FORECASTING FOR AUSTRALIAN AGRICULTURE

J. W. FREEBAIRN*

Australian National University

The paper provides a review of the objectives of forecasts and of the techniques for generating forecasts in the context of agriculture. Forecasts provide information to facilitate decision making. The techniques are evaluated in terms of assumptions about the processes generating the forecast variables, their relative requirements for time, data and other resources, and their relative forecast accuracy. An evaluation of naïve, informal model and econometric model forecasts of Australian agricultural commodity prices and production levels is reported.

Introduction

Forecasts provide information about the levels of prices, quantities and other variables expected to occur in the future. The need for forecasts stems from the time lag between making decisions and the time at which the outputs flowing from these decisions reach the market place. Here the realized welfare of individuals and of society is positively related to the extent to which forecast prices and quantities on which decisions are made correspond to realized market prices and quantities.

This paper has two objectives. In the context of agriculture, the first part of the paper provides a review of the types of forecasts required for effective decision making and of the different procedures by which forecasts might be prepared. The review is kept at a non-technical level; references to studies of a more detailed and a more technical nature are noted. The second part of the paper evaluates some attempts to forecast prices and quantities for some Australian agricultural commodities. Forecasts of average annual market prices and quantities produced one year ahead and five years ahead are considered. A final section summarizes the major findings of the paper.

Forecasting What and for Whom?

Questions relating to what variables to forecast and the forecast horizon, the time of release of forecasts, and the methods of presentation and dissemination of forecasts should be considered in the context of the decision problems and procedures of decision makers. For purposes of discussion it is useful to distinguish three categories of decision makers: producers, marketers, and policy makers.[1]

The individual producer's decision problem can be characterized as one of maximizing utility (of which profits is a special case) subject to technical and resource constraints and to market prices. To facilitate

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[1] Final consumers are not considered because their decision lags are assumed to be very short.

their decision making producers require forecasts of short term market prices to determine the appropriate time to market available supplies of products and they require forecasts of longer term market prices to determine investment decisions affecting, for example, machinery, livestock inventory, area of crops, and pasture improvement. With respect to the longer term forecasts the forecast should relate to an average price to be received for outputs flowing from the decision over the life of the investment. For some decisions, such as choice of an enterprise mix, forecasts of relative prices would be as useful as forecasts of absolute prices. Because forecasts will be less than perfect and since the utility functions of many producers will include risk aversion properties, producers require information on the likely distribution of future prices as well as the expected or mean estimate. The uncertainty about future prices could be presented by means of probability distribution functions, a range forecast, or by parameterizing the forecasts in terms of important causal relationships and variables for which there is imperfect knowledge.

Marketers are taken to embrace decision makers involved in the transport of commodities, both to domestic and foreign markets, the processing of commodities, e.g. abattoirs and canneries, and the storage of commodities, e.g. grains and wool. To assist in the making of cost minimizing decisions regarding the utilization of existing facilities and investment for more facilities, marketers require forecasts of quantities of commodities requiring transport, storage and processing. For the longer term forecasts the forecast horizon should relate to the life of the investment. Information on the variability of quantities over time would be required to make efficient decisions.

A prerequisite for successful government policy making affecting the agricultural sector would be forecasts of the future state of the sector in terms of variables considered important by the policy makers. Forecasts would focus on prices, quantities, gross and net receipts and on the distribution of these measures conditional on the continuation of current policy and conditional on alternative policies.

The Forecasting Game

Forecasting involves making estimates of the future values of variables of interest using information available in the current period. It embraces the obtaining of information about the processes generating the forecast variables and of inferring future values on the basis of observed regularities in past behaviour. Within this framework there is a diversity of forecasting techniques which might be used.

Forecasting procedures differ in the way past regularities in behaviour of the forecast variables are ascertained, and the way in which these regularities are used to infer future values. The theory of the processes generating the forecast variables range from the very simple theory of no change in the variable to complex models based on technical relationships and economic theory of causal processes. At least conceptually the potential accuracy of a forecasting procedure would seem to be positively related to the degree to which the specified model of the processes generating the forecast variables approximates the true and unknown causal processes. Against this view, however, is the school of thought which holds that assumptions do not matter, all that matters is the accuracy of the forecasts. The complexity of the model influences the requirements for knowledge about the causal processes, for data to estimate the model and for personnel to construct and apply the model.

A number of factors are considered when evaluating and comparing forecasting procedures. Of prime importance is the extent to which the forecasts foretell the future with minimum errors. Ideally the criterion of forecasting performance would be defined in terms of the loss functions of users of the forecasts. However, the information required for such an evaluation is rarely available. In practice resort is made to a number of test statistics which include the mean forecast error (associated with a linear loss function), mean square forecast error (associated with a quadratic loss function), Theil's inequality statistics, and the number of times changes in the direction of the variable are correctly and incorrectly forecasted. These and other evaluation measures are discussed in Theil [45], Dhrymes *et al.* [12], and Mincer and Zarnowitz [33] and, as noted in recent contributions by Granger and Newbold [18] and Leuthold [29], there are still many unresolved issues. Given the opportunity cost of resources, the relative demands placed on data, personnel and other resources are an important factor in evaluating different forecasting techniques.

Forecasting Techniques

For expositional convenience the techniques which might be used for forecasting for agriculture are discussed under the headings of:

1. formal models;
2. informal models;
3. time series models;
4. indicators;
5. balance sheet methods; and
6. surveys.

The classification is an artificial one and several techniques might be used in an actual forecasting exercise. Most of the literature on techniques for economic forecasting, e.g. Roos [40], Wold [48], Stekler [43] and Mackrell [31] has focused on forecasting macroeconomic variables, e.g. national product and employment. The objective of this section is to recast these writings in the context of forecasting for agriculture.

The discussion outlines the assumptions and methods of each technique and compares the advantages and disadvantages of the different techniques. The latter discussion provides a starting point for choosing between the different techniques; unfortunately our limited understanding of and experience with the techniques means it is not possible, at this stage, to draw definite conclusions about the relative forecast accuracy of the techniques for different forecasting problems.

1. *Formal Models.*

Quantitative models describing economic activity in a sector, e.g. econometric models, input-output models, programming models and simulation models, provide a formal framework for constructing, evaluating and revising forecasts and for presenting the forecasts to users. With no loss of generality the discussion of the formal model technique will focus on the construction and application of an econometric model.[2]

The construction of an econometric model, which embodies the assumed form of the processes generating the forecast variables, involves the related activities of model specification, estimation and validation. Knowledge of technical relationships and of institutional arrangements together with economic theory are used to specify functions describing the main causal forces influencing the forecast variables. The specified model will include supply functions, demand functions and functions describing market equilibrating processes. While the model attempts to capture the more important causal relationships it simplifies the complexity of reality. Regression procedures are used to obtain estimates of the parameters of the specified model. The parameter estimates are subject to sample errors. The estimated model is validated with respect to the signs and magnitudes of estimated parameters, dynamic properties and ability to explain historical levels of the forecast variables.

As an illustration, a validated econometric model describing the price of wool may be written as

$$y_t = b_0 + b_1 y_{t-1} + b_2 x_{1t} + b_3 x_{2t} + e_t \tag{1}$$

where y_t is the average annual wool price, y_{t-1} is last year's wool price, x_{1t} is annual wool production, x_{2t} is an index of level of economic activity, e_t is an error term representing other explanatory variables, and the b's are estimated parameters. Further examples and additional details may be found in Theil [45], Norton [37] and econometric texts.

Application of a formal model for forecasting may involve subjective judgement as well as mechanical manipulation. The mechanical manipulation involves substituting values for the explanatory variables in (1). In practice it is likely that the forecaster will have imperfect knowledge about some of the explanatory variables; procedures for handling this situation are discussed in Gruen *et al.* [19], Feldstein [15] and Schmidt [41]. The formal model can be used to construct probability confidence internal forecasts as well as forecasts of the mean or expected value.

A number of econometric model forecasters argue the case for adjusting the mechanically derived forecasts with reference to additional information. Since a model simplifies an actual economy adjusting the mechanical forecasts seems justified when the additional information is over and above that which is explicitly included in the model. For example, adjustment of the constant term to reflect changes in values of excluded variables, e.g. increase the term b_0 in (1) to reflect a taste change to natural fibres. Controversy surrounds validity of the common practice of adjusting the constant term for previous levels of the error term, e.g. it raises questions about the choice of the estimation procedure and the amount of the adjustment has to be specified (for further details see Cooper [9] and McCarthy, Howrey and Klein [30]). Another view argues for the complete interaction between formal model and judgemental forecasts whereby the model is used as an information input for the formation of 'expert' opinion—in concept the final forecast will be compatible with judgemental opinion on future developments

[2] For a discussion of the application of input-output models see Theil [45].

and will be consistent with the restrictions and observed causal relationships of the formal model. Substantial gains in forecast accuracy using this approach have been reported by Haitovsky and Treyz [20] for macroeconomic forecasts and by Crowder [10] for forecasts of U.S. annual broiler prices.

As time progresses and additional information becomes available both the forecasts and the formal model should be revised and updated. Haitovsky and Treyz [21] discuss procedures for decomposing econometric model forecast errors and using this information to improve the model specification. Experience with the use of macroeconomic models for forecasting suggests that model revisions contribute to improved forecasting accuracy (see, for example, Simms [42] and special issues in 1974 and 1975 *International Economic Review*).

The use of formal models for forecasting has a number of advantages over other forecasting techniques. Without a formal framework it is difficult to allow for the complexity of interrelationships and feedback effects influencing the variables of interest. A formal model provides a convenient device for understanding the sector and for organizing information to be incorporated in the forecasts. In particular, a formal model can be used to enforce objectively consistency constraints on the forecasts associated with, for example, observed supply and demand response relationships and with accounting identities. It should be noted that the foregoing advantages are potential advantages only; the extent to which they are realized will depend on the characteristics of the estimated model. By making explicit all the assumptions underlying the forecasts, the formal model forecasting procedure offers opportunities to replicate forecasts, to evaluate the sources of forecast errors, and to learn from these errors in improving forecasts in subsequent periods.

A number of disadvantages of the use of formal models for forecasting have been discussed. By definition models simplify the complexity of behaviour in economic systems. Of particular concern is that the assumptions invoked in the specification and estimation of a formal model due to, say, inadequate data or the need to impose simplifying algebraic functions may impose intolerable assumptions relative to those which are required by an informal model. Since estimated formal models refer to historical behaviour they may be inappropriate for making forecasts when the future is characterized by changing institutional and behaviour patterns; the practices of judgemental adjustment of formal model forecasts and of updating the formal model reduce but do not eliminate the force of this argument. The relative requirements of formal models for data and personnel may be a disadvantage. However, the most important requirement is a non-recurring item for the initial specification, estimation and validation of a formal model. Clearly the importance of the disadvantages of formal models will vary from one forecasting problem to another.

The accuracy of formal model forecasts can be traced to three related considerations. The first concerns the ability of the model to explain historical levels of the forecast variables. The second concerns the extent to which historical behaviour will be repeated in the forecast period. The third consideration involves the accuracy with which the explanatory variables can be estimated. In a recent evaluation of the forecast accuracy of U.S. macroeconomic models, Christ [8, p. 54] concluded '. . . forecasters who use (econometric models) can forecast real and nominal GNP two or three quarters ahead with root mean squares of less than one per cent, and six quarters ahead with RMS errors of one or two per cent. The best of them now usually do better than forecasters who do not use such models'. In the context of forecasting for agriculture we might expect the absolute level of forecast accuracy to be less than the results encountered by Christ because of the relatively greater importance of difficult to estimate explanatory variables, e.g. seasonal conditions, in explaining agricultural prices, quantities and incomes. There is limited information available about the relative forecast accuracy of formal model and other techniques in forecasting for agriculture and the available evidence is inconclusive, e.g. Leuthold *et al.* [28] find econometric model forecasts of U.S. daily hog prices and supplies to be slightly more accurate than time series model forecasts while an evaluation of econometric model and naïve forecasts of five year ahead production of some Australian agricultural commodities reported below is inconclusive.

2. *Informal Models*

Informal model or judgemental forecasting embraces a multitude of procedures in which the assumed form of the processes generating the forecast variables is implicit rather than explicit and the method of reasoning is qualitative rather than quantitative. The differences between formal model and informal model forecasting procedures are largely differences of degree. Informal model forecasts are illustrated by commodity forecasts reported at the National Agricultural Outlook Conferences.

The informal model forecasting technique involves a background description of the current state of the sector and of recent trends, and a subjective assessment of future levels of the forecast variables. The background discussion may include tabulations of statistical data, quantitative information about important causal relationships, e.g. elasticity estimates, assessments of policy strategies and discussion of technical constraints. Economic theory and experience are combined to subjectively assess future levels of the forecast variables and particularly of their future levels relative to present levels. The informal model forecasts are not constrained by the explicit and formal constraints of a quantitative model of the assumed causal processes generating the forecast variables. The forecasts may be qualitative or quantitative and the latter may include interval estimates and estimates of probability distributions as well as point estimates.

The informal model forecasting technique has a number of advantages and disadvantages relative to other forecasting techniques. Compared with a formal model the informal model allows for greater flexibility in terms of conceptual modelling of the causal processes generating the forecast variables and it avoids having to make restrictive assumptions to facilitate the estimation and application of a formal model. On the other hand, the greater importance of subjective judgement would seem to increase the chances of personal biases having a marked effect on the forecasts and of failures to impose consistency constraints on informal model forecasts. The difficulty of replicating informal model forecasts and of pinpointing the sources of forecast errors may be a disadvantage when compared to formal model and time series model forecasting techniques, particularly in terms of improving subsequent forecasts. The resource and information requirements for informal models are similar to those required for the specification of a formal model but they are less in terms of estimating and applying the model.

Accuracy of informal model forecasts will be influenced by the degree of knowledge about the causal processes generating the forecast variables, the degree to which this information is imposed on the forecasts, and by the accuracy of estimates of the levels of important causal variables. Gellatly [17] finds informal model forecasts of N.S.W. quarterly beef production to be at least as accurate as a number of time series model forecasts, and the evaluation of informal model forecasts of commodity prices and quantities reported below suggests a significant gain in forecast accuracy over naïve model forecasts.

3. *Time Series Models*

Time series model forecasts relate the future value of a series to its own past values. The forecasts have little to do with economic theory and for this reason often they are referred to as naïve forecasts. Time series models vary from the very simple to technically complex statistical models.

The simplest forecasting method is the no change forecast, i.e. the forecast value is the current value. A conceptual argument favouring the no change forecast is provided by the efficient market model of price formation (see, for example, Fama [14] with respect to security prices and Labys and Granger [27] with respect to short term (weekly and monthly) commodity prices). A market is said to be efficient when current prices reflect all available information about the future and estimates of the future price differ from the current price by no more than a product transformation charge, typically storage cost. Since new information appears randomly, the current price is an unbiased forecast of the future price. The efficient markets model rationale for the no change price forecast assumes very low product transformation charges, and for this reason its applicability is greater for short term than for long term forecasts. Of course, the market may not be efficient, e.g. because of information lags or because of inequalities in the distribution of information among market participants, and there may be better ways of extracting and analysing available information.

Other simple naïve forecast procedures include the same change forecast, i.e. the forecast change in the variable is the same as the change in the last period, and the average change forecast.

An important subclass of time series models involve decomposition of a time series into trend, cyclical, seasonal and random components and extrapolating the nonrandom components to derive forecasts. Details of the procedures followed are given in Karmel [26], Brown [3] and time series texts.

A sophisticated subclass of linear time series models which have known and desirable forecast properties are the autoregressive integrated moving average (ARIMA) models. Basically, a time series is regarded as an observed sample realization of an underlying stochastic process. Procedures involved in the estimation and application of ARIMA models for forecasting are discussed in Box and Jenkins [2], Nelson [36] and Naylor *et al.* [35]. Illustrative applications to agriculture are reported in Leuthold *et al.* [28] and Gellatly [17]. ARIMA models are parsimonious with the data. In practice Box and Jenkins suggest that a stationary time series can be modelled by a maximum of two autoregressive and two moving average parameters, and most economic time series can be transformed to stationary time series by differencing. Available computer programs compute mean forecasts, confidence intervals for forecasts, and provide rules for adaptive revision of forecasts. The ARIMA mean forecast has the desirable property of being the minimum mean square error forecast. However, this property is conditional on the hypothesized ARIMA model which, in practice, may be subject to errors in both identification and estimation. Further, since the ARIMA forecast uses information contained in the sample time series of the forecast variable only, smaller forecast errors might be obtained by incorporating additional information in the forecasts, e.g. that in variable interrelationships suggested by economic theory.

A number of advantages and disadvantages of time series model forecasting techniques can be noted. The relative simplicity and ease of application of the techniques relative to other forecasting techniques can be an important advantage. Allied with this advantage is the favourable comparative forecast accuracy of time series model forecasts encountered by studies reported in the literature, e.g. the macroeconomic forecast evaluation study by Christ [8] and the agricultural forecast studies by Leuthold *et al.* [28], Gellatly [17] and the evaluation reported below. While conceptually one would expect forecast techniques using additional information about factors influencing a forecast variable, e.g. causal relationships between variables suggested by economic theory, as well as stochastic properties of the time series to generate more accurate forecasts than time series model forecasts, the potential accuracy gains are not always realized or they are not very large. The fact that time series model forecasts are devoid of economic theory and other causal relationships may have further disadvantages. For example, how can the causes of an inaccurate time series model forecast be explained and used to improve the accuracy of subsequent forecasts? In this respect formal model forecast procedures have a relative advantage.

4. *Indicator Analysis*

Forecasting by indicator analysis involves a detailed classification of a number of economic time series according to whether they lead, or are coincident with, or lag behind the variable to be forecast and then using observed movements in the leading time series to infer changes in future levels of the forecast variable. The classification of economic time series is based on historical relationships between variables and may be based on economic and technical relationships and on statistical analysis. Indicator analysis is widely used as a procedure for forecasting changes of the economy into recession and expansion phases of the business cycle (for details see, for example, Moore and Shiskin [34] or Reserve Bank of Australia [38]). The wool price forecasting equation reported by Hussey [24] in which an index of interest rates explains wool price movements four quarters ahead provides an illustrative application in a formal framework. A potential application in an informal framework might be based on studies of livestock cycles, e.g. changes in livestock inventory numbers indicate changes in future levels of production and perhaps also of prices. Indicator analysis is a relatively simple short term forecasting technique.

Forecasting by indicator analysis can be regarded as special and restrictive examples of formal model and informal model forecasting techniques; the latter distinction depends on whether the relationship between forecast variable and leading indicator is specified in a quantitative or qualitative way, respectively. Indicator analysis assumes a simplified model of the processes generating the forecast variable, in fact, the choice of a leading series may be based primarily on statistical correlation rather than on a theory of economic causation. The forecast accuracy of indicator analysis depends on historical correlation between the leading indicator and the forecast variable and on the correlation being maintained into the forecast period.

5. *Balance Sheet Methods*

The balance sheet forecasting method involves building up a picture of supply and demand for a commodity and then using the results to infer future prices and quantities. It is widely used in preparing one year ahead forecasts of the world market for grains and sugar and by the FAO in its long term forecasts (see, for example, Ashby [1] and FAO [16]).

A balance sheet of supply and demand is constructed from independent forecasts of the supply and demand for each commodity for each country. Assuming constant prices, demand quantities are based on population growth, income growth and estimated income elasticities of demand. Production forecasts are based on extrapolations of trends adjusted for special knowledge about production conditions, e.g. technical constraints and policy changes. From the balance sheet is computed a surplus or deficit gap of supply over demand. This gap indicates the direction of pressure for changes in prices, stocks and/or agricultural policies. Further steps may be taken to sequentially revise elements of the balance sheet for anticipated price and/or policy changes required to restore a state of near equilibrium between aggregate supply and demand.

Several advantages and disadvantages of the balance sheet forecasting technique can be noted. It provides a compact and objective format for presenting information about future levels of market supply and demand. The simplifying assumptions of constant prices and independent commodity markets simplify the analysis relative to that required by a formal model based on more general supply and demand response functions; in this sense a balance sheet can be considered a step towards a formal model. The simplifying assumptions and the subjective procedures used to sequentially adjust the supply and demand estimates to arrive at a final picture of supply and demand balance constitute the principal disadvantage of the balance sheet technique.

6. *Surveys*

Surveys of decision makers' intentions provide a direct source of forecasting information. Regular surveys of consumers' intended purchases and of producers' planned investment, sales and inventories are widely used in forecasting macroeconomic variables (see, for example, Evans [13]). In Australian agriculture there are surveys of intended wheat acreage plantings and sheep matings for the coming year. The questions might be extended to cover longer planning horizons and other decisions including acreages of fruit trees and numbers of livestock. In practice the intentions data may be extrapolated as a direct forecast or it may be combined with other information in the preparation of informal model and formal model forecasts.

The intentions information can contribute to greater forecast accuracy in a number of ways. In particular, the survey information reduces the specification problems encountered in having to specify models of price expectations and desired investment or consumption levels in terms of historical data, e.g. the various *ad hoc* distributed lag models of price expectations used in supply studies can be replaced by a direct index of producers' price expectations. At the application level survey intentions data has provided relatively more accurate forecasts of manufacturing investment than naïve and econometric model forecasts (see, Evans [13] and Rippe and Wilkinson [39]). To the author's knowledge no comparable evaluations have been made for agriculture. The forecast accuracy of intentions data will depend on the degree to which intended decisions are executed and on the use of satisfactory sample procedures. With respect to the former, the forecasts are likely to be more accurate the longer the decision lag, the shorter the forecast horizon, the less the flexibility for and the more the cost of decision revisions, and the more accurately survey participants foresee the future. In a practical context the costs of running surveys may be a disadvantage.

Some Australian Forecasts

This section provides quantitative data on the accuracy of some attempts to forecast annual prices and annual quantities produced of selected Australian agricultural commodities over the period 1966-7 to 1973-4. Three forecasting exercises are discussed:[3]

1. time series model or naïve forecasts prepared by the author;

[3] A number of other studies which are directly involved in forecasting for Australian agriculture include: Gellatly [17]—quarterly forecasts of N.S.W. meat production using econometric, judgemental, Box-Jenkins and simple naïve techniques; Throsby [44]—quarterly forecasts of beef supply, demand, prices and exports using an econometric model; Chopping [7]—annual forecasts of beef cow inventory using an econometric model; White [47]—annual forecasts of beef cattle inventory and beef production using a demographic model; U.S. Department of Agriculture [46]—production forecasts using subjectively adjusted trend extrapolations; Jarrett [25], Hussey [24] and Dalton [11]—wool price forecasts using exponential smoothing, indicator analysis, and econometric model techniques, respectively; FAO [16]—production, trade, and consumption forecasts using balance sheet methods; Harris [22]—long term price forecasts using informal model techniques; and Bureau of Agricultural Economics [5]—forecasts of five year quantities using informal model techniques. Also, other reported commodity analysis studies provide background information for generating forecasts.

2. informal model forecasts prepared by the Bureau of Agricultural Economics (B.A.E.) [6]; and
3. formal model forecasts prepared by the Monash study and reported in Gruen *et al.* [19].

Three criteria are used in evaluating the forecasts. The mean absolute error measures the average value by which the forecasts represented over- or under-estimates of the realized value of the variable. Similarly, the mean per cent error measures the average per cent by which the forecast over- or under-estimated the realized value of the forecast variable. The ratio of turning points criteria measures the number of times the forecast falsely anticipated a directional change in the level of the variable, e.g. forecast a rise from the present level when the realized value in fact fell, relative to the realized number of directional changes. The measures are subject to sampling errors and they are peculiar to the period of analysis. For these reasons the evaluation is suggestive only of forecast accuracy in a general context.

Tables 1 and 2 evaluate naïve forecasts of the average annual price and the annual level of production, respectively, of selected Australian agricultural commodities for the period 1966-7 to 1973-4. Each forecast is generated as a function of the variable in the current and previous two years and of a time trend. The parameters of the forecast function are ordinary least squares estimates for the 1946-7 to 1965-6 period. The forecast function is a comparatively simple substitute for the optimal time series model; the simplification stems from the exclusion of consideration of moving average error components and no attempt was made to delete non-significant explanatory variables. Clearly, a number of alternative naïve forecast procedures might have been considered.[4] For the one year ahead price forecasts of Table 1 the mean per cent forecast error ranges from 3 per cent for beef to 45 per cent for sugar. The mean per cent price forecast error for most grain, livestock and horticultural commodities fell in the range of 10 to 20 per cent. In terms of forecasting changes in the direction of prices the forecasts gave about as many false leads as there were turning points. For the one year ahead naïve production forecasts of Table 2 the mean per cent forecast error was around 10 per cent for the livestock and horticultural commodities and in excess of 30 per cent for the grains. The production forecasts gave about as many false leads of changes of direction as there were actual changes of direction. Comparing the three year ahead forecasts with the one year ahead forecasts in Tables 1 and 2 the former were less accurate for most commodity prices and for about a half of the commodity quantities.

In the September issue of 'Trends in Australian Production and Exports' the B.A.E. [6] reports forecasts of the annual gross value and production (and by implication price) levels of agricultural commodities for the current financial year. They are comparable in time of

[4] The no change forecast was also evaluated. In terms of mean absolute error the no change forecasts were superior to the naïve forecasts reported in Tables 1 and 2 for wool, apples, sugar and cotton prices and quantities and for barley, sorghum and potato quantities, they were inferior for beef and citrus prices and quantities and for wheat quantity, and they were about the same for the other forecast variables.

TABLE 1

Evaluation of Naïve Model Forecasts of Annual Prices of Selected Agricultural Commodities 1966-7 to 1973-4

Commodity	Unit	Average Level 1970/4	Forecast One Year Ahead[1]			Forecast Three Years Ahead[2]		
			Mean absolute error[3]	Mean per cent error[4]	Ratio of turning point errors[5]	Mean absolute error[3]	Mean per cent error[4]	Ratio of turning point errors[5]
Grains:								
Wheat	$/t	65·9	8·5	12·2	3:3	12·1	13·2	4:3
Barley	$/t	54·8	8·5	17·0	3:4	16·6	36·8	6:4
Sorghum	$/t	53·0	8·9	18·8	3:5	12·0	27·2	3:5
Livestock:								
Wool	c/kg	120·0	32·5	20·8	3:3	32·4	24·1	3:3
Beef	c/kg	70·9	3·8	3·1	4:3	4·7	6·6	3:3
Lamb	c/kg	44·4	8·7	18·0	4:3	9·6	20·0	3:3
Butter	c/kg	103·8	6·0	6·0	3:5	7·4	8·1	4:5
Horticultural:								
Citrus	$/t	119·7	10·3	8·0	5:7	14·2	11·0	6:7
Apples	$/t	151·4	22·5	14·8	3:2	26·8	17·7	4:2
Others:								
Sugar	$/t	109·7	30·1	44·8	3:2	16·1	28·9	3:2
Cotton	$/t	773·8	154·7	22·9	2:4	104·2	16·5	3:4
Potatoes	$/t	90·0	23·9	27·6	3:5	52·3	83·8	4:5

1 Forecast model: $\hat{y}_{t+1} = a_0 + a_1 t + a_2 y_t + a_3 y_{t-1} + a_4 y_{t-2}$ with a's being ordinary least squares estimates for 1948-9 to 1965-6 sample.

2 Forecast model: $\hat{y}_{t+3} = b_0 + b_1 t + b_2 y_t + b_3 y_{t-1} + b_4 y_{t-2}$ with b's being ordinary least squares estimates for 1952-3 to 1965-6 sample.

3 Measured $\Sigma \mid \hat{y}_t - y_t \mid /8$.

4 Measured $\Sigma \mid ((\hat{y}_t - y_t)/y_t)*100 \mid /8$.

5 Measured as number of turning point errors: number of turning points.

TABLE 2

Evaluation of Naïve Model Forecasts of Annual Quantities Produced of Selected Agricultural Commodities 1966-7 to 1973-4

Commodity	Unit	Average level 1970/4	Forecast One Year Ahead[1]			Forecast Three Years Ahead[2]		
			Mean absolute error[3]	Mean per cent error[4]	Ratio of turning point errors[5]	Mean absolute error[3]	Mean per cent error[4]	Ratio of turning point errors[5]
Grains:								
Wheat	'000 t	8732	2695	33·3	5:6	2786	35·6	4:6
Barley	'000 t	2387	910	42·2	2:4	545	28·1	3:4
Sorghum	'000 t	1164	533	54·3	5:4	501	57·1	4:4
Livestock:								
Wool	Mkg	800	92	12·3	4:1	82	10·5	3:1
Beef	'000 t	1239	89	7·7	1:2	94	7·6	2:2
Lamb	'000 t	292	32	10·7	1:1	41	13·7	2:1
Butter	'000 t	190	26	9·1	4:3	22	12·6	5:3
Horticultural:								
Citrus	'000 t	382	28	7·4	0:7	57	15·6	6:7
Apples	'000 t	389	48	13·1	3:5	61	16·5	4:5
Others:								
Sugar	'000 t	18,810	3147	267	2:3	2214	11·1	1:3
Cotton	'000 t	31	47	174·6	5:4	88	296·5	2:4
Potatoes	'000 t	732	130	17·1	2:3	115	15·2	3:3

1, 2, 3, 4, 5 as for Table 1.

release and forecast horizon to the one year ahead naïve forecasts described above. The forecasts are based on knowledge of technical and economic factors influencing the production, trade, and consumption of the commodities, and on discussions with individuals involved in the trade.[5] While the forecasting procedure varies between commodities and over time they fall under the general heading of informal model procedures.

In Tables 3 and 4 the B.A.E. one year ahead forecasts of annual prices and production levels of selected Australian agricultural commodities for the period 1966-7 to 1973-4 are evaluated. The mean per cent error for the forecasts lie within the range of 5 to 15 per cent for most prices and quantities. For most commodities the forecasts gave less false leads about the direction of change in the variable than there were turning points, but there were many turning point errors. Comparing the B.A.E. and naïve one year ahead forecasts, the former were significantly more accurate in most cases (the exceptions being butter price, citrus price and citrus production) at the 0·15 level using a non-parametric sign test.

The Monash study reported in Gruen *et al.* [19] represents an ambitious and comprehensive exercise at forecasting long term trends for Australian agriculture. The 1970 forecasts evaluated below represent five year ahead forecasts.

TABLE 3

Evaluation of Bureau of Agricultural Economics Forecasts of Annual Prices of Selected Agricultural Commodities 1966-7 to 1973-4

Commodity	Unit	Average Level 1970/4	Forecasts One Year Ahead[1]		
			Mean absolute error[3]	Mean per cent error[4]	Ratio of turning point errors[5]
Grains:					
Wheat	$/t	65·9	2·7	4·1	1:3
Barley	$/t	54·8	6·0	12·5	1:4
Sorghum	$/t	53·0	5·2	12·8	1:5
Livestock:					
Wool	c/kg	120·0	14·3	12·6	1:3
Beef	c/kg	70·9	3·8	5·2	3:3
Butter	c/kg	103·8	10·3	10·5	3:5
Horticultural:					
Citrus	$/t	119·7	14·7	11·9	5:7
Apples	$/t	151·4	19·0	12·6	6:2
Others:					
Sugar cane	$/t	109·7	6·8	6·8	3:2
Potatoes	$/t	90·0	16·3	18·5	4:5

1 Forecasts published in September issues of Bureau of Agricultural Economics, *Trends in Australian Rural Production and Exports,* Canberra. Crop forecasts refer to year ending March 31. Livestock forecasts refer to year ending June 30.
3, 4, 5 as for Table 1.

5 The B.A.E. forecasts discussed at the National Agricultural Outlook Conference in February each year and in the commodity Situation Reports record the reasoning underlying their short term forecasts.

TABLE 4

Evaluation of Bureau of Agricultural Economics Forecasts of Production of Selected Agricultural Commodities 1966-7 to 1973-4

Commodity	Unit	Average Level 1970-74	Forecasts One Year Ahead[1] Mean absolute error[3]	Mean per cent error[4]	Ratio of turning point errors[5]
Grains:					
Wheat	'000 t	8732	946	9·4	0:6
Barley	'000 t	2387	269	15·4	2:4
Sorghum	'000 t	1164	167	21·0	2:4
Livestock:					
Wool	Mkg	800	38	4·7	1:1
Beef	'000 t	1239	68	5·4	1:2
Butter	'000 t	190	13	6·5	3:3
Horticultural:					
Citrus	'000 t	382	45	13·8	2:7
Apples	'000 t	389	36	9·4	3:5
Others:					
Sugar cane	'000 t	18,810	698	3·8	2:3
Potatoes	'000 t	732	79	10·8	0:3

1, 3, 4, 5 as for Table 3.

Five year ahead forecasts of average 1970 prices of wool, beef, lamb, wheat and barley prepared by the Monash study, together with comparable naïve forecasts, are evaluated in Table 5. The Monash forecasts were derived from an informal model. Average 1958-9 to 1961-2 price, termed the base period price, was adjusted after consideration of a balance sheet of world supply and demand. For example, the meat balance sheet suggested persistent under production relative to demand at base period prices and thus the long term beef and lamb price estimates were estimated to be above base period levels. For the Monash team price forecasts the per cent forecast error varied from 3 per cent for barley to 85 per cent for wheat, and for two of the five commodities the forecasts estimated the wrong direction of change of the price series. Taking the five commodity price forecasts as a sample and applying a nonparametric sign test, the Monash team informal model five year ahead price forecasts were neither significantly more or less accurate than naïve forecasts.

The Monash study five year ahead forecasts of 1970 production of wool, beef, lamb, wheat and barley are evaluated in Table 6. An econometric model was used to generate the forecasts. Based on the concept of a constant elasticity of transformation production frontier the annual production of each commodity was explained by its expected output price, the expected prices of alternative outputs, seasonal conditions, indexes of production capacity (typically previous output), and productivity trends. To allow for uncertainty about future period prices and seasonal conditions Monte Carlo procedures were used to generate a probability distribution function of forecast outcomes for each commodity. Both the mean forecast and the standard error of the forecast probability distribution function are reported in Table 6. The per cent

TABLE 5

Comparison of Naïve Model and Monash Model Five Year Ahead Forecasts of Prices for Selected Agricultural Commodities

Commodity	Unit	Actual Average 1969-70 & 1970-1	Naïve Model Forecasts for 1970[1]			Monash Model Forecasts for 1970[2]		
			Forecast	Per cent error[3]	Correct direction[4]	Forecast	Per cent error[3]	Correct direction[4]
Wool	c/kg	73·7	82·7	—12·2	Yes	107·4	—45·6	Yes
Beef	c/kg	59·4	47·4	20·2	Yes	48·4	18·5	Yes
Lamb	c/kg	36·3	48·4	—33·3	No	67·0	—84·5	No
Wheat	$/t	45·4	53·8	—18·4	No	55·1	—21·4	No
Barley	$/t	43·0	65·9	—53·3	No	44·1	— 2·5	Yes

1 Forecast model $z_{t+5} = a_0 + a_1 t + a_2 z_t + a_3 z_{t-1}$ where z's are two year averages of forecast variable and a's are ordinary least squares estimates for 1946-7 to 1964-5 sample.

2 From Gruen *et al.* [19].

3 Computed as $((\hat{z}_t - z_t)/z_t) * 100$.

4 If forecast is in the correct direction relative to the 1964-6 average level of the variable it is denoted by a 'yes', if not by a 'no'.

forecast error for the Monash study mean forecasts are 4 per cent for wool and beef, 12 per cent for butter, 23 per cent for wheat, 32 per cent for lamb and 36 per cent for barley. For two of the six commodities the forecasts estimated the wrong direction of change of the production level relative to base period (1958-9 to 1961-2) production level. With the exception of lamb the realized values fall within the mean forecast plus or minus two estimated standard errors. Taking the six commodities as a sample and applying a nonparametric sign test the Monash study quantity forecasts are neither significantly more or less accurate than the naïve forecasts reported in Table 6.

A useful contribution of the Monash study forecasts is the study's explicit recognition of uncertainty in forecasting. The forecast standard errors in Table 6 are large relative to the mean forecasts (and further, the estimates assume away uncertainty associated with the regression equation error terms and the sample estimates of the parameters). They indicate the order of effect of likely variations in commodity prices and seasonal conditions on the levels of production, and they highlight some of the problems to be overcome in improving the accuracy of commodity production forecasts.

Conclusions and Implications

Forecasts provide information to facilitate effective decision making. Producers require estimates of future period market prices for commodities they buy and sell. Marketers require estimates of the quantities of goods they are to transport, store and process in the future. Policy makers require information about the future state of the rural sector under different policies.

A number of forecasting techniques may be used. The choice for any situation will be influenced by time and available resources, and by the degree of accuracy required. In general there is a positive relationship between resource requirements and forecast accuracy, but the available information does not enable us to make conclusive statements about the trade-off relationship. Conceptually, the formal model forecasting technique would be expected to provide the most accurate forecasts provided that time and data permit a satisfactory representation of the important causal forces. However, in practice the potential gains in relative forecast accuracy are not being realized in all cases, or they have been small, as a result of errors of model specification and estimation. Where decision makers' intentions and expectations are important explanatory variables and the variables are not well articulated by available data, properly conducted intentions surveys have provided relatively accurate forecasts. Informal models offer greater flexibility and less stringent data requirements than formal models but these advantages must be balanced against the higher probability of personal biases and inconsistencies affecting forecasts, particularly where large and complex sectors are involved. While time series models are devoid of economic theory they are simple to apply, they require information only on historical values of the forecast series and, in practice, their forecast accuracy often has been second to that of more sophisticated techniques by small margins. Opportunities for analysing the sources of forecast errors

TABLE 6

Comparison of Naïve Model and Monash Model Five Year Ahead Forecasts of Production of Selected Agricultural Commodities

Commodity	Unit	Actual Average 1969-70 & 1970-71	Naïve Model Forecasts for 1970[1]			Monash Model Forecasts for 1970[2]			
			Forecast	Per cent error[3]	Correct direction[4]	Mean Forecast	Per cent error[3]	Forecast standard error[6]	Correct direction[4]
Wool	Mkg	904	1002	—10·7	Yes	870	3·8	119	Yes
Beef	'000 t	1012	1040	— 2·8	Yes	970	4·2	52	No
Lamb	'000 t	329	277	15·5	Yes	225	31·6	39	Yes
Butter	'000 t	213	216	— 1·4	Yes	188	11·7	14	No
Wheat	'000 t	9212	9138	0·8	Yes	11 296	—22·6	2395	Yes
Barley	'000 t	2025	676	66·6	No	1292	36·1	769	Yes

1, 2, 3, 4 as for Table 5.
[6] See Gruen *et al.* [19].

and for improving subsequent forecasts are enhanced when the forecasts are based on formal models or when all assumptions underlying forecasts are made explicit. Finally, alternative forecasts almost always contain a unique component of information that may be usefully exploited by combining available forecasts (see, for example, Nelson [36] and Granger and Newbold [18]).

An evaluation of naïve, informal model and formal model forecasts of one year ahead and five year ahead prices and quantities for some Australian agricultural commodities for the period 1966-7 to 1973-4 provided sample data about the accuracy of forecasts for Australian agriculture and of the relative accuracy of the different forecasting techniques. Taking the naïve forecasts as a basis of comparison the mean per cent error exceeded 10 per cent in most cases and in many cases it exceeded 30 per cent. Informal model forecasts of one year ahead prices and quantities prepared by the B.A.E. had mean per cent errors of between 5 and 15 per cent—a large and significant gain in accuracy relative to the naïve forecasts. For five years ahead forecasts the informal model price forecasts and the formal model quantity forecasts prepared by the Monash study group were not significantly more or less accurate than the naïve forecasts. Clearly the results provide a tentative guide only to the accuracy of future period forecasts.

Even so, it seems likely that forecasts of Australian agricultural commodity prices and quantities will continue to be subject to wide errors. To a large degree the errors can be attributed to the importance of causal variables such as seasonal conditions at home and abroad and national agricultural policies which are difficult to predict. Also, our knowledge of the supply, demand, and other relationships influencing the levels of the forecast variables is imperfect, these relationships may be changing over time, and consideration needs to be given to the reactions of decision makers to forecast information (for a discussion of reaction functions see Smyth [42]). The extent of errors in forecasts and the reasons behind the errors make it imperative that the uncertain nature of forecasts be communicated to users by, for example, interval estimates and estimates of probability distributions. For the practising forecaster there is a need to employ procedures for revising forecasts in the light of forthcoming information.

Finally, several reasons point to the desirability of public participation in the provision of forecasts. The atomistic structure of agricultural markets and the public good nature of forecast information suggest that the resources devoted by individuals to forecasting will be less than a social optimum. Information collected by one individual may be used by others without diminishing his use of the information and it is difficult and costly to restrict nonpaying individuals from having access to the forecasts. There will be cost economies of size and benefits associated with specialization in the supply of forecasts. Public provision of forecasts may be advocated on the grounds of equity and impartiality to ensure that all market participants are equally informed.

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