autoregressive process, p, which is the problem attempted to be resolved. In this study, however, the Shazam statistical package is used to compute sample autocorrelations, partial autocorrelations, and their respective standard errors which are used in significance tests.

Using the guidelines outlined above, the following models are tentatively identified for estimation.

Weekly Models:

Model 1:

$$(1-\phi_1 B)(1-\phi_{1,52}B^{52})Z_t=(1-\psi_1 B)(1-\psi_{1,52}B^{52})a_t.$$

Model 2:

$$(1-\phi_1 B)(1-\phi_{1,52}B^{52})Z_t=(1-\psi_1 B-\psi_2 B^2)(1-\psi_{1,52}B^{52})a_t.$$

Model 3:

$$(1-\phi_1 B)Z_t=(1-\psi_1 B)(1-\psi_{1,52}B^{52})a_t.$$

Model 4:

$$Z_t=(1-\psi_1 B)(1-\psi_{1,52}B^{52})a_t.$$

Monthly Models:

Model 1:

$$(1-\phi_1-\phi_2)(1-\phi_{1,12})Z_t=(1-\psi_{1,12})a_t.$$

Model 2:

$$(1-\phi_1-\phi_2)(1-\phi_{1,12}-\phi_{2,12})Z_t=a_t.$$

Note that δ, the constant term, is excluded from all the above models because the mean of the working series is not statistically different from zero.

Model Estimation

Data used for this section comprises of both weekly and monthly live slaughter hog prices ($/cwt) of the Manitoba hog industry. The sample size for weekly model parameter estimates ranged from January, 1986 to August, 1991 (that is, 294 weekly observations) and for monthly models the sample size was from January, 1986 to December, 1990 (that is, 60 monthly observations). The data were collected from the Canadian Livestock Weekly Review (various issues) and Manitoba Hog Marketing Board.

The section of model estimation is concerned with provision of estimates for the autoregressive and moving average seasonal and nonseasonal parameters of the tentatively identified models. The objective here is to obtain a set of autoregressive and moving average parameter estimates that minimize the sum of squared errors (Pindyck and Rubinfeld, 1991, p.500):

$$S(\phi_1,\ldots,\phi_p;\Phi_1,\ldots,\Phi_P;\psi_1,\ldots,\psi_q;\Psi_1,\ldots,\Psi_Q)=\sum_t \varepsilon_t^2$$

where S represents the sum of squared errors.

Parameter estimates for the monthly models are presented in table 2, while table 3 contains parameter estimates for the weekly models.

Table 2

Parameter Estimates for the Univariate Time Series Monthly Models, Manitoba Hog Industry, 1986-1990

	Type	Order	Parameter Estimate	Std. Error	T Value
Model 1	Reg. AR	1	1.29	0.12	10.45
	Reg. AR	2	-0.36	0.12	-2.93
	Sea. AR	12	1.00	0.07	147.90
	Sea. MA	12	0.81	0.05	16.06
Model 2	Reg. AR	1	1.31	0.13	10.42
	Reg. AR	2	-0.37	0.13	-2.96
	Sea. AR(1)	12	0.45	0.10	4.39
	Sea. AR(2)	12	0.52	0.10	5.25

Table 3

Parameter Estimates for the Univariate Time Series Weekly Models, Manitoba Hog Industry, January, 1986 to August, 1991

	Type	Order	Parameter Estimate	Std. Error	T-Value
Model 1	Reg. AR	1	-0.42	0.14	-2.98
	Reg. MA	1	-0.70	0.11	-6.34
	Sea. AR	52	-0.27	0.06	-4.16
	Sea. MA	52	0.75	0.03	22.16
Model 2	Reg. AR	1	-0.21	0.36	-0.59
	Reg. MA	1	-0.50	0.36	-1.40
	Reg. MA	2	0.02	0.14	0.16
	Sea. AR	52	-0.27	0.06	-4.20
	Sea. MA	52	0.75	0.04	21.03
Model 3	Reg. AR	1	-0.43	0.15	-2.89
	Reg. MA	1	-0.70	0.12	-5.85
	Sea. MA	52	0.81	0.03	28.92
Model 4	Reg. MA	1	-0.28	0.06	-4.38
	Reg. MA	2	0.11	0.06	1.77
	Sea. MA	52	0.81	0.03	26.80

Model Diagnostic Checking

The tentatively identified models are tested for adequacy by utilising residuals to choose, among the tentative models, the model that adequately describes the data generating process. Several statistics have been developed to deal with the situation but the two most commonly used include the Box-Pierce statistic and the Ljung-Box statistic (Bowerman and O'Connell). However, the Ljung-Box statistic is used in this study because it has been theoretically shown that it gives better results than the Box-Pierce statistic (Bowerman and O'Connell). The Ljung-Box test statistic is given as (Bowerman and O'Connell, P.149):

$$Q = T'(T'+2)\sum_{i=1}^{K}(T'-i)^{-1}r_i^2$$

where,

T'	=	T-(d+LD);
T	=	number of observations in the original series;
L	=	span of the seasonal cycle;
d	=	degree of nonseasonal differencing used in data transformation;
D	=	degree of seasonal differencing;
r_i	=	sample autocorrelation of the residuals separated by a lag of i time units; and,
K	=	is arbitrary but it is often chosen in such a way that $K-n_p=20$, where n_p represents the number of estimated parameters in the model under

consideration.

If the computed Q statistic is less than $\chi^2_{[.05]}(K-n_p)$, that is the critical chi-square value with $K-n_p$ degrees of freedom, or if the probability value is greater than 0.05, then it is reasonable to conclude that the model is adequate (Bowerman and O'Connell).

Tables 4 and 5 (for monthly and weekly series respectively) contain the computed Q-values and tabular chi-square values, with respective degrees of freedom.

Table 4

Computed Q-Statistics for the Univariate Time Series Monthly Price Forecasting Models for the Manitoba Hog Industry

Model Type	Computed Q-values	Table-χ^2 Value	P-value	Model Status
Model 1	25.75	$\chi^2_{[0.05,20]}=31.41$	0.17	Adequate
Model 2	28.91	$\chi^2_{[0.05,20]}=31.41$	0.09	Adequate

Table 5

Computed Q-Statistics for the Univariate Time Series Weekly Price Forecasting Models for the Manitoba Hog Industry

Model Type	Computed Q-values	Table-χ^2 Value	P-Value	Model Status
Model 1	14.02	$\chi^2_{[0.05,20]}=31.41$	0.83	Adequate
Model 2	14.11	$\chi^2_{[0.05,19]}=30.14$	0.78	Adequate
Model 3	11.87	$\chi^2_{[0.05,21]}=32.67$	0.94	Adequate
Model 4	11.40	$\chi^2_{[0.05,21]}=32.67$	0.95	Adequate

From the results presented above, it is seen that all the computed Q statistics are less than their respective chi squared critical values. Hence, it is concluded that all the tentatively identified models (both weekly and monthly) adequately explain the generating processes of the observed time series observations. The implication is that the residuals are unrelated. This is further supported by the fact that all the probability-values are greater than the set α-value of 0.05, an indication of white noise process. Therefore, all the models are used to predict future values and forecasting performance is used as a criterion for model choice.

Forecasting Using Univariate Models

In this section, seasonal, univariate ARIMA models (estimated above) are used to forecast hog prices. The objective is to produce an optimum forecast. An optimum forecast in this case refers to that forecast with the least mean-square forecast error (Pyndick and Rubinfeld). However, as McCleary and Hay (p. 205) put it that

> ...preparing the forecast itself is not a difficult task and requires little experience. Recognizing the idiosyncrasies of each situation, and accounting heuristically for these idiosyncrasies in the forecast, requires some experience.

The underlying assumption in univariate forecasts is that the identified data generating process carries on to future periods, which might not necessarily be the case. However, this limiting assumption is required for univariate forecasting models (McCrealy and Hay).

Tables 6 and 7 below, represent twelve monthly forecasts generated using the estimated monthly models, and twelve weekly forecasts for the weekly models. Twelve periods ahead are used for forecasting because short term forecasting models have been shown to perform poorly if stretched deep into future periods (Newbold, 1983).

Table 6

Univariate Time Series Monthly Price Forecasts for the Manitoba Hog Industry, January-December, 1991

Month	Model 1 Forecasts	Model 2 Forecasts	Actual Price
1	61.59	62.57	63.96
2	64.01	64.65	68.38
3	61.54	62.86	66.13
4	60.40	62.22	65.88
5	66.47	69.06	70.42
6	71.57	74.09	71.49
7	72.60	73.74	67.47
8	72.57	72.77	65.68
9	69.81	66.95	57.72
10	68.33	69.52	57.15
11	64.63	65.57	49.78
12	61.45	58.56	49.72

Table 7

Univariate Time Series Weekly Price Forecasts for the Manitoba Hog Industry, September-November, 1991

Steps Ahead	Model 1 Forecasts	Model 2 Forecasts	Model 3 Forecasts	Model 4 Forecasts	Actual Price
1	58.57	58.60	58.70	58.82	57.61
2	58.87	58.91	58.99	59.08	57.15
3	58.56	58.58	59.12	59.28	56.70
4	57.74	57.73	59.33	59.46	59.42
5	56.96	56.92	58.80	58.94	59.42
6	56.42	56.37	57.88	58.02	59.87
7	55.99	55.94	57.22	57.36	55.79
8	54.58	54.51	56.17	56.31	53.52
9	54.35	54.31	55.21	55.35	51.26
10	53.09	53.07	53.94	54.07	49.89
11	52.65	52.64	53.51	53.65	48.53
12	53.76	53.78	54.27	54.41	49.44

For the forecasts generated above, the relationship between successive forecasts and the behaviour of the associated forecast error variances are all determined by the degree of differencing or order of integration (Mills).

A preliminary forecast evaluation for time series weekly and monthly model forecasts is conducted so as to determine the best models to be used in the composite forecasting model. The evaluation methods used are explained in detail in chapter six. Generally, the evaluation is done for both quantitative and qualitative model characteristics; that is, the size of the forecast errors and the models' ability to predict turning points. The results of the quantitative preliminary evaluation are summarised in tables 8 and 9 for monthly and weekly series respectively.

Table 8

Preliminary Quantitative Evaluation Results of Univariate Time Series Monthly Models for the Manitoba Hog Industry

Model Type	MSE	MAPE	Theil's U1 Coefficient
Model 1	63.96	12.29	0.09
Model 2	58.56	10.91	0.06

Table 9

Preliminary Quantitative Evaluation Results of Univariate Time Series Weekly Models for the Manitoba Hog Industry

Model Type	MSE	MAPE	Theil's U1 Coefficient
Model 1	59.29	11.18	0.09
Model 2	59.29	11.18	0.09
Model 3	62.35	12.19	0.12
Model 4	64.38	14.20	0.14

For weekly models, the results of the evaluation measures indicate that models 1 and 2 are assigned exactly the same degree of accuracy from all the three evaluation measures. The measures also show model 3 to perform better than model 4. Overall, models 1 and 2 outperform models 3 and 4 based on the three quantitative forecast evaluation measures presented above. At the monthly level, all the three measures consistently put model 2 as a better performing model than model 1.

Qualitative Evaluation Results

Table 10 contains results for the preliminary qualitative evaluation. Using the RAF measure, one would conclude that all the four weekly models are of equal qualitative performance with a RAF value of 0.556, and that model two of the monthly models is of a better qualitative value (with a RAF value of 0.800) than model one with a RAF value of 0.778. The overall conclusion would, therefore, be that generally monthly models do a better job forecasting hog prices than weekly models.

Table 10

Preliminary Qualitative Model Evaluation Results of Univariate Time Series Weekly and Monthly Models for the Manitoba Hog Industry

Model Type	RAF	HM Confidence Level[a]
Weekly Models		
Model 1	0.556	0.382
Model 2	0.556	0.382
Model 3	0.556	0.530
Model 4	0.556	0.530
Monthly Models		
Model 1	0.778	0.667
Model 2	0.800	0.976**

[a] (1 - the HM confidence level) equals the significance level, i.e the highest level at which one would fail to reject the null hypothesis of no information using a one-tail test (McIntosh and Dorfman).
** significant at the 95% level using a one-tailed test.

Additionally, it would be concluded that for weekly models, any one model of the four would do as good a job qualitatively forecasting hog prices as any other. A similar conclusion would be made for monthly models. However, using the HM test for value of information, different conclusions are made. First of all for weekly models, one would reject the null hypothesis of no information value at the 0.618 level for models

1 and 2, and at the 0.470 level for models 3 and 4. The implication in this case is that weekly models 1 and 2 are considered equivalent qualitatively and models 3 and 4 are also equivalent. However models 3 and 4 in this case are assigned a better qualitative value than models 1 and 2. This is because models 3 and 4 predict turning points better than models 1 and 2.

At the monthly level, some consistency is observed between the RAF measure and the HM test. The null hypothesis of no information value would be rejected at the 0.333 level for model 1 while the rejection level for model 2 would be 0.024.

Overall, using 0.50 as the critical significance level and using a one-tail test, one would fail to reject the null hypothesis of no information value for all the weekly models and model 1 of the monthly models. However, the null hypothesis would be rejected for model 2 at the monthly level. The implication in this case is that model 2 for the monthly series successfully predicted price increases and decreases in a more balanced manner than all the other models (McIntosh and Dorfman). Generally, for the weekly series, models 1 and 2 perform better than models 3 and 4 quantitatively while models 3 and 4 do a better job predicting turning points than models 1 and 2. For the monthly series model 2 proved superior to model 1 in all categories. Model 2 for the monthly series is, therefore, selected to be used in a composite forecasting model in Chapter Five.

Chapter Four

ECONOMETRIC MODEL

Introduction

Econometric or structural models, unlike univariate models, attempt to capture the effect of many of the variables (economic or noneconomic) believed to have an effect on the dependent variable. That is, the method assumes that the value of the dependent variable is influenced by one or more other variables, thereby modelling the interdependencies that do exist. An adequate representation of interdependencies is essential for a forecasting model (Wheelwright and Makridakis). In so doing, the method creates an environment in which there is an increased understanding of the networking of the economic setting.

Identification of the variables to include in structural models is achieved by way of general economic theory (Brandt and Bessler). Less judgemental requirements are necessary for the model construction stage in contrast to the identification stage of a univariate time series model. In general, however, judgemental intervention cannot be ruled out entirely irrespective of the model used. Brandt and Bessler report that many agricultural commodity price forecasts are largely influenced by industry expertise by way of calibrating model results to include information believed to have been left out by the model.

Advantages and Disadvantages of Econometric models

In choosing a model to use, given a particular situation, it is advisable to compare advantages and limitations of various models and relate them to the study objectives and resource constraints. Following below is a brief discussion of some of the advantages and disadvantages associated with econometric models.

Advantages of Econometric Models

a) Moore (1989) points out that econometric models, as compared to univariate time-series models, provide statistical proofs and mathematical expressions of the specific relationships that exist between some variables and the variable being forecasted;

b) econometric models have been found to be very useful especially when dealing with behavioral simulations and policy issues (Diebold and Pauly);

c) econometric models use economic theory in identifying variables to include and what to expect as far as parameter magnitudes and signs are concerned (Brandt and Bessler);

d) econometric models attempt to capture the interrelationships of economic factors by using multiple variables (Moore, 1989).

Limitations of Econometric Models

a) With econometric models, unlike time-series models, the complex nature of the properties of the residual terms may not be adequately addressed. Specifically, the interrelationships of the residuals over time are ignored (Granger and Newbold);

b) the models lack a set of defined rules that one can apply across different situations. That is, their development is dependent upon specific situations and therefore need the involvement of someone skilled or quite conversant with econometric principles (Wheelwright and Makridakis);

c) econometric models call for a continuous monitoring and interference in form of incorporating the feedback due to actions taken and updating for periodic changes;

d) the method needs more time, expenses, and resources than univariate time-series models and, therefore, may not as appropriate for short term purposes.

Model specification

The theory underlying forecasting of economic variables allows for the derivation of forecasts for a given random variable using alternative forecasting techniques. Choice of variables involves consideration of such things as the economic logic of the problem, and aims and objectives of the study. It is also important to do an exploratory analysis of the possible alternatives, bearing in mind the objectives, before coming up with the final model. Fildes and Howell (1979) warn against the possible dangers of using model fit as the most important criterion of model choice, and specifically discourage the use of *ex post* fit as the desired objective of model selection. They suggest some points that should be considered in a model specification process. Such points include:

a) prior theory - which should be used in choosing among the possible functional forms and in formulating more appropriate null hypotheses, as opposed to using the conventional 'zero effect' null hypothesis, when deciding on the variables to include in the model;

b) *ex ante* testing - should be used in comparing forecasting performance of different models since a good *ex post* data fit does not necessarily imply a good forecasting performance and vice versa; and,

c) comprehensibility - models for forecasting purposes should be developed in such a manner so as to suit user needs in terms of interpretation, possibility of user interventions, and the ease of understandability.

The nature of the economic system to be analyzed, equations to be used together with the method of analysis are all important considerations when specifying an econometric model. Time divisions are another important consideration since the extent to which variables interact is largely influenced by time. Nerlove and Addison found recursive systems to be more appropriate than simultaneous systems for shorter time periods. However, with longer-run analyses where variables have more time to interact, they found that simultaneous systems do a better job. Koutsoyiannis defines a model as recursive if its structural equations are in such a manner that the first equation comprises of exogenous independent variables; the second equation comprises of exogenous independent variables and the first endogenous variable of the first equation; and so on. A hypothetical example is given below to clarify the point:

$$p_1 = f(k_1, k_2, k_3; u_1)$$

$$p_2 = f(k_4, k_5, k_6, p_1; u_2)$$

$$p_3 = f(k_7, k_8, k_9, p_1, p_2; u_3)$$

where, both p and k are hypothetical variables and k_i (where i=1, ..., 9) is a predetermined variable.

The econometric model developed and estimated in this study comprises of structural equations for demand and supply of live hogs.

Demand for hogs

In developing the demand function, it is assumed that all the buyers have intentions of reselling hogs that are purchased. However, they do not know the price at which they are to sell the processed product with certainty, but formulate expectations based on the available information and their willingness to buy slaughter hogs at the going prices is dependent on these price expectations. It is assumed that buyers use all the available information when formulating their price expectations. Based on that assumption, an adaptive expectations model is developed in an attempt to explain the observed behaviour, bearing in mind the restrictions associated with non-experimental model building (Judge et al). Adaptive was chosen over rational expectations because the concept of rational expectations has received little success as far as applied work is concerned. This could be attributed to its restrictive assumption of perfect information yet in real life economic agents are faced with a lot of uncertainties. To represent these expectations, two models were tested using hog prices lagged one period and a two period lagged moving average. The lagged price model was found to be a better proxy for the buyers' expectations.

Economic theory suggests that price of a close substitute is an important explanatory variable in the demand of a commodity. The Winnipeg monthly consumer price index for beef is included as the substitute commodity price.

It is also hypothesised that the prices of pork and pork products are relevant factors in determining the price offered by buyers. To represent this effect, the monthly consumer price index for pork is included in the demand function.

There are certain periods of the year during which the demand for pork and its products is higher than normal. Christmas time is one of such periods during which there is an increased demand for pork products. Summer is another season identified as a high demand season for the same products meant for 'bar-b-que' activities. To account for the observed differential in demand, dummy variables are included in the demand function for the months of June, July, August, and December.

Previous studies have found that the price offered by buyers for slaughter hogs is highly dependent on the number of hogs from previous purchases still in their possession and the amount of pork in cold storage. A problem is that of adequate representation since monthly data on cold storage are not readily available. This study adopts the method used by Leuthold to represent these storage variables. Several models were tested to determine an adequate proxy for the storage variable. Quantity supplied the previous period was found to be a good proxy and therefore included in the demand function to represent storage.

The model can be represented as:

$$Ph_t = f(Ph_{t-1}, Pp_t, Pb_t, Q_t, Q_{t-1}, D)$$

where,

Ph_t	=	average price (dollars per hundredweight) for slaughter hogs in month t;
Ph_{t-1}	=	defined the same as Ph_t but lagged one period; it is used as a representation of output price expectations by the buyers;
Q_t	=	total number of slaughter hogs sold in month t;
Q_{t-1}	=	defined the same as Q_t but lagged one period; it is used as a proxy variable for storage;
Pp_t	=	Winnipeg monthly consumer price index for pork;
Pb_t	=	Winnipeg monthly consumer price index for beef;
D	=	dummy variable for the demand differential which=1 if June, July, August, and December; 0 otherwise.

Supply of hogs

Hog producers, like commercial packers, formulate price expectations when making marketing decisions. Such expectations are based on the available information and, therefore, supposed to reflect the prevailing market conditions. To represent the producers' price expectations in the supply model, two models were tested using monthly average hog prices ($/cwt) lagged one period and a two period moving average of the same variable. A two period moving average performed better and, therefore, it is included in the supply function as a proxy for producers' hog price expectations.

The supply of market hogs is dependent on the prices of feeder hogs (Manitoba Department of Agriculture, (MDA)). Hog producers need to decide whether to sell a market hog this period and replace it with a feeder hog in the same period or sell a market hog now and replace it with a feeder hog at a future date. Such a decision depends, in part, on the prevailing prices of feeder hogs. In the short run, high feeder hog prices are expected to be inversely related to the quantity of market hogs.

According to economic theory, the supply of live hogs is a function of the cost of production. In Manitoba, as in the other Western Canadian Provinces, barley is the major ingredient in hog feed. To represent the cost of production, the hog-barley price ratio is included in the supply function as a proxy variable. With a high ratio, producers respond by increasing their hog inventories. On the other hand, when the ratio is low the response is to liquidate a sizable percentage of their holdings (MDA).

The Manitoba hog economy is closely linked to that of Omaha in the United States. It is, therefore, hypothesised that the number of slaughter hogs supplied to the Manitoba market is, in one way, influenced by the Omaha/Winnipeg price ratio. The higher the price ratio the less the number of hogs supplied to the Manitoba market and vice versa. To capture that relationship, the Omaha/Winnipeg price ratio is included in the supply function as an explanatory variable, with the Omaha prices converted to Canadian dollars using the appropriate exchange rates.

Biologically, the farrowing of hogs is seasonal and this has an effect on hog supplies. To represent this effect, a supply function shifter is included as an explanatory variable.

That is:

$$Q_t = f(Q_{t-2}, Ph^*_t, HB_{t-4}, FP_t, OWPR_t, H)$$

where,

Q_t = total number of slaughter hogs sold at the Winnipeg market in month t;

Q_{t-2} = defined the same as Q_t but lagged two periods;

Ph^*_t = a two period moving average of the monthly hog prices used as a representation of the producers price expectations in dollars per hundredweight of slaughter hogs;

HB_{t-4} = hog-barley price ratio lagged four periods, used as a proxy for feed costs;

FP_t = feeder hog prices;

$OWPR_t$ = Omaha/Winnipeg price ratio in month t;

H^1 = a dummy variable for seasonal patterns for hog farrowing which = 1 if January, March, April, June, July, September, and 0 otherwise.

Statistical Model

Many econometricians have advocated for the use of first differences of the data rather than the absolute values themselves as a means of removing, or at least reducing, multicollinearity and its associated problems (Webster, p.33). Leuthold (1970) points out that the use of first differences of the data variables instead of the actual variables themselves helps in the reduction of multicollinearity in the original data variables and also reduce autocorrelation in the error terms to insignificant levels. However, it has been shown that the practice of differencing as a remedy to multicollinearity cannot achieve its aims when the effects on the disturbance terms are considered (Burt).

For this study, a double-log functional form is used. This practice has the associated advantages of reducing heteroskedaciticity since it compresses the data, gives elasticities as coefficients, and allows for comparison across commodities since it deals with percentage changes (Johnston).

In this study, it is assumed that the supply function is quite inelastic in the short-run, and therefore a recursive model of the cobweb type is defined where first the

[1] To reflect farrowing patterns, the method used by Leuthold was adopted whereby the year was divided into two seasonal groups. The first group (listed months) represents those months with quantity supplied being greater, on the average, than the previous month, while the other group is for months with the supplied quantities being generally less than the previous months.

quantity supplied is determined through the supply function. This quantity is then sold in the market at a price determined through the demand function. That is, quantity demanded is considered to be a predetermined variable and price adjusts to clear the market. Hence the demand function is estimated in a price dependent form. It is also assumed that the error terms of the demand and supply functions are independent of each other. The functions are represented as follows:

Supply

$$lnQ_t=\beta_{10}+\beta_{11}\ln Q_{t-2}+\beta_{12}\ln Ph^*_t+\beta_{13}\ln HB_{t-4}+\beta_{14}\ln FP_t+\beta_{15}\ln H+U_{1t}$$

Demand

$$lnPh_t=\beta_{20}+\beta_{21}\ln Ph_{t-1}+\beta_{22}\ln PP_t+\beta_{23}\ln PB_t+\beta_{24}\ln Q_t+\beta_{25}\ln Q_{t-1}+\beta_{26}\ln D+U_{2t}$$

where,

t = time in months;

H = 2.71828 if January, March, April, June, July, September, and 1 otherwise;

D = 2.71828 if June, July, August, December, and 1 otherwise, and the rest of the variables are as defined before.

The two distribution variables, U_{1t} and U_{2t}, are assumed to be independent and normally distributed.

Estimation and Results

Five years of data, 1986 to 1990 inclusive, were used to estimate the parameters. The data were collected from Manitoba Hog Marketing Board, Manitoba Year Book (various issues), and Canada Grains Council Statistical Year Book (various issues).

With a recursive model, constituent equations were estimated, one at a time, using the Ordinary Least Squares (OLS) estimation procedure without encountering the problems associated with simultaneous equations bias yet obtaining consistent parameter estimates (Koutsoyiannis). The results of the estimated equations are presented in tables 11 and 12 for supply and demand functions respectively.

Table 11

Estimated Equation for the Manitoba Hog Supply, 1986-90

(Dependent Variable: $\ln Q_t$)

Variable	Estimated Coefficient and Standard Error
Constant	17.383**
	(1.11)
$\ln Q_{t-2}$	-0.306**
	(0.08)
$\ln Ph^*_t$	-0.401**
	(0.05)
$\ln HB_{t-4}$	-0.080*
	(0.03)
lnH	0.195**
	(0.02)
DW	2.19
R^2	0.71
F-statistic	31.72**

Figures in parentheses denote standard errors.

** Significant at the 99% level of confidence.

* Significant at the 95% level of confidence.

Table 12

Estimated Equation for the Manitoba Packer Hog Demand, 1986-90

(Dependent Variable: $\ln Ph_t$)

Variable and	Estimated Coefficient Standard Error
Constant	3.653*
	(1.63)
$\ln Ph_{t-1}$	0.608**
	(0.07)
$\ln PP_t$	0.407**
	(0.15)
$\ln PB_t$	-0.356*
	(0.14)
$\ln Q_t$	-0.164*
	(0.08)
$\ln Q_{t-1}$	-0.020
	(0.07)
lnD	0.031*
	(0.01)
DW	1.47
R^2	0.88
F-statistic	71.13**

Figures in parentheses denote standard errors.
** Significant at the 99% level of confidence.
* Significant at the 95% level of confidence.

Since a double log functional form was used and since the demand function was estimated in a price dependent form, then the estimated coefficients are approximations of flexibilities; the inverse gives elasticities or percentage changes and the dummy variables H and D serve as supply and demand function shifters, respectively. Tests for first-order autocorrelation were conducted and found not to be a problem. All signs of the demand function were as expected and all demand variables, but the proxy for storage, were significant. However, the variable was not dropped because studies, such as Leuthold et. al., have found it to be a relevant variable. Overall, the variables did a good job explaining packers demand for hogs and this is manifested through a substantial R^2 of 0.88 and a highly significant F-statistic of 71.13.

On the other hand, modelling producers' supply of hogs was not without problems. This was attributed to the fact that supply was modelled as a single stage operation. The reality of the matter is that "... dynamic production decisions typically are made in successive stages at which particular functions are performed...", (Chavas and Johnson, p. 558). This was found to be specifically true with livestock production due to the relatively long and well defined biological lags. The implication of this observation is that livestock supply should be modeled as a system of equations whereby each equation represents a certain stage in the production process that is functionally related by the overall technology of production. However, it was necessary to amalgamate all the stages into a single stage due to the unavailability of required data for the various relevant stages.

The variables feeder pig prices (FP_t) and Omaha/Winnipeg price ratio ($OWPR_t$) caused multicollinearity and were, therefore, dropped out of the model. The variable $OWPR_t$ was specifically found to be quite collinear with the Winnipeg prices. All the remaining variables were statistically significant and the signs were as expected except for Ph^*_t, proxy variable for producers' expected price which had a negative sign. This is, however, consistent with Jarvis' findings which were contrary to the conventional belief of a positive relationship between supply and output price. In this particular case, it was argued that due to the double role of hogs, both as an output and as capital input for future output production, a long run increase in the supply of hogs necessarily requires an increase in capital stock which in turn requires a short run decrease in output. This was further confirmed by the MDA Annual Report (1990-91, p.44) where it is reported that

> ... in 1990-91 fiscal year, slaughter hog prices increased more than expected. The result of the price increase in the market place was a desire to increase production which led to more stock being kept for breeding versus slaughter.

This illustrates the tendency of static models with a varying number of fixed inputs to ignore the intertemporal decisions associated with capital accumulation.

Price Forecasts

Using the above parameter estimates, twelve, one-period-ahead, monthly price forecasts were generated for the year 1991 (data not used in estimation). The procedure involved inserting the known values of the independent variables into the supply function to get an estimate of quantity supplied. This estimate together with known values of the other independent variables were inserted into the demand function to get an estimate of the clearing price. The resulting price forecasts are presented in table 13 below.

Table 13

Econometric Model Monthly Hog Price Forecasts for the Manitoba Hog Industry, January-December, 1991

Period Ahead	Price Forecast	Actual Price
1	64.43	63.96
2	63.05	68.38
3	64.78	66.13
4	64.85	65.88
5	66.42	70.42
6	68.31	71.49
7	71.24	67.47
8	68.31	65.88
9	63.24	57.72
10	63.24	57.15
11	55.70	49.78
12	53.57	49.72

The above generated forecasts together with forecasts from the time-series model of the previous chapter are used to formulate a combined forecast model in the next chapter.

Chapter Five

COMBINED FORECAST MODEL

Introduction

Past research has shown that there can be gains in forecast accuracy by combining different forecasting models (Flores and White). One of the highly desirable properties of a forecast is that of minimum mean square forecast error. Incorporating more of the available information into a forecast has been found to greatly reduce the degree of uncertainty surrounding the course of future events thereby improving the quality of forecasts (Keen).

Different forecasting methods rarely produce the same results even when subjected to similar conditions. A typical reaction by decision makers when faced with such a situation is an attempt to discover and use the best of the available models (Brandt and Bessler, 1981). In so doing, decision makers neglect useful information embedded in those other models. The study by Brandt and Bessler further implies that forecasts generated strictly by individual models are not likely to provide the users with the most accurate information to base their decisions on. One of the techniques for incorporating the information provided by various methods is to develop a composite forecasting model. Bates and Granger demonstrated that a combined forecast of two alternative models for forecasting monthly airline passenger mileage outperformed each model considered individually. This, however, should not be surprising when one considers the possibility that each set of forecasts is likely to contain useful information which the other does not contain and therefore a combination is expected to be superior (Brandt and Bessler).

Advantages and Disadvantages of Combined Models

Generally, combined forecasts are portrayed in the literature as being superior to the best of the individual models making up the combinations (Brandt and Bessler, 1981). However, a closer look reveals that superiority depends on the circumstances and/or methods used to build the combined model. Following below are some of the advantages and disadvantages depending on a given situation.

Advantages

a) A systematic combination of forecasts has been shown to greatly reduce post-sample forecasting errors even in the presence of structural changes (Diebold and Pauly);

b) if each of the individual method is an unbiased predictor of the outcome, then a restricted least squares regression provides unbiased weights and, therefore, unbiased combined forecasts (Holden and Peel).

Disadvantages

a) If any of the individual forecast series is biased, then restricted least squares would yield biased weights and therefore inefficient combined forecasts (Holden and Peel);

b) combining forecasts requires time and skills and, therefore, could be considered an expensive venture.

Constructing a Combined Model

Several methods of combining forecasts have been developed and used by various researchers. Holden et al.(1990) illustrate that it is difficult to have a single combining technique dominating all other techniques in all situations. However, they suggest the use of a regression method with a constant term to account for any possible biases in the case of two forecasts. To obtain optimal and efficient weights, they suggest using a restricted regression (developed by Granger and Ramanathan) in which the weights are constrained to equal to one. That is (Holden and Peel, 1990, p.89):

$$P_t=\beta_0+\beta_1F_{1t}+\beta_2F_{2t}+v_t.$$

s.t. $\beta_1+\beta_2=1$

$\beta_0=0$

where,

P_t = series being forecast;

F_{1t} = univariate time series model forecast in period t;

F_{2t} = econometric model forecast in period t;

β_0 = constant term;

β_1,β_2 = derived weights for forecasts F_{1t},F_{2t} respectively;

v_t = stochastic error term.

The regression was run using OLS and the weights (β_1,β_2) were found to be -0.49 and 1.49 for the time series and econometric model components respectively. Since β_0=0 and $\beta_1+\beta_2=1$, the implication is that the component forecasts are individually unbiased (Keen).

The best of the time series monthly model results (model 2) were combined with the econometric monthly model results using the method outlined above to produce composite forecasts of hog prices. The results of the combination are presented in table 14 below.

Table 14

Composite Model Monthly Hog Price Forecasts for the Manitoba Hog Industry, January-December, 1991

Month	Price Forecast	Actual Price
1	66.83	63.96
2	62.27	68.38
3	65.72	66.13
4	66.14	65.88
5	65.13	70.42
6	65.48	71.49
7	70.02	67.47
8	66.12	65.88
9	61.42	57.72
10	60.16	57.15
11	50.86	49.78
12	51.12	49.72

All the forecasts generated by monthly time series, econometric, and composite models are subjected to an evaluation for their quantitative and qualitative forecast characteristics in the next chapter.

Chapter Six

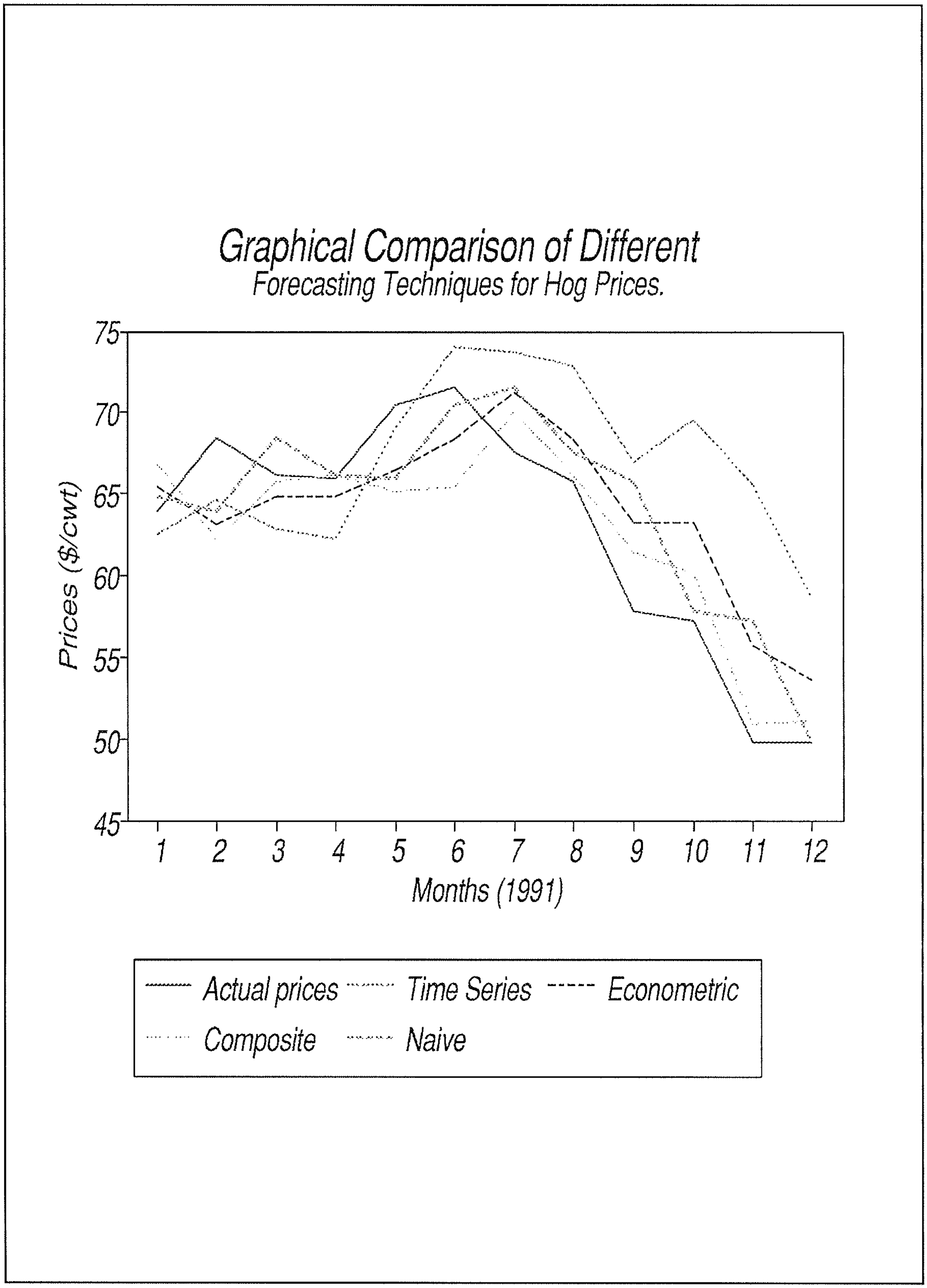
Forecasting Evaluation

It is a globally desirable property for forecasts to be as close to the actual outcome as possible. It is also important for the forecasting models to be able to predict changes in the direction of movement of the series at hand. However, some variables are more difficult to forecast than others and the time units also play a major role in forecast accuracy (Holden et al.). That is, shorter time periods (e.g weekly and monthly) are harder to forecast than longer periods (e.g quarterly and annually).

In this section, different measures are used to determine forecasting accuracy of the models in the previous three chapters. Evaluation in this case is conducted from both the quantitative and qualitative perspectives. Quantitative measures are concerned with the size of the forecast error (Naik and Leuthold, 1986); while qualitative measures deal with the model's ability to predict turning points (McIntosh and Dorfman, 1992).

Figure 6 below shows how forecasts generated by the three different techniques together with the naive model relate to the actual outcomes. However, with forecast evaluation not much can be concluded from a graphical comparison. This, therefore, leads to the detailed investigation of both quantitative and qualitative characteristics of the forecasts in the next two sections respectively.

Figure 6



Graphical Comparison of Different
Forecasting Techniques for Hog Prices.
75
70
65
60
55
50
45
Prices ($/cwt)
1
2
3
4
5
6
7
8
9
10
11
12
Months (1991)
Actual prices
Time Series
Econometric
Composite
Naive

Quantitative Forecast Evaluation

The measures employed here are purely descriptive statistics which are used to summarise the characteristics of sample evidence. Such measures include:

a) mean squared error (MSE) - the method has been used repeatedly both in applied and theoretical work concerning forecasting (Brandt and Bessler, 1983). The objective is to have MSE as low as possible;

b) mean absolute percentage error (MAPE) - unlike MSE, MAPE is a linear loss function and, therefore, does not assign extra weights to large forecast errors (Holden et al., p. 37). Again a method with the lowest MAPE is a preferred method;

c) Theil's U1 inequality coefficient - the coefficient lies between 0 (for perfect forecasts) and 1 (for forecasts that are always 0 and the actual values are non-zero). Hence, the desire is to have U1 as close to zero as possible (See Holden et al., p.38 for details).

While the first two measures could be affected by the units of measurement of the data, Theil's inequality coefficient has the advantage of being a unitless measure which is a desirable property when comparing forecasts of different variables (Holden et al.). The U1 inequality coefficient has an added advantage over the other Theils' inequality coefficients in that it sets both the lower and upper limits a measure could assume.

Quantitative evaluation results of the models are presented in table 15 below.

Table 15

Quantitative Model Evaluation Results of the Manitoba Short Term Hog Price Forecasting Models

Model type	MSE	MAPE	Theil's U1 Coefficient
Time Series	58.65	10.91	0.06
Econometric	16.51	6.11	0.03
Composite	11.89	4.29	0.03
Naive	15.38	4.83	0.03

From the table of quantitative evaluation results above, all the three measures consistently put the composite model as the best model and the time series model as the worst. The mean squared error (MSE) measure assigns 11.89 to the composite model, 15.38 to the naive model, 16.51 to the econometric model, and an MSE of 58.65 to the time series model to finish in the worst position. A similar trend is observed with the mean absolute percentage error (MAPE) measure which assigns 4.29 to the composite model, 4.83 to the naive model, 6.11 to the econometric model, and 10.91 to the time series model for the worst performance. On the other hand, the Theil's U1 coefficient assigns the same performance value of 0.03 to the composite model, naive model, and the econometric model; a coefficient of 0.06 is assigned to the time series model.

Generally, the quantitative model evaluation results above suggest that out-of-sample forecasts from a composite model (which comprises of time series and econometric models) offer some improvement over each of the comprising models considered individually and the naive or no change model. This is consistent with the findings of Brandt and Bessler (1981) who used agricultural data, and Keen (1984) with non-agricultural data.

On the other hand, both the time series and econometric models, individually, perform poorly relative to the naive model. This finding is contrary to Brandt and Bessler's study (1983) in which they found econometric and ARIMA models both giving superior out-of-sample forecasts to the naive model.

Qualitative Forecast Evaluation

This is concerned with evaluating the models' ability to predict turning points of the series in question. Naik and Leuthold (1986, p.721) define a turning point (TP) as "... the change in direction of the movement of a variable". Symbolically, a turning point occurs if $P_t > P_{t-1} < P_{t-2}$ or $P_t < P_{t-1} > P_{t-2}$. The latter refers to a peak turning point (PTP) while the former refers to a trough turning point (TTP).

Theil proposed the use of over predictions and under predictions and the turning point method as a means of evaluating how well a given forecasting technique predicts turning points of the series under consideration. The traditional method makes use of a 2 x 2 contingency table and has been used by various researchers including Bessler and Brandt (1981); Brandt and Bessler, 1981; and Harris and Leuthold, 1985. The method was found to be a better measure of qualitative forecasting performance than the directional change method used by several researchers. However, a closer look at the method by Naik and Leuthold reveals that there is some available information being neglected which may lead to misleading interpretation of the results. Specifically, the method fails to "...account for differences in peak and trough TPs or upward or downward no-turning points (NTP)"

(Naik and Leuthhold, p.722).

Naik and Leuthold suggest, as an alternative, the development of a 4 x 4 (as opposed to a 2 x 2) contingency table with a clear distinction between a peak TP and a trough TP and an upward NTP as opposed to a downward NTP. An upward no-turning (UNTP) is said to occur if $P_t > P_{t-1} > P_{t-2}$ and a downward NTP occurs if $P_t < P_{t-1} < P_{t-2}$ (Naik and Leuthold, p.724). Based on the information given above, Naik and Leuthold defined several ratios to be used as summary measures in forecast evaluation[2]. Such ratios include:

a) ratio of accurate forecasts (RAF);

b) ratio of worst forecasts, RWF; (RWF=1-RAF-RIF);

c) ratio of accurate to worst forecasts (RAWP); and

d) ratio of inaccurate forecasts, RIF; (RIF=1-RAF-RWF).

The desire is to have RAF and RAWP as high as possible and, therefore, RWF and RIF quite low. A disadvantage associated with this evaluation system is that it ignores the possibility of prices staying the same from one period to another. In a situation where constant prices occur for at least two periods, it is up to the user to choose the best way of dealing with it. That in itself could be a potential source of error to the analysis. As an alternative, a 9 x 9 contingency table method is suggested below.

[2]For details regarding the ratios, see Naik and Leuthold, 1986, p.724.

9 x 9 Contingency Table Method

The desire for forecasting methods that do a good job predicting turning points (TP), *ceteris paribus*, cannot be over emphasised. A variety of qualitative forecast evaluation methods have evolved over time. Theil proposed using over predictions and under predictions and the turning point method as a means of evaluating how well a given forecasting method predicts turning points. This more traditional method makes use of a 2 x 2 contingency table and has been used by many researchers (Bessler and Brandt, 1981; Brandt and Bessler, 1981; Harris and Leuthold). The method can, however, be a potential source of forecast misinterpretation, so Naik and Leuthold suggest, as an alternative, the development of a 4 x 4 contingency table with the ability to differentiate between a peak TP and a trough TP and between an upward NTP and a downward NTP. The implicit assumption with their suggestion is that prices cannot stay the same from one period to another. But prices which do not change for at least two periods are often encountered with daily, weekly, and even monthly series. So the method as outlined by Naik and Leuthold may not be appropriate. An alternative method, which is an improvement of the Naik and Leuthold method, is suggested.

The Naik and Leuthold Method

In this section the Naik and Leuthold method is outlined along with the associated summary measures. They identify four possible situations whose definitions are given below (Naik and Leuthold, p.724):

a) peak ($\wedge$) TP (PTP) exists if $P_t < P_{t-1} > P_{t-2}$;

b) trough (⋁) TP (TTP) exists if $P_t > P_{t-1} < P_{t-2}$;

c) upward (↗) NTP (UNTP) exists if $P_t > P_{t-1} > P_{t-2}$; and

d) downward (↘) NTP (DNTP) exists if $P_t < P_{t-1} < P_{t-2}$.

From the definitions above, a 4 x 4 contingency table (table 16 below) is constructed from which the summary measures are derived.

Table 16

Naik and Leuthold 4 x 4 Contingency Table

		FORECAST VALUES			
		PTP(⋀)	TTP(⋁)	UNTP(↗)	DNTP(↘)
ACTUAL	PTP(⋀)	f_{11}	f_{12}	f_{13}	f_{14}
	TTP(⋁)	f_{21}	f_{22}	f_{23}	f_{24}
	NTP(↗)	f_{31}	f_{32}	f_{33}	f_{34}
	DNTP(↘)	f_{41}	f_{42}	f_{43}	f_{44}

f_{ij} in table 16 represents the outcome of turning point or no turning point prediction j compared to the actual realization i. Situations where i=j represent perfect predictions of turning points or no turning points.

From table 16, Naik and Leuthold constructed four summary measures (ratios) to be used in qualitative forecast evaluation. The following are the ratios as defined by Naik and Leuthold (p.724):

a) ratio of accurate forecasts

$$(RAF) = \frac{f_{11}+f_{22}+f_{33}+f_{44}}{\sum_i \sum_j f_{ij}};$$

b) ratio of worst forecasts

$$(\text{RWF}) = \frac{f_{12}+f_{21}+f_{34}+f_{43}}{\sum_i \sum_j f_{ij}};$$

c) ratio of accurate to worst forecasts

$$(\text{RAWF}) = \frac{f_{11}+f_{22}+f_{33}+f_{44}}{f_{12}+f_{21}+f_{34}+f_{43}};$$

d) ratio of inaccurate forecasts

$$(\text{RIF}) = \frac{f_{13}+f_{14}+f_{23}+f_{24}+f_{31}+f_{32}+f_{41}+f_{42}}{\sum_i \sum_j f_{ij}},$$

for i, j = 1, ..., 4.

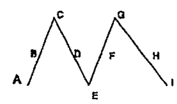
The desire is to have both RAF and RAWF quite high and, thus, low values of RWF and RIF. Naik and Leuthold also point out that a high value of RIF is not as bad as that for RWF.

Basically, the method as outlined above is applicable to those price movements with no possibility of constant prices for at least two periods. Such a scenario is depicted in figure 7(a). However, if the price movement is as depicted in figure 7(b), then the Naik and Leuthold method cannot offer much help around the situation.

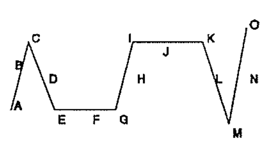
Figure 7

Hypothetical Price Movements

a)



b)



Hence, an alternative method that accounts for both situations is suggested.

Alternative Method

The alternative method suggested here involves redefining Naik and Leuthold's price movement scenarios to incorporate the possibility of constant prices, developing a 9 x 9 contingency table, and redefining the four ratios used in forecast qualitative performance evaluation.

First, from figure 7(b) above it is noted that if the possibility of constant prices is considered, then there exists three different types of peak turning points and three different types of trough turning points which if ignored could lead to misleading conclusions. The first type of a peak TP is at C which is a Sharp peak TP (SPTP). This is defined as $P_t<P_{t-1}>P_{t-2}$. The second type of a peak TP is at I, that is where prices change from an upward movement to a constant level. Such a TP is called Upward movement to Constant level Peak Turning Point (UCPTP). UCPTP is defined as $P_t<P_{t-1}=P_{t-2}$. The last type of a peak TP is at K, that is where prices change from a constant level to a downward movement. It is referred to as a Constant level to Downward movement Peak Turning Point (CDPTP). It is defined as $P_t=P_{t-1}>P_{t-2}$.

A similar situation is identified regarding trough TPs. The first type is at point M, which is the Sharp Trough TP (STTP). It is defined as $P_t>P_{t-1}<P_{t-2}$. The second type is at point E, which is the Down movement to Constant level Trough TP (DCTTP). It is defined as $P_t>P_{t-1}=P_{t-2}$. The last type is at point G and is the Constant level to Upward movement Trough TP (CUTTP). It is defined as $P_t=P_{t-1}<P_{t-2}$.

The two noturning points (NTP) are exactly as defined by Naik and Leuthold. That is upward NTP (UNTP) exists if $P_t>P_{t-1}>P_{t-2}$, and downward NTP (DNTP) exits if $P_t<P_{t-1}<P_{t-2}$. However, a third NTP situation is added. Such a case exists if prices remain unchanged for more than two periods (e.g. EFG in figure 7(b) above). It is referred to as Constant NTP (CNTP) and defined as $P_t=P_{t-1}=P_{t-2}$.

From the definitions given above, a 9 x 9 contingency table (table 17) that accounts for all the possible movements of a given series is constructed.

Table 17

The Suggested 9 x 9 Contingency Table

	FORECAST VALUES								
	PTPs			TTPs			NTPs		
ACTUAL VALUES	SPTP	UCPTP	CDPTP	STTP	DCTTP	CUTTP	UNTP	DNTP	CNTP
SPTP	f_{11}	f_{12}	f_{13}	f_{14}	f_{15}	f_{16}	f_{17}	f_{18}	f_{19}
UCPTP	f_{21}	f_{22}	f_{23}	f_{24}	f_{25}	f_{26}	f_{27}	f_{28}	f_{29}
CDPTP	f_{31}	f_{32}	f_{33}	f_{34}	f_{35}	f_{36}	f_{37}	f_{38}	f_{39}
STTP	f_{41}	f_{42}	f_{43}	f_{44}	f_{45}	f_{46}	f_{47}	f_{48}	f_{49}
DCTTP	f_{51}	f_{52}	f_{53}	f_{54}	f_{55}	f_{56}	f_{57}	f_{58}	f_{59}
CUTTP	f_{61}	f_{62}	f_{63}	f_{64}	f_{65}	f_{66}	f_{67}	f_{68}	f_{69}
UNTP	f_{71}	f_{72}	f_{73}	f_{74}	f_{75}	f_{76}	f_{77}	f_{78}	f_{79}
DNTP	f_{81}	f_{82}	f_{83}	f_{84}	f_{85}	f_{86}	f_{87}	f_{88}	f_{89}
CNTP	f_{91}	f_{92}	f_{93}	f_{94}	f_{95}	f_{96}	f_{97}	f_{98}	f_{99}

From table 17, the following summary measures (ratios) are defined:

a) ratio of accurate forecasts

$$(\text{RAF}) = \frac{f_{11}+f_{22}+f_{33}+\ldots+f_{99}}{\sum_i \sum_j f_{ij}};$$

b) ratio of worst forecasts

$$(\text{RWF}) = \frac{f_{14}+f_{15}+f_{16}+f_{41}+f_{52}+f_{63}+f_{78}+f_{87}}{\sum_i \sum_j f_{ij}};$$

c) ratio of accurate to worst forecasts

$$(\text{RAWF}) = \frac{f_{11}+f_{22}+f_{33}+\ldots+f_{99}}{f_{14}+f_{15}+f_{16}+f_{41}+f_{52}+f_{63}+f_{78}+f_{87}};$$

d) ratio of inaccurate forecasts

$$(\text{RIF}) = 1-(\boldsymbol{RAF}+\boldsymbol{RWF}),$$

where, $\boldsymbol{i,j}$=1,2,...,**9**.. Again, as Naik and Leuthold point out, the desire is to have a high RAF and a low RWF.

Hence, the 4 x 4 contingency table method developed by Naik and Leuthold implicitly assumes that there will always be a price change from one period to another. This is likely (but not always) to be the case when dealing with long-range data series like quarterly and annual series. It has been demonstrated that in situations where prices are likely to stay unchanged for at least two periods (e.g. daily, weekly, or monthly series) the Naik and Leuthold method ignores some features of the series. A 9 x 9 contingency table that accounts for all the possible movements is suggested and the associated summary measures defined. It should be noted that in cases where prices change from period to period, then the Naik and Leuthold 4 x 4 contingency table method should give the same results as the suggested 9 x 9 contingency table method.

McIntosh and Dorfman (1992) compared the Naik and Leuthold measure with the Henriksson-Merton (HM)[3] measure regarding qualitative forecast evaluation performance. They found out that although the Naik and Leuthold (4 x 4 contingency table) measure provides more information than the more traditional 2 x 2 contingency table measure, it also ignores some vital information. Specifically, the measure is criticized for being an ordinal measure and, therefore, does not provide ways of determining how much better a RAF measure of 0.81 is than 0.63. McIntonsh and Dorfman concluded that the Henriksson-Merton method, being a probability measure, and also given the fact that it has a formally stated null hypothesis and a known sample distribution, provides a statistical means of evaluating the qualitative performance of forecasts. It was also found that "... the Henriksson-Merton test provides an accurate basis for comparison even when the series are characterized by a predominant upward or downward trend" (McIntosh and Dorfman, p.213).

This study makes use of the Henriksson-Merton measure in evaluating the qualitative performance of the forecasting models. However, for comparison purposes, the RAF evaluation measure suggested by Naik and Leuthold is also computed. It should be noted that with the Naik and Leuthold method, only X–2 (where X refers to the number

[3]see Henriksson and Merton, (1981) or McIntonsh and Dorfman, (1992) for details.

of forecasts generated) between period evaluations are possible since the first two forecasts are used as initial direction indicators. The results are presented in table 18 below.

Table 18

Qualitative Model Evaluation Results of the Manitoba Short Term Hog Price Forecasting Models

Model Type	RAF[a]	HM[b]
Time Series	0.80	0.976**
Econometric	0.50	0.576
Composite	0.40	0.121
Naive	0.40	0.340

** significant at 95% level using a one-tail test.

a RAF is the number of correct turning points forecasted divided by one less the total number of forecasts.

b 1-HM confidence level=the highest level at which one would fail to reject the null hypothesis of no information using a one tail test.

From the results presented above, it is observed that while the study by McIntosh and Dorfman was able to show that the Naik and Leuthold's RAF measure and the Henriksson-Merton test give contrasting results, the results in this study by both measures are consistent most of the time. Where they contrast, the Henriksson-Merton test measure results have been chosen over the RAF results since it has been shown to be a better qualitative evaluation measure.

The results here are almost the opposite of what was depicted by the quantitative model evaluation measures. Both the RAF and Henriksson-Merton measures put the time series model in the number one spot with a RAF value of 0.80 and an Henriksson-Merton value of 0.976. That is, the hypothesis of no information value would be rejected for the time series model at the 0.024 level. On the other hand, the composite model (which ranked the best using the quantitative measures) has an extremely low Henriksson-Merton value of 0.121. The null hypothesis of no information value would not be rejected at a level similar to the rejection level (0.024) for the time series model. Similarly, the econometric and naive models both have RAF values (0.50 and 0.40 for econometric and naive models respectively) and Henriksson-Merton values (0.576 and 0.340 for econometric and naive models respectively) that are inferior to those for the time series model but better or equal to those for the composite model.

Generally, using the HM measure and at a 99 percent confidence level, the null hypothesis of no information value would not be rejected for the econometric, composite, and naive models. The time series model is the only model for which the hypothesis would be rejected. The measure, however, shows the econometric model to have more information value than the naive model which, in turn, contains more information than the composite model.

Implication of Forecast Evaluation

The results of forecast evaluation above are not deterministic. There is no model that performs consistently well both quantitatively and qualitatively. The composite model performs better than the rest quantitatively while the time series model is the best qualitatively. Generally, none of the models does a great job quantitatively. Some forecasting errors are as high as 17 percent. This is perceived to suggest that perhaps on a month to month basis, predicting turning points is more important. That is, if a model can successfully predict whether prices will go up or down, then hog producers may use such signals and make the appropriate marketing decisions. An example is given below to illustrate how producers may benefit from the turning point information generated by the univariate time series model.

Consider a hog producer who, on the average, markets four hundred and eighty (480) slaughter hogs per month. Assuming that in January of 1991 the producer had access to both time series and the naive model forecasts for five months as indicated in table 19.

Table 19

Time Series and Naive Model Monthly Hog Price Forecasts for Manitoba, January-May, 1991

Month	Time Series	Naive	Actual
January	62.57	64.86	63.96
February	64.65	63.96	68.38
March	62.86	68.38	66.13
April	62.22	66.13	65.88
May	69.06	65.88	70.42

From table 19 above, it is observed that the time series model predicts an increase in prices from January to February while the naive model predicts a decrease in prices. The producer gets totally different signals from the two models and the decisions taken are bound to be different depending on which model is used. With time series forecasts the decision could be to market less hogs in January with a hope of benefiting from the predicted price increase for February. For example, the producer could choose to market 360 hogs in January at the going price of $ 63.96/cwt with a hope of marketing about 600 hogs for the month of February at an anticipated higher price. Assuming an average weight of 200 pounds per hog, then the total January gross revenue would amount to $ 46,051.20. In February, the producer markets 600 hogs at $ 68.38/cwt amounting to a gross revenue of $ 82,056. On the other hand, using a naive model the producer is likely to market more hogs in January in an attempt to reduce the effect of the predicted price decrease for the month of February. For example, the producer could choose to market 600 hogs in January at a going price of $ 63.96/cwt with a hope of marketing a smaller number of about 360 hogs at a lower anticipated February price. The January gross revenue would be $ 76,752. The February gross revenue would be $ 49, 233.60. Clearly the total gross revenue for both months would be a lot higher using signals from the univariate time series model than using the naive model signals.

A similar situation is observed with the other months. The direction of price change for the month of March again differs for the two models. The time series model predicts it right as a price decrease while the naive model has it as a price increase. Both models have the right prediction for the month of April but again the naive model predicts a wrong direction for the month of May while the time series model is still consistent with what turns out to be actual direction change.

Hence, it has been demonstrated that over a period of four months (January-May, 1991), a producer who bases his marketing decisions on the naive model forecasts would get wrong signals regarding the direction of price change for the months of February, March and May. On the other hand, the time series model would predict the right direction of price change for all the months in this case. This example is not used to suggest that the time series model will predict the right direction of price changes all the time. It is, however, suggesting that based on the qualitative forecast evaluation results, the time series model will predict the correct direction of price changes more often than the naive model. This implies that the producer is likely to gain by choosing the time series model over the naive model when making marketing decisions.

However, it should be noted that there are other factors that need be considered when deciding on the number of live hogs to market at a given time. Such factors may include the interest that could be received, extra costs of production incured due to carrying forward a certain number of hogs to a future period as opposed to selling in the current period, and some others.

Chapter Seven

Conclusion

The Manitoba hog industry, like many other business ventures, is a dynamic industry that changes from time to time. A hog production home study course by the Manitoba Department of Agriculture (MDA) identifies four of the factors that contribute to the changes undergone by the industry. Such factors include:

a) high costs of new facilities;

b) rising energy costs;

c) variable prices for grains and protein supplements; and

d) uncertainties about future hog market prices.

Under such conditions, it becomes quite necessary for hog producers to make use of the available information to prepare for the likely constraints and at the same time take advantage of possible opportunities to enhance the well being of their respective enterprises.

It was recognised, from past studies, that hog producers could have up to forty-five days to make their marketing decisions. Such decisions are mainly concerned with determining whether to sell slaughter hogs in the present period at the known going prices or to wait and sell in a future period at anticipated prices. Many factors are thought to play major roles in the afore mentioned decision making process. This study attempted to identify some of the factors together with their interrelationships and use some of the existing forecasting techniques so as to provide some useful information to hog producers. The desire was to develop weekly and monthly hog price forecasting models for the Manitoba hog industry. However, the inability to get weekly data for most of the identified variables made it impossible and, therefore, weekly models were not developed beyond the univariate time series model.

Specifically, the study used time series, econometric, and composite forecasting techniques and then compared the generated forecasts to a naive or no change model to determine whether there are any gains in indulging in more elaborate models. The three techniques used were chosen mainly because they are relatively simple to use, update, and interpret. The generated forecasts were subjected to quantitative and qualitative forecast evaluation measures to determine their relative performances. The quantitative evaluation measures used included mean squared error (MSE), mean absolute percentage error (MAPE), and Theils' U1 inequality coefficient.

The results of quantitative evaluation suggested that a composite model (comprising of econometric and univariate time series models) can improve the accuracy of hog price forecasting over the naive or no change model. Using the mean squared error as a performance measure, the composite model was found to have a smaller error (11.89) than the naive model (15.38). The naive approach, however, had a smaller error than both the econometric (16.51) and the univariate time series model (58.65). This was a demonstration that, although the univariate model forecasts had an error value that was almost four times as big as that for the naive approach, combining them with another model's forecasts (econometric in this case) can significantly reduce the forecast error of the resulting forecasts.

Results with the mean absolute percentage error (MAPE) as a performance criterion mirrored those of MSE quite closely. The composite model forecasts had an error of 4.29 as compared to 4.83 for the naive approach which, in turn, had a smaller error than the econometric model forecasts (6.11) and univariate model forecasts (10.91). Again this was yet another confirmation that combining forecasts from different sources can help reduce the forecast error.

The story with Theil's U1 inequality coefficient was slightly different. The measure showed no apparent differences between forecasts generated by econometric, composite, and the naive approaches all of which had a coefficient value of 0.03. Univariate forecasts again had the worst performance with a value of 0.06. But still it was observed that one would be better off using a composite model than using the univariate model individually.

Using the three quantitative evaluation measures, two major conclusions were arrived at. First of all, it was concluded that forecast error could greatly be reduced by combining forecasts from different sources. Secondly, it was concluded that there was not much to be gained in terms of forecasting accuracy by using univariate time series and econometric approaches over the naive approach. The results, however, suggested that using a composite approach can significantly improve the accuracy of hog price forecasting over the naive approach. The results here were partially consistent with the study results by Brandt and Bessler (1983). They found that it was advantageous to use either the econometric or univariate models individually over the naive approach (which is contrary to the findings of this study), and that combining forecasts from different sources into a composite reduced the forecast error below that of any individual approach (which is consistent with the findings here).

A qualitative forecast evaluation was conducted with the aim of evaluating the information content of various forecasts. The Henrikkson-Merton measure was used primarily because of its provision of an "...additional measure to judge the qualitative accuracy of forecasts where the ability to predict direction of revision is important" (McIntosh and Dorfman, p.213) which characteristic is lacked by the Naik and Leuthold 4 x 4 contingency table method.

The results obtained suggested that in terms of value of information, the univariate time series model significantly outperformed all the others with a confidence level of 0.976. The second best in this category was the econometric model with a confidence level of 0.576. The surprising finding in this case was that the composite model, which outperformed all the others with the lowest forecast error, came in last in this category with a very low confidence level of 0.121 behind the naive approach which had a higher confidence level of 0.340. The success of the univariate time series model was attributed to its ability to predict both downward and upward movements in a more balanced fashion than all the other models.

Generally, the results obtained here demonstrated the fact that merely combining forecasts from two or more sources does not necessary lead to better forecasts both in terms of a lower forecast error and qualitative performance. A study by Keen concluded that the key to achieving better composite forecasts is to combine those models that provide information that is not provided by other models in the composite.

Overall the results of the study are non-deterministic. The composite model, which performs better than all the others quantitatively, does not do a good job predicting turning points. On the other hand, the univariate time series predicts turning points better than any other model but its forecast errors range as high as 17 percent in some cases. It was demonstrated in chapter six that turning point information generated by the univariate time series model may help guide hog producers when making marketing decisions better than the naive model information.

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