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Forecasting N.S.W. Beef Production: An Evaluation of Alternative Techniques *

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This paper reports on the evaluation of the performance of several forecasting methods used to forecast New South Wales quarterly beef production, one quarter ahead. The forecasting procedures used are a single equation regression model, a Box-Jenkins univariate time series model, a forecasting committee's judgement and a naive model. Absolute accuracy and relative accuracy measures are used to evaluate *ex ante* forecasts. Although the evaluation gave some mixed results according to the criteria used, it appears that the forecasting committee performed better than the alternative forecasting procedures considered in this study. However, the results indicate that the committee's performance was not much better than that of a naive (no change) model, indicating there is room for improvement.

1 Introduction

Decision makers at all levels in the economy require some forecast of the future behaviour of factors which affect their decisions. A forecaster has to choose between the various forecasting methods which are available.[1] To enable the forecaster to determine the reliability of his forecasts he must evaluate the forecasting methods used.

This study reports and evaluates the performance of several forecasting methods used to forecast New South Wales quarterly beef production, one quarter ahead. The quarters are based on a production year ending October each year, *i.e.*, the quarters are November–January, February–April, May–July and August–October. The forecasting procedures used are:

(i) Single equation regression model.

(ii) Box-Jenkins univariate time series model.

(iii) Judgemental—New South Wales Meat Production Forecasting Committee.

(iv) Naive model—no change from last period.

The evaluation of the forecasting methods in this study uses only *ex-ante* forecasts. All the forecasting procedures examined use only information available at the time the forecast is made, *i.e.*, before the actual event. This

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[1] For a detailed discussion of the various techniques, see Mackrell (1974), Granger and Newbold (1977) and, with particular reference to Australian agriculture, Freebairn (1975).

is in contrast to evaluation studies which use *ex-post* forecasts, which make use of information which would not be known at the time the forecast would be required by decision-makers. *Ex-post* forecasts usually result from either:

(i) considering "fitted" values of the model over the estimation period as forecasts; or

(ii) incorporating in the forecasting model, exogenous variables, whose values would not be known at the time the forecast is made, and then using the actual values of the exogenous variables when constructing the forecast.

Sections 2, 3 and 4 describe the forecasting procedures in more detail. Section 5 reviews the methods of forecast evaluation and section 6 presents the results. Conclusions are drawn in section 7.

2 Single equation regression model

A supply response model was specified based on the adaptive expectations model first formulated for agricultural supply analysis by Nerlove (1956).[2] The model is of the form

$$Q_t = a_0 + a_1 P_t^* + a_2 W_{t-1} + U_t \qquad 2.1$$

where

Q_t = quantity of beef produced at time t (tonnes)

P_t^* = expected price level of beef at time t (cents/kg)

W_{t-1} = weather index[3] at time $t-1$

U_t = error term

Producers are assumed to form their expectations of price in the following way:

$$P_t^* - P_{t-1}^* = \beta (P_{t-1} - P_{t-1}^*) \qquad 2.2$$

where β = coefficient of expectation.

By rewriting equation 2.2 and using the Koyck transformation the following formulation of the supply model is obtained:

$$Q_t = a_0\beta + a_1\beta P_{t-1} + (1-\beta)\, Q_{t-1} + a_2 W_{t-1} + (\beta - 1)\, a_2\, W_{t-2} + [U_t - (1-\beta)\, U_{t-1}] \qquad 2.3$$

which can be rewritten as

$$Q_t = C_0 + C_1 P_{t-1} + C_2\, Q_{t-1} + C_3\, W_{t-1} + C_4\, W_{t-2} + V_t \qquad 2.4$$

and is the specification to be used to obtain the econometric forecasts.[4]

[2] Anderson (1975) discusses in detail the various specifications of distributed lag models and the associated econometric questions. An Almon lag model was estimated for this study but goodness of fit (as measured by $\bar{R}^2$) and forecasting performance were not as good as the simple adaptive expectations model.

[3] The weather index was calculated from monthly rainfall figures for meteorological regions. In aggregation, regions were weighted by breeding cow numbers. It is planned in future work to re-define this variable to measure deviations from the mean, rather than total rainfall.

[4] The model used in this study is rather simplistic. Work is proceeding on extending the model to include separate equations for slaughter numbers and slaughter weights. It is also planned to incorporate some type of inventory variable: inclusion of a variable which measured annual numbers of beef cattle did not improve either the explanatory power or forecasting performance.

3 Univariate Box Jenkins Model

The use of parametric time series models for forecasting both stationary and non-stationary series has become popular following the work of Box and Jenkins (1970). While the Box-Jenkins' approach uses parametric models, it is essentially a sophisticated extrapolation technique with the inherent shortcoming that the models are not based on economic theory.

Since the Box-Jenkins approach is well covered in the literature, *e.g.*, Box and Jenkins (1970) and Nelson (1973), no attempt will be made to describe the theory behind the approach. However it is necessary to briefly explain the notation which is in general use. The general multiplicative seasonal autoregressive—integrated—moving—average (ARIMA) model for a seasonal series X_t, $t = 1, 2, \ldots T$ with a known period S can be written as

$$\varphi_p(B)\,\Phi_P(B^s)\,(1 - B)^d\,(1 - B^s)^D\,X_t = \theta_q(B)\,\Theta_Q(B^s)\,a_t \qquad 3.1$$

where a_t is a random disturbance assumed to be distributed as $N\,(0, \sigma_a^2)$; B is a backward shift operator such that $BX_t = X_{t-1}$ and $B^k X_t = X_{t-k}$; $\varphi_p(B)$ is the regular autoregressive operator of order p, i.e., $\varphi_p(B) = (1 - \varphi_1 B - \varphi_2 B^2 - \ldots - \varphi_p B^p)$; $\Phi_P(B^s)$ is the seasonal autoregressive operator of order P; d is the number of regular differences; D is the number of seasonal differences; $\theta_q(B)$ is the regular moving average operator of order q, i.e., $\theta_q(B) = (1 - \theta_1 B - \theta_2 B^2 - \ldots - \theta_q B^q)$; $\Theta_Q(B^s)$ is the seasonal moving average operator of order Q; and s is the order of the seasonal difference. Equation (3.1) is an ARIMA model of order (p, d, q) times $(P, D, Q)_s$.

The Box-Jenkins method of forecasting has four main stages:

(1) Identification of the particular model to be used. Identification is based on the comparison of estimated autocorrelation and partial autocorrelation functions, with the characteristics of known theoretical autocorrelation and partial autocorrelation functions. (Choosing, p, d and q and P, D, Q).

(2) Fitting the identified model to the time series data, *i.e.*, estimating the parameters of the particular model. (Estimating the coefficient $\varphi_1 \ldots \varphi_p$, $\theta_1 \ldots \theta_q$, $\Phi_1 \ldots \Phi_P$, $\Theta_1 \ldots \Theta_Q$).

(3) Diagnostic checking to detect model inadequacy and, where necessary, to initiate a further iterative cycle of identification, fitting and diagnostic checking.

(4) Having arrived at an "adequate" model, optimal forecasts are generated by recursive calculation.

There have been a number of studies showing the use of Box-Jenkins techniques (e.g., Chatfield and Prothero (1973), Bhattacharyya (1974), Watts and Schmitz (1970) and Ryland (1975)). Daub (1973 and 1974) use Box-Jenkins models to provide benchmark extrapolations in his evaluation of judgemental G.N.P. forecasts.

4 Other Forecasting Methods

4.1 Judgemental

The New South Wales Meat Production Forecasting Committee makes forecasts of quarterly beef (and veal, mutton and lamb) production based on an October ending production year. The Committee chairman is the A.M.L.C.'s New South Wales state manager with other members of the

Committee being representatives from various sections of the meat industry, including Department of Agriculture officers, livestock agents, producer group representatives and commercial meat traders. The Committee's forecasts are a typical example of a judgemental forecast derived from the subjective opinion of experts in the field of interest.

4.2 Naive Models

These types of models are usually used as benchmarks as they are the cheapest and simplest forecasting procedure. There are a number of alternative models that could be used, *e.g.*, same change, average. The naive model used in this study is no change, *i.e.*, use last period's value as the forecast.

5 Evaluating Forecasts

There have been two main approaches to forecast evaluation; absolute and relative accuracy evaluation. Both of these methods originated from the pioneering work of Theil (1966) on the evaluation of econometric model forecasts. Indeed, most forecast evaluation has been done with econometric forecasts. However, econometric model forecasting[5] is unique in that the model can be reproduced to test the predictive power, and it is also possible to identify the source of error, *e.g.*, Haitovsky and Treyz (1970). This study is aimed at judging forecasting procedures on their ability to predict—not to evaluate the type of model. To enable informal forecasting procedures to be evaluated on a comparable basis to those procedures generating scientific forecasts, an evaluation procedure that is based only on comparing forecast values with actual values is required.

The basic criterion must be, does the forecast help the decision maker make a better decision? Ideally, the criterion would be based on the user's loss function. (If we are using a statistical model for prediction, it must first satisfy a statistical criterion.) In general we may assume that the loss function is some function of the forecast errors.

There are other problems in evaluation. For example, the effect on forecasting accuracy of data errors. Data errors not only affect the variables underlying a forecast (the direct effect). They also affect the estimates of the parameters of the relationship among these variables (the indirect effect). There would seem to be considerable scope for improving forecasting accuracy by improving the accuracy of preliminary data, *e.g.*, Burns (1973). There is also the problem of deciding whether to use preliminary or revised data when measuring the actual series.

Another problem is whether to measure the variable being forecasted in terms of either:

(i) levels;
(ii) changes;
(iii) percentage changes;
(iv) log percentage changes.

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[5] See Steckler (1968), Jorgenson (1970) among others.

5.1 Absolute Accuracy

The simplest forms of absolute accuracy are mean absolute forecast error (MAE) and absolute percentage error. The $MAE = \frac{\Sigma(A - F_t)}{n}$ is the ideal criterion if the users loss function is linear in forecast errors. Another commonly used measure of absolute accuracy is the Mean Square Error (MSE) which is defined as

$$MSE = \frac{\sum_{t=1}^{n} (A_t - F_t)^2}{n}$$

where A are the actual values and F are the forecast values. There are n of each. The MSE statistic derives from the criterion of forecasting performance in which the loss function of the user of the forecasts is quadratic in the forecast errors. A quadratic loss function means larger errors represent an increased cost to the user than smaller errors and that the loss is symmetrical with respect to under and over estimation.

Using Theil (1966) as a basis, most forecasting studies have employed various decompositions of MSE (called inequality coefficients). However both Jorgenson (1970) and Granger and Newbold (1973) have shown there are problems with using the MSE decomposition. The basic difficulty with the MSE criterion is that in practice, the statistics are based on limited samples. Thus the MSE and its components are all estimates subject to sampling variation, and little is known about the small sample coefficients of the underlying population distributions of the equality coefficients.

A commonly used absolute accuracy analysis method is to use regressions involving the predicted and actual values of the series. Although the predicted values can be regressed on the actual values, a more preferred method, explained by Daub (1973) is the regression of actuals on the prediction.

$$A_t = \alpha + \beta P_t + U_t$$

where A_t denotes revised value, P_t denotes forecast values, U_t the error term and α and β are parameters. Under the assumptions of independence and normality, a simple F-test can be used to investigate the joint null hypothesis that $\alpha = 0$, $\beta = 1$, i.e., the forecast is unbiased. Two separate null hypotheses that $\beta = 1$ and $\alpha = 0$ may also be tested. Thus, rejection of the joint null hypothesis of no bias may be due to the same bias at all levels of actuals $\beta = 1$ but $\alpha \neq 0$ or to a systematic, but different bias, above and below the common mean of predictions and actuals $\beta \neq 1$ but $\alpha = 0$.[6]

Another absolute accuracy analysis method used is to determine the number of turning points that were forecast correctly.

5.2 Relative Accuracy Analysis

The quality of forecasting performance is not fully evaluated by the size and characteristics of forecasting error because it is impossible to compare forecasting errors when different economic variables are to be predicted. To overcome this difficulty and to emphasize the distinction between the size of the forecasting error and the consequences of the forecasting error, Mincer and

[6] For a more detailed discussion of this approach see Daub (1973), Granger and Newbold (1973) and Dhrymes *et al.* (1972).

Zarnowitz (1969, p. 21) suggest an index of forecasting quality based on the ratio of the MSE of the forecast and the MSE of a benchmark (extrapolation). "The ratio represents the relative reduction in forecasting error. It ranks the quality of forecasting performance the same way as a rate of return index, in which the return (numerator) is inversely proportional to the MSE of forecast and the cost (denominator) is inversely proportional to the MSE of extrapolation, the latter representing the difficulties encountered in forecasting a given series". This approach had been used informally by Theil (1966) in his inequality coefficient[7] U_2, which was $U_2^2 = \frac{\Sigma (P_i - A_i)^2}{\Sigma A_i^2}$ where the benchmark is the "most naive" no change extrapolation, *i.e.*, $U_2 = 1$ results when the prediction procedure leads to the same MSE as a no change extrapolation. The statistic is thus defined as

$$RM = \frac{MSE_P}{MSE_E}$$

where RM is relative mean square error, MSE_P is mean square error of prediction and MSE is mean square error of extrapolation. Hopefully $RM < 1$, that is, the forecaster performs better than an extrapolation of past data, which can be obtained at relatively little cost. To give further indication of the relative merits of the extrapolations and the prediction correlations,[8] r^2_{AP} and r^2_{AE} can be calculated. Hopefully, r^2_{AP} would be higher. Rather than just consider extrapolations as alternatives to predictions, this analysis can be extended further if we consider predictions to be composed of an extrapolative and a non-extrapolative or autonomous component. Mincer and Zarnowitz (1969) show that the correlation $r^2_{AP.E}$ measures the extent to which the predictive power of the forecast is due to the autonomous component. If $r^2_{AP.E} > 0$, the forecast P contains predictive power based not only on extrapolation but also on its autonomous component. A measure of how efficiently the predictions used all the available extrapolative information is the correlation coefficient, $r^2_{AE.P}$. If $r^2_{AE.P} > 0$ then E contains some predictive power that was not used in P. As Daub (1973) points out "to say however, that most of the available predictive value of the extrapolations was used in the forecast does not necessarily mean that the extrapolations were a significant factor in the predictions". To obtain information on the actual importance of extrapolations in generating the forecasts, r^2_{PE} can be calculated.

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[7] As discussed by Leuthold (1975) U_2^2 is preferred to

$$U_1^2 = \frac{\Sigma(P_i - A_i)^2}{\Sigma P_i^2 + \Sigma A_i^2}$$

[8] r^2_{AP} — simple correlation between actual values and predicted values.

r^2_{AE} — simple correlation between actual values and extrapolation values.

r^2_{PE} — simple correlation between predicted values and extrapolations.

$r^2_{AP.E}$ — correlation between actual and predicted values given extrapolation values.

$r^2_{AE.P}$ — correlation between actual and extrapolation values given predicted values.

Granger and Newbold (1973) have shown a relatively new approach to forecast evaluation and that is the "conditional efficiency" concept.[9] This concept is based on the fact that two forecasts can be combined, *e.g.*,

$$P_n^c = k\,P^{(1)} + (1 - k)\,P_n^{(2)}$$

where $k = \dfrac{S_2^2 - r\,S_1S_2}{S_1^2 + S_2^2 - 2r\,S_1S_2}$ and where

$e^{(i)} = (P^{(i)} - X)$ and $i = 1, 2.$

S_i are sample variances of $e^{(i)}$

r is sample correlation between e_n^1 and e_n^2

$P_n^{(i)}$ are forecasts of X_n

Taking k as above results in

$$S_c^2 < \min\,(S_1^2, S_2^2)$$

and conditional efficiency CE being defined as

$$CE\,(P^{(1)}/P^{(2)}) = \frac{S_c^2}{S_1^2} \quad \text{if } S_1^2 < S_2^2$$

If $CE = 1$ then $P^{(1)}$ is the optimum forecast of X_n. At present, this method relies on the restrictive assumption that forecast errors are bivariate stationary.

The final evaluation approach to be mentioned is a diagnostic check on the errors of forecast. These should be a random series. Such methods could include a Von Neuman ratio test.

$$Q = \frac{\dfrac{1}{N-1}\displaystyle\sum_{t=2}^{N}(e_t - e_{t-1})^2}{\dfrac{1}{N}\displaystyle\sum_{t=1}^{N}(e_t - \bar{e})^2}$$

If enough observations were available, a more sophisticated test could be run on the error series to see if it was a zero-mean white noise series, using a correlogram or a spectral analysis of the series. It will be clear from the above discussions that forecasting and evaluation theory is still developing, *e.g.*, discussion at the American Agricultural Economics Association winter meeting (1973) with papers by Shapiro, Fromm, and Rausser.

6 Results

The forecast evaluation was for ten quarters from November–January, 1976, to February–April, 1978.

6.1 Single Equation Regression Model

The coefficients in the adaptive expectations model

$$Q_t = C_0 + C_1\,P_{t-1} + C_2\,Q_{t-1} + C_2\,W_{t-1} + C_4\,W_{t-2} \qquad 5.1$$

were estimated by ordinary least squares. The forecast for November–January, 1976, was obtained from the estimated model using data from May–July, 1968, to August–October, 1975 (29 observations).[10] Subsequently, the model was re-estimated using the new data and the one-period ahead forecast obtained,

[9] The concept of combining forecasts is discussed in detail in Granger and Newbold (1977).

[10] Data definitions and sources are given in Appendix A.

Table 1: Regression Model Results

Time Period	Independant Variables							Dependant Variable (Q_t)		Percentage Error
	Constant	P_{t-1}	Q_{t-1}	W_{t-1}	W_{t-2}	$\bar{R}^2$	h^a	Forecast $t+1$	Actual $t+1$	
1	16159 (1.24)	−267.3 (−2.28)	0.965 (10.60)	10.77 (1.45)	−1.796 (−0.26)	0.83	0.104	133914	121261	+10.4
2	16801 (1.29)	−231.7 (−2.04)	0.931 (10.75)	9.16 (1.25)	−0.969 (−0.14)	0.84	0.544	126657	130993	− 3.3
3	15865 (1.25)	−238.1 (−2.15)	0.942 (11.73)	9.93 (1.42)	−0.876 (−0.13)	0.86	0.336	135545	134624	+ 0.7
4	16156 (1.35)	−237.5 (−2.19)	0.939 (12.94)	9.82 (1.46)	−0.99 (−0.15)	0.87	0.313	135055	128412	+ 5.2
5	17256 (1.47)	−234.8 (−2.19)	0.925 (13.52)	10.26 (1.55)	−1.84 (−0.28)	0.88	0.415	128047	127437	+ 0.5
6	17285 (1.50)	−234.7 (−2.23)	0.924 (14.07)	10.27 (1.58)	−1.80 (−0.28)	0.89	0.401	127184	157676	−19.3
7	16230 (1.24)	−240.8 (−2.01)	0.964 (13.15)	9.59 (1.29)	−3.24 (−0.45)	0.88	0.696	161616	167614	− 3.6
8	14432 (1.16)	−236.4 (−1.99)	0.980 (14.85)	10.42 (1.46)	−3.49 (−0.49)	0.90	0.222	170152	161101	+ 5.6
9	17517 (1.49)	−245.4 (−2.10)	0.957 (16.26)	10.02 (1.41)	−4.40 (−0.63)	0.91	0.21	158790	150540	+ 5.5
10	18609 (1.61)	−251.5 (−2.17)	0.944 (16.91)	10.97 (1.58)	−4.93 (−0.72)	0.91	0.430	153301	149886	+ 2.3

(a) The h statistic indicates significant first order autocorrelation at the 5 per cent level if $|h| > 1.96$ since $h \sim N(0, 1)$.

e.g., the forecast for February–April, 1976, was obtained from the estimated model using data from May–July, 1968, to November–January, 1976 (30 observations). The estimated coefficients and forecasts for the 10 time periods are presented in Table 1.

6.2 Box-Jenkins Model

The techniques of Box and Jenkins were used to forecast New South Wales beef production on a quarterly basis. A programme obtained from the University of Wisconsin was used for the Box-Jenkins identification, estimation and forecasting. The estimated autocorrelations and partial autocorrelations are given in Appendix B. From these it was decided no differencing was needed to be applied to the series to achieve stationarity.

After following the Box-Jenkins procedure of estimation and diagnostic checking the following model was chosen:

$$(1 - \varphi_1 B)(1 - \Phi_1 B^4)(X_t - \bar{X}) = a_t \qquad 5.2$$

where $\varphi_1 = 0.908$ $\quad \Phi_1 = 0.238$ $\quad \bar{X} = 84{,}591$

S.E (.061) (.125)

Residual standard error = 10,240;71 df.

The Q statistic calculated from the autocorrelations of the estimated model residuals was 42.27 which when compared to the table value of Chi-squared variable with 33 degrees of freedom (5 per cent level is 47.3685) means we cannot reject the hypothesis that the model residuals are white noise. The estimated model was then used to obtain forecasts for the ten quarters beginning November–January, 1976. The one period ahead forecasts were then calculated making use of new data as it became available. The updating procedure which makes use of last period's deviations and the updating parameters is described by Box and Jenkins (1970, p. 132).[11]

Table 2: Forecasts—Box-Jenkins, Committee and Naive Model

Forecast Time Period	Actual	Box-Jenkins Model	Percentage Error	Committee	Percentage Error	Naive Model (no change)	Percentage Error
1	121 261	125 238	3.78	110 000	9.29	125 516	3.51
2	130 993	118 292	− 9.70	117 000	−10.68	121 261	− 7.43
3	134 624	130 933	− 2.74	133 000	− 1.21	130 993	− 2.70
4	128 412	130 859	1.91	132 000	2.79	134 624	4.84
5	127 437	124 251	− 2.50	127 000	− 0.34	128 412	0.77
6	157 676	126 595	−19.71	132 000	−16.28	127 437	−19.18
7	167 141	152 805	− 8.86	155 000	− 7.55	157 676	− 5.95
8	161 101	159 138	− 1.22	164 000	1.80	167 141	4.04
9	150 540	154 763	2.81	146 000	− 3.01	161 101	7.02
10	149 886	152 570	4.61	144 000	− 3.93	150 540	0.44

[11] An alternative procedure would have been to re-estimate the model each time a new observation was obtained and construct one period ahead forecasts, in a similar manner to that used for the regression model.

The final forecasts obtained from the Box-Jenkins model are given in Table 2 along with the A.M.L.C. Meat Production Forecasting Committee forecasts and the naive model forecasts.

6.3 Evaluation Results

The evaluation procedure was to calculate absolute accuracy analysis, relative accuracy analysis and conditional efficiency statistics for the four types of forecasts over a data period of ten observations (November–January, 1976, to February–April, 1978). Absolute changes were used as the data unit for evaluation.

Presented below in Table 3 are Mean Square Errors, Relative Mean Square Errors, Mean Absolute Percentage Error and Turning Point Errors and U statistics.

Table 3: *Error Analysis of Forecasts*

Forecast	Mean Square Error	Relative Mean Square Error (U statistic)	Mean Absolute Percentage Error	Ratio, Turning Points Errors to Number of Turning Points
Committee ..	122 031 904.3	0.92	5.69	2:4
Regression ..	135 163 248.9	1.01	5.64	3:4
Box-Jenkins ..	146 162 260.5	1.10	5.73	3:4
Naive.. ..	133 308 315	1	5.59	4:4

The absolute accuracy analysis using the regression technique gave the results presented in Table 4.

Table 4: *Regression Analysis of Forecasts*

Forecast	α	β	t value: $H_o\ \beta = 1$	R^2
Committee	7873.25 (2.12)	1.21 (2.47)	0.42	0.43
Regression	2222.19 (.43)	0.086 (0.65)	0.70	0.0005
Box-Jenkins	6085.08 (1.17)	1.269 (1.02)	0.22	0.12

Following Mincer and Zarnowitz (1969) the various correlation coefficients were calculated. The Box-Jenkins projections were used as the extrapolation results. The various correlation coefficients are given in Table 5.

Table 5: Correlation Analysis of Forecasts

Zero order correlations		
$r^2_{\text{COMM, Actual}} = 0.4336$	$r^2_{\text{BJ, Actual}} = 0.1151$	$r^2_{\text{COMM, BJ}} = 0.0163$
First order correlations		
$r^2_{\text{COMM, Actual. BJ}} = 0.4347$	$r^2_{\text{Actual, BJ. COMM}} = 0.1170$	
Other correlation coefficients of interest		
$r^2_{\text{Regr, Actual}} = 0.0231$	$r^2_{\text{Regr, BJ}} = 0.1278$	$r^2_{\text{Regr, COMM}} = 0.0351$

The conditional efficiency analysis presented by Granger and Newbold (1973) was used to consider three possible combinations of forecasting procedures.

(i) Committee and Box-Jenkins.

The conditional forecast is given by $F^c = k\ COMM + (1 - k)\ BJ$ and using the appropriate formula we calculate $K = 0.7924$, i.e., $F^c = 0.7924\ COMM + 0.2076\ BJ$. The estimated variances of forecast errors are given below:

$S^2_{F^c} = 82{,}821{,}293$ $S^2_{COMM} = 111{,}026{,}687$ $S^2_{BJ} = 134{,}761{,}232$

therefore $CE\ (COMM/BJ) = 0.746$

(ii) Committee and Regression.

The conditional forecast is given by $F^c = 1.2364\ COMM - .2364\ REGR$. The estimated variances of forecast errors are given below:

$S^2_{F^c} = 83{,}472{,}316$ $S^2_{COMM} = 111{,}026{,}687$ $S^2_{REGR.} = 150{,}177{,}493$

therefore $CE\ (COMM/REGR.) = 0.752$

(iii) Box-Jenkins and Regression.

The conditional forecast is given by $F^c = 0.9076\ BJ + 0.0924\ REGR$. The estimated variances of forecast errors are given below:

$S^2_{F^c} = 127{,}088{,}202$ $S^2_{BJ} = 134{,}761{,}232$ $S^2_{REGR.} = 150{,}177{,}493$

therefore $CE\ (BJ/REGR.) = 0.943$.

Finally, using the Von Neuman ratio as a diagnostic check of the forecast errors the following Q values were obtained:

$$Q_{COMM} = 2.155$$
$$Q_{REGR.} = 1.812$$
$$Q_{BJ} = 1.541$$
$$Q_{NAIVE} = 1.855$$

Q values greater than 3.2642 and 3.6091 indicate negative first order autocorrelation at the 5 per cent and 1 per cent level of significance respectively. While Q values less than 1.1803 and 0.8353 indicate positive first order autocorrelation at the 5 per cent and 1 per cent level of significance respectively.

6.4 Discussion of Evaluation Results

We can consider the evaluation from the point of view of the Forecasting Committee, *i.e.*, ask the following question. "Are we forecasting accurately? If not, can we improve our performance by making use of Box-Jenkins or Regression techniques?"

Based on a simple but possibly misleading measure such as mean absolute percentage error the Committee forecast ranks third. However, both the turning point analysis and the relative mean square errors (U statistic) indicate that the Committee forecast is better than both the Box-Jenkins and Regression forecasts. The Committee forecast is the only forecast to have a lower mean square error than the naive forecast of no change.

The absolute accuracy analysis using the regression results shows that for both the Regression and Box-Jenkins forecasts it is not possible to reject the hypotheses that $\alpha = 0$ and $\beta = 1$. However, we reject the hypothesis that $\alpha = 0$ while not rejecting that the hypothesis $\beta = 1$, which implies a bias in forecast which is the same at all levels.

The Committee forecast has the highest simple correlation with actual values (0.4336). The partial correlation coefficients provide further information, particularly on the usefulness of the Box-Jenkins results. The $r^2_{\text{COMM, Actual. BJ}}$ which measures the extent to which the predictive accuracy of the forecasts is due to the non-extrapolative or autonomous part, has a value of 0.4347. The $r^2_{\text{BJ, Actual. COMM}}$ measures how well the forecasts utilized the information from the extrapolation (Box-Jenkins). The low value of 0.1170 indicates that the information in extrapolations was utilized significantly.

The actual importance of the extrapolations in generating the forecasts is low as indicated by the $r^2_{\text{COMM, BJ}}$ of 0.0163.

In terms of conditional efficiency no forecasting procedure was optimal. A weighted combination of forecasts would be expected to yield a forecast with lower variance, *i.e.*, each forecast contains information the other could usefully use.

Finally, all forecast error series appeared to be random series based on the Von Neuman ratio test against first order autocorrelation.

7 Conclusion

It is a recurrent theme throughout the forecasting literature that one cannot lay down strict guidelines as to when a particular forecasting method should be used. Therefore, if we are interested in forecasting agricultural production, experience must be gained in forecasting such time series, and the performance of various methods evaluated. This study has evaluated the performance of several forecasting methods in forecasting New South Wales quarterly beef production one-quarter ahead. Although the evaluation gave some mixed results according to the criteria used, it appears that the Forecasting Committee performed better than the alternative forecasting procedures considered in this study. However, the results indicate that the Committee's performance was not much better than that of a naive (no change) model, indicating there is room for improvement. A simple combination of forecasts indicates there is some potential gain from combining techniques to provide the final forecast value to be used by decision makers.

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Appendix A

Q_t = Production of beef in New South Wales in tonnes in quarter t. Source, A.B.S. Meat Statistics (various issues).

P_t = Price of Ox and/or Heifer, 295–318 kg, First and Second export quality, estimated dressed weight basis, in cents per kg, at Homebush, in quarter t. Source, Australian Meat and Livestock Corporation, Annual Report (various issues).

W_t = Weather index in quarter based on monthly rainfall figures for meteorological regions weighted by number of breeding cows. Source, New South Wales Department of Agriculture, Division of Marketing and Economics, Monthly Production Trends, and A.B.S. Livestock Statistics.

Appendix B

Appendix B Table 1

Sample autocorrelation function

Lags	Autocorrelations											
1–12	.87	.72	.64	.59	.52	.49	.53	.58	.56	.52	.43	.35
S.E.	.11	.18	.21	.24	.25	.27	.28	.29	.30	.32	.33	.34
13–24	.27	.18	.12	.12	.13	.12	.11	.12	.07	.02	−.00	−.02
S.E.	.34	.34	.34	.34	.35	.35	.35	.35	.35	.35	.35	.35
25–36	−.06	−.09	−.08	−.08	−.09	−.09	−.09	−.09	−.10	−.11	−.14	−.17
S.E.	.35	.35	.35	.35	.35	.35	.35	.35	.35	.35	.35	.35

Appendix B Table 2

Sample partial autocorrelation function

Lags	Partial autocorrelations											
1–12	.87	−.17	.22	.01	−.08	.24	.20	.11	−.09	−.06	−.24	−.01
13–24	−.08	−.14	−.05	.04	−.08	.07	.04	.13	−.15	.15	.10	−.07
25–36	−.07	−.05	−.03	−.11	.10	−.08	.00	−.01	.06	−.01	−.06	.00