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FORECASTING IN THE NEW SOUTH WALES PRIME LAMB MARKET

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ABSTRACT

Regular market forecasts are important requirements of the Australian and state prime lamb markets. Lamb production is highly seasonal while the product faces strong retail competition. These factors often translate into substantial market variability and highlight the importance of supply and demand forecasts to lamb market participants in planning their activities.

Previous state-level lamb market forecasts have attracted some industry criticism on the grounds of inaccuracy, subjectivity and cost. In New South Wales, the main focus and the approaches hitherto adopted for lamb market forecasting have been the judgemental forecasts of lamb slaughterings and production by an expert industry committee and the Australian Meat and Livestock Corporation's producer surveys of breeding intentions and lamb numbers.

This paper assesses the comparative accuracy of a range of forecast methods in the New South Wales lamb market. The methods include econometric models (single-equation regressions, a structural market model, time-series ARIMA models and composites of these models), naive no-change models and composites of the econometric and the naive models. They are applied to the forecasting of three main lamb market variables, slaughterings, per capita consumption and real saleyard lamb prices. The results indicate that no single method is clearly superior in all situations and the best scope for improving forecast accuracy is through the use of combined econometric and naive approaches.

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FORECASTING IN THE NEW SOUTH WALES PRIME LAMB MARKET

D T Vere and G R Griffith*

1. Introduction

The Australian prime lamb market is characterised by high production seasonality and a competitive retail demand. Because these factors often translate into significant instability in lamb production and prices, the provision of regular market forecasts is an important requirement of the Australian prime lamb industries. Lamb producers use forecasts in production planning, while processors, exporters and industry organisations require regular market outlook information for their decision making, planning lamb promotion and other activities.

There has been some previous forecasting activity in the New South Wales lamb market. Prior to 1988, the New South Wales Meat Production Forecasting Committee (NSWMPFC) made judgemental forecasts of lamb slaughterings and production which were disseminated to the industry on a quarterly basis. This activity has now been discontinued. In 1986, the Australian Meat and Livestock Corporation (AMLC) initiated lamb producer surveys in south-eastern Australia to enable quarterly forecasts of breeding intentions and lamb market numbers in response to industry requests. This focus has since been restricted to forecasting lamb turnoffs. There has been industry criticism of these prior efforts on the grounds of accuracy, subjectivity and cost.

Part of the problem with forecasting in the Australian lamb market might be attributed to the complexity of lamb production relative to other livestock systems. Most lamb is produced under a variety of cross-breeding structures which are strongly influenced by demographic constraints (e.g. ram breed proportions and seasonal mating patterns) and price relativities which impact on production decisions, and exogenous factors modify these decisions. Hence, it is desirable that a practical lamb market forecasting mechanism explicitly incorporates these factors.

This paper compares the application of a range of forecasting methods in the New South Wales prime lamb market. Section 2 contains details of the models used to produce the state-level lamb market forecasts. The relative merits of the individual forecasting methods are documented elsewhere (e.g. Gellatly 1979; Brandt and Bessler 1983) and are not discussed in any detail in this paper. The procedures adopted for assessing lamb market forecast accuracy are indicated in Section 3, while the results of these comparisons are presented in Section 4. A concluding section discusses the implications of the results and indicates several problem areas.

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2. Forecasting Methods and Models

The main livestock market forecasting methods can be categorised as being either formal and informal. The formal methods include the econometric or explanatory models (e.g. single-equation regressions and structural models), and the time-series or mechanistic models. The informal methods include expert judgements, surveys and simple extrapolation or no-change approaches. Previous studies have indicated the difficulties in clearly demonstrating the superiority of individual methods or category of methods in applied livestock market forecasting (e.g. Leuthold *et al.* 1970; Gellatly 1979; Brandt and Bessler 1983). Choice is determined by available resources, the degree of accuracy required and the method which is the most appropriate for a given set of conditions.

2.1 Types of Forecasts

The formal forecasting methods generate a point forecast and the confidence intervals within which the forecast lies. These forecasts are either *ex post* (or unconditional) where the values of all the variables are known, or *ex ante* in which some values may be unknown. This distinction can be illustrated in the econometric model forecasting context as follows;

model estimation and historical validation	ex post forecast	ex ante forecast
< known data	>	< unknown data >

Because *ex post* forecasts are derived from known data, forecast errors can only be attributable to the model. With *ex ante* forecasts, errors may be due to either (or both) problems in model specification or in projecting the data (Stekler 1968).

Formal methods can produce both static and dynamic forecasts where the forecasting model contains dynamic elements. For example, a single-equation regression model can produce a dynamic forecast if its right-hand includes a lagged dependent variable. Static forecasts utilise the actual values of the lagged dependent variables (or endogenous variables in a structural model) while dynamic forecasts incorporate the solved values of these variables.

These methods were applied to forecasting three major New South Wales lamb market variables, lamb slaughterings, real saleyard lamb prices and per capita lamb consumption. The methods were used to produce both static and dynamic forecasts where applicable, and the forecasts were compared on the basis of their relative accuracies. The NSWMPFC's forecasts and those of the no-change approach were considered to be static. The quantitative analysis utilised the TSP Version 4.1 econometric package and all variables and data sources are defined in the Appendix.

2.2 Formal Methods

Single-equation regressions

These models forecast the dependent variable beyond the estimation period using a relationship of the form;

$$(1) \quad Y_{T+1} = \alpha + \beta X_{T+1} + \quad {}_{+1}$$

where α and β are the coefficient estimates and u is the disturbance. This model produces one period ahead forecasts of Y_t for successive known values of X_t, a process which requires separate estimation for each forecast period.

The equations for the three series were estimated by OLS from quarterly data between 1969(1) and 1984(4) and were used to produce 12 static quarterly forecasts to 1987(4). Dynamic forecasts were made from the slaughterings and consumption equations, both of which contained a lagged dependent variable. These equations are numbered 1 to 3 in the Appendix.

Structural models

The structural econometric model is typically specified as a system of simultaneous equations which represent the market's behavioural relationships and linkages. This model produces two types of forecast, (i) an ex post simulation using known data for the set of exogenous variables to validate the accuracy of the model, and (ii) an ex ante forecast which involves projecting the values of the exogenous variables and simulating the model beyond the sample period. In both forecasts, the values are determined by the model's previously estimated relationships and the model's forecasting value depends on the accuracy with which these relationships represent true market values over previous and future periods.

The general (reduced) forecasting form of a structural model can be given as;

$$(2) \quad Y_t = Y_{t-1}\Pi_1 + Z_t\Pi_2 + u_t$$

where Y_t is a vector of endogenous variables to be forecast, Z_t is a vector of exogenous variables, Y_{t-1} are the lagged endogenous variables, Π_1 and Π_2 are the coefficient matrices and u is a vector of disturbances. This model generates single period ahead forecasts for the endogenous variables using the form;

$$(3) \quad Y_{T+1} = Y_T\Pi_1 + Z_{T+1}\Pi_2 + u_{T+1}.$$

The structural model used to produce the forecasts is a twelve-equation simultaneous system of the New South Wales lamb market (Vere and Griffith 1988). It comprises four blocks representing lamb production capacities (three individual and two composite breeding inventories), lamb production (slaughterings and total production), lamb demand (per capita and aggregate consumption), lamb prices (saleyard and retail). The model's supply and demand sides are linked by an equilibrium market-clearing condition with current prices influencing both production and demand. An additional equation determines total industry revenue. This model was used to produce 12 static and dynamic forecasts of the three series to 1987(4).

Time-series models

The time-series class of models is most often applied in situations in which little is known about the determinants of the forecast variable. The main objective of the time-series approach is to derive a descriptive model which can be used to forecast the series beyond the known data on the basis of this description (this differs from structural model's objective which attempts to reproduce the data series rather than describe it). Time-series models are not based on economic theory and assume that the forecast series has been generated by a stochastic process which can be characterised and described. This assumption creates the error component in the forecast which allows the forecast confidence intervals (based on standard errors) to be calculated.

Newbold and Granger (1974) suggest the main advantages of the time-series models to be (i) they are quick and inexpensive to operate, (ii) they provide a formal basis for comparing the efficiency of other forecasting methods and (iii), they indicate the extent to which past behaviour and other external factors influence a variable's current values. A major attraction of this approach is the wide range of forecast functions available, wherein the data are allowed to suggest the eventual form of the forecast function. This flexibility is seen to be both the strength and the weakness of the time-series models.

The ARIMA (autoregressive integrated moving average) model is form of the time-series class of models which is commonly applied to forecasting non-stationary agricultural series. The general specification for a nonstationary ARIMA process of order (p,d,q) for a series Y_t is given as;

$$(4)\ \mathrm{ARIMA}(p,d,q);\ \phi_p(B)(1-B)^d Y_t = \theta_q(B)e_t$$

where the coefficients $\phi(B)$ and $\theta(B)$ are the ordinary autoregressive and moving average operators of order p and q respectively, d is the order of ordinary differencing and e_t is the underlying white noise process. This equation is expanded to represent a ARIMA process of order (p,d,q) times $(P,D,Q)_s$ for a seasonal series Y_t after Box and Jenkins (1970);

$$(5)\ \mathrm{ARIMA}(p,d,q)(P,D,Q);\ (1-\phi_1 B-\ldots-\phi_p B^p)(1-\Phi_1 B^s-\ldots-\Phi_P B^{Ps})Y_t$$
$$= (1-\theta_1 B-\ldots-\theta_q B^q)(1-\Theta_1 B-\ldots-\Theta_Q B^{Qs})\ e_t$$

where the coefficients $\Phi(B)$ and $\Theta(B)$ are the seasonal autoregressive and moving average operators of orders P^s and Q^s respectively, D is the order of seasonal differencing and the other parameters are defined as for equation (4).

The ARIMA models for the three series were estimated between 1969(1) to 1984(4). They were based on first-differences with white noise residuals at 10 per cent after a Q-test with k-p-q degrees of freedom over 25 lags (equations 4 to 6 in the Appendix).

2.3 Informal Methods

Judgemental methods

These approaches rely on qualitative reasoning rather than quantitative analysis with accuracy depending on the forecasters' knowledge of the market processes and linkages and their ability to estimate the levels of the major market variables (Freebairn 1975). The judgemental forecasts considered are the third revisions of the NSWMPFC's quarterly lamb slaughterings forecasts between 1985 and 1987 and here are regarded as static forecasts. This Committee has made no forecasts since 1987(3).

Naive methods

The most commonly applied variation of this approach to forecasting is the no-change which holds the previous period's value as the forecast. No-change forecasts for each series were the actual data lagged one period. These were considered to be both static and dynamic forecasts as they are components of the Theil relative accuracy measure and several of the composite forecasting models.

Composite methods

Alternate forecasting methods rarely yield the same results and individual forecasts often contain independent information relevant to the forecast user (Bates and Granger 1969). This may result where a forecast contains unique variables or data, or where each forecast makes different assumptions about the causal relationships between variables. Improved forecasts are possible where each forecast in the composite contains unique information (Newbold and Granger 1974). Composite forecasts often contain quantitative and qualitative elements, e.g., an econometric forecast modified by expert opinion. It is common practice to judgementally adjust econometric forecasts with non-quantitative information (Granger and Newbold 1973), a practice followed by most agricultural commodity analysts (Jolly and Wong 1987).

Some difficulties arose in determining appropriate composite forecasting models for the New South Wales lamb market. The present forecasts are *ex post* forecasts based on known data to 1987(4). This obviated the approach of subjective modification of a quantitative forecast as proposed by Brandt and Bessler (1981). Also, this lamb market has been subjected to only one continuous forecasting activity over the forecast comparison period (the NSWMPFC's slaughterings forecasts to 1987(4)) and there was no basis for assigning weights based on the past accuracies or otherwise of other forecast methods (after Bates and Granger 1969). Nor could an objective weighting system be adopted for each series as there have been no previous state-level forecasts of lamb's farm prices or consumption.

After preliminary testing, four composite forecasting models were determined: (i) a combination of the econometric forecasts using weights of 50 per cent for regression models and 25 per cent each for the structural and the ARIMA models; (ii) an average of the forecasts derived under (i) with the no-change forecasts; (iii) an average of the single-equation regression and the no-change forecasts; and (iv) an average of the forecasts of the structural and the ARIMA models. These models were used to produce 12 static and dynamic forecasts of the three series to 1987(4). As the single-equation regression model for saleyard price contained no dynamics, it was replaced by the ARIMA model in the dynamic forecasting composite model (iii). Inclusion of the no-change forecasts as comparative benchmarks is a standard procedure where forecasting in a particular market has been minimal (Theil 1966). Composite model (iv) was included after Granger and Newbold's (1973) conclusion that the test of the forecast accuracy of a structural market model was to assess whether its forecasts could not be significantly improved through combination with ARIMA model forecasts.

3. Evaluating Forecast Accuracy

Because the main objective of a market forecast is facilitate planning under uncertainty, its economic value depends on the extent to which users benefit from its adoption through improved decisions. Relative forecast quality (which includes accuracy)[1] is largely determined by the requirements of the user (Makridakis and Hibon 1979). These requirements vary from indications of future trends such as predicting a series turning points, to quantitative estimates of a series' future levels within confidence bounds. The differing needs of the users of forecast information prevent any categorical statement of the objectives of forecast evaluation.

It is convenient to consider the requirement for forecast accuracy in terms of a users' loss function which measures the consequences of forecast errors. A linear loss function assumes that each forecast inaccuracy is similar to the user and its marginal loss is constant, while losses are proportional to error size in a quadratic loss function. While there is some debate as to the actual forms of the loss functions confronting forecast users, quadratic loss is assumed to be the most suitable measure of the cost of forecast error in most applied situations (Fildes 1979). The loss function's true form becomes important where the objective of forecast evaluation is to determine the extent to which one forecasting method outperforms another, rather than the ordinal ranking of the methods (Granger and Newbold 1973). These criteria are central to the forecast accuracy measures discussed below.

Four accuracy measures were considered in evaluating the forecasts on the basis of their comparative accuracies;

(i) Mean square error (MSE) which measures the size of the individual forecast errors from the actual data and is defined as $\Sigma(A_t - F_t)^2/N$ where A and F are the actual and forecast values for all t and N is the number of observations. MSE is an absolute measure of forecast accuracy and assumes a quadratic loss function.

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[1] Other elements of forecast quality are clarity, credibility and timeliness (Longmire and Watts 1981).

(ii) Mean absolute percentage error (MAPE) defined as $\Sigma((A_t - F_t)/A_t)/N$ where the parameters are defined as above. MAPE is an absolute accuracy measure based on a linear loss function.

(iii) Theil's inequality coefficient U_2 (Theil 1966) is an index of relative forecast accuracy based on the ratio of the MSE of the forecast and the MSE of a benchmark (usually a no-change) forecast. This measure of relative MSE assumes a quadratic loss function and is defined (in a condensed form) as $U_2 = MSE(F_t)/MSE(A_{t-1})$ where the denominator is an implicit no-change forecast. A perfect forecast has $U_2 = 0$ while $U_2 = 1$ indicates a forecast is the same as the no-change extrapolation. If U_2 is greater than one, the model has lesser predictive powers than the no-change forecast. This measure mainly relates to econometric forecasts which can be reproduced to identify sources of error (such as by error decomposition).

(iv) Analyses of the series' actual and forecast turning points expressed as an error ratio defined as the ratio of turning point errors (incorrect directions of change forecast and actual turning points not forecast) to the number of turning points in the actual series. This ratio is a measure of absolute forecast accuracy.

4. Results

Static forecast comparisons

From Table 1, the absolute error criteria indicated a reasonable level of accuracy in the individual econometric and composite models' forecasts of lamb slaughterings and consumption. The most accurate forecasts were produced by composites of the econometric models and the no-change forecasts, while the structural model was the least accurate. On these same criteria, only the ARIMA model accurately forecast real saleyard lamb prices. The low percentage mean errors for the NSWMPFC's judgemental forecasts of lamb slaughterings were due to the Committee's under-predictions of the series to 1986(2) and over-predictions thereafter offsetting each other.

The Theil U_2 statistic relative accuracy measure confirmed the superiority of the single-equation regression and the composite models in forecasting lamb slaughterings and consumption while the ARIMA model provided the best price forecasts. The turning point analysis produced similar conclusions. For lamb slaughterings, all methods except the ARIMA model had low error ratios but only the single-equation regression model and the structural model correctly anticipated four or more of the actual turning points. The ARIMA model failed to predict any actual turning points and all methods produced two or more of these turning point errors. All methods correctly predicted three or more of the five actual turning points in the saleyard price series although each of the three econometric models forecast non-existent turning points. These errors were not evident in the composite forecasts. No method correctly forecast more that three of the five turning points in the lamb consumption series and their error ratios were relatively high.

Dynamic forecast comparisons

These results were generally consistent with those for the static forecasts (Table 2). The single regression and the composite models provided the most

TABLE 1

Static Forecast Accuracy Analysis by Forecast Method

	Single-equation Regression	Structural Model	Restricted Reduced Form Model	ARIMA Model	Composite Models (i)	(ii)	(iii)	(iv)	NSWMPFC Forecast	No-char Forecas
Lamb Slaughterings										
Mean Square Error	0.02	0.02		0.02	0.01	0.01	0.01	0.01	0.04	0.02
Mean Absolute % Error	0.0	0.09		0.02	0.02	0.0	0.01	0.03	0.0	0.01
Theil's U_2 Statistic	0.95	1.19		1.57	0.63	0.62	0.65	0.76	2.29	1.00
Turning points in series	7									
Turning points correct	4	4		0	2	1	2	2	1	
Turning point error ratio[b]	2:7	1:7		6:7	0:7	4:7	3:7	2:7	4:7	
Real Saleyard Lamb Price										
Mean Square Error	119.11	168.51	150.37	9.88	77.07	76.79	37.15	46.83		15.08
Mean Absolute % Error	0.49	0.58	0.56	0.03	0.04	0.22	0.27	0.30		0.04
Theil's U_2 Statistic	7.9	11.17	9.97	0.65	5.11	1.78	2.46	3.11		1.00
Turning points in series	5									
Turning points correct	4	4	3	3	4	3	3	3		
Turning point error ratio[b]	3:5	1:5	2:5	3:5	1:5	1:5	1:5	1:5		
Per Capita Lamb Consumption										
Mean Square Error	0.05	0.18		0.14	0.06	0.05	0.05	0.09		0.12
Mean Absolute % Error	0.03	0.09		0.01	0.03	0.01	0.01	0.03		0.01
Theil's U_2 Statistic	0.44	1.49		1.17	0.53	0.45	0.41	0.77		1.00
Turning points in series	5									
Turning points correct	2	3		2	3	3	3	2		
Turning point error ratio[b]	3:5	3:5		3:5	2:5	2:5	3:5			

Notes: [a] turning point analysis not applicable; [b] ratio of turning point errors to the number of turning points in the series.

accurate dynamic forecasts of lamb slaughterings and consumption. Combining the ARIMA model and the no-change forecasts offered significant accuracy gains in forecasting real saleyard lamb prices. The Theil U_2 statistics for each of the three series were consistent with the two absolute error criteria, as were the results of the dynamic turning point analysis with all but the ARIMA models having acceptable error ratios. Lamb slaughterings was the most difficult series in which to predict directional change and most methods failed to predict one or more actual turning points in the series. Conversely, most methods correctly predicted more than 60 per cent of the turning points in the saleyard price and consumption series.

5. Discussion and Summary

There are certain accuracy advantages in using econometric methods for forecasting in the New South Wales prime lamb market. Lamb slaughterings and consumption were most accurately forecast by the single regression and the composite models. Real saleyard prices were the most difficult to accurately forecast and here the ARIMA models produced superior static forecasts and also dynamic forecasts in combination with the no-change model. However, no single method was superior in all situations and the main opportunities for improving forecast accuracy appeared to be in combining the forecasts of the econometric models and the no-change approaches.

One result of concern was the relatively weak forecasting performance of the structural model. The model used to generate the forecasts was considered to be statistically strong (Vere and Griffith 1988) and the forecasts were based on known values of the explanatory variables to 1987(4). Freebairn (1975) suggested that the forecast accuracy of a formal model partly depended on whether the modelled past behaviour will be repeated in forecast period. There is some evidence that this might not be so in the New South Wales lamb market as there were events after 1984 which were atypical to the normal market cycles (e.g. very high wool prices and lamb skin values). These events were not explicitly modelled in the econometric estimates and they might have influenced the structure of the forecast variables after 1984. The likelihood of change in the three series' structures was examined using a coefficient stability test on the structural model's estimates over two sub-samples 1969(1) to 1984(4) and 1985(1) to 1987(4) (Chow 1960). These tests indicated some evidence of structural change in each of the three series after 1984, and in the pattern of real lamb saleyard prices in particular[2]. It appears that the ARIMA models may also have faced similar problems of unincorporated change in the estimated forecasting structures for lamb slaughterings and consumption after 1984. Short-term instability is a characteristic of many economic time-series and models should be continually revised according to new information (Fildes 1979; Leuthold et al. 1970). The significantly improved forecasting performance of the combined structural and ARIMA models (composite model iv) is noteworthy and validates the test proposed by Granger and Newbold (1973)

Overall, the composites produced the best forecasts of lamb slaughterings and consumption. All four composite models were more accurate than the component methods in static forecasting lamb slaughterings and consumption. The ARIMA model provided the most accurate forecasts of lamb prices. The dynamic forecasts of lamb slaughterings and consumption were similar in terms of accuracy while the combination of the ARIMA and the no-change models offered accuracy improvements in lamb price forecasting. This indicated that the

TABLE 2

Dynamic Forecast Accuracy Analysis by Forecast Method

	Single-equation Regression	Structural Model	Restricted Reduced Form Model	ARIMA Model	Composite Models (i)	(ii)	(iii)	(iv)	No-change Forecast[a]
Lamb Slaughterings									
Mean Square Error	0.01	0.03		0.03	0.01	0.01	0.01	0.04	0.02
Mean Absolute % Error	0.01	0.11		0.01	0.02	0.0	0.00	0.05	0.01
Theil's U_2 Statistic	0.76	1.84		1.96	0.74	0.55	0.59	0.90	1.00
Turning points in series	7								
Turning points correct	5	4		1	4	2	3	3	
Turning point error ratio[b]	2:7	1:7		4:7	0:7	3:7	3:7	1:7	
Real Saleyard Lamb Price									
Mean Square Error		150.26	122.74	38.88	47.52	43.79	28.23	76.93	15.08
Mean Absolute % Error		0.54	0.52	0.29	0.35	0.20	0.15	0.41	0.0
Theil's U_2 Statistic		9.96	8.14	2.58	3.54	1.25	1.07	5.10	1.00
Turning points in series	5								
Turning points correct		4	3	3	4	3	2	4	
Turning point error ratio[b]		1:5	2:5	3:5	1:5	1:5	1:5	1:5	
Per Capita Lamb Consumption									
Mean Square Error	0.07	0.24		0.22	0.03	0.04	0.03	0.05	0.12
Mean Absolute % Error	0.04	0.12		0.07	0.03	0.01	0.02	0.02	0.01
Theil's U_2 Statistic	0.64	2.04		1.90	0.42	0.35	0.44	0.43	1.00
Turning points in series	5								
Turning points correct	3	3		3	3	3	2	3	
Turning point error ratio[b]	2:5	2:5		4:5	2:5	2:5	1:5	1:5	

Notes: [a] turning point analysis not applicable; [b] ratio of turning point errors to the number of turning points in the series.

individual forecasts contained independent information which in combination, resulted in improved forecasts of the three series. For the one series to which it was applicable (lamb slaughterings), the accuracy of the judgemental forecasts of the NSWMPFC suffered in comparison to the accuracy of the other forecasting methods.

Two relevant questions in forecast evaluation are the acceptability of a set of forecasts to the user and the extent to which the forecast methods can be modified to improve forecasting performance (Granger and Newbold 1973). To this end, the forecasting procedures reported in this paper are the subject of ongoing monitoring and evaluation. This analysis has tended to confirm the latter question, i.e. that improved forecasts in the New South Wales lamb market are possible from modified approaches based on composites of the individual econometric and the naive no-change methods.

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2 The Chow-test F statistics for the series were $F(9,66) = 53.2$ for saleyard prices; $F(6,69) = 16.9$ for slaughterings, and $F(9,66) = 2.3$ for consumption.

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APPENDIX

Estimates of the Econometric Forecasting Models

(t values in brackets)

(i) Single-equation Estimates;

Lamb slaughterings

$$\underset{(OLS)}{(1)\ SLLBNW} = \underset{(4.6)}{0.56} + \underset{(3.3)}{0.24\ NABI} + \underset{(4.8)}{0.11\ AFNW} - \underset{(-6.1)}{0.01\ PALBNW} - \underset{(-3.8)}{0.003\ PFWLAU(-1)}$$
$$- \underset{(-1.2)}{0.09\ DUMDRT(-1)} + \underset{(4.8)}{0.43\ SLLBNW(-4)}$$

Adjusted $R^2 = 0.88$; $h = 1.32$; $N = 64$

Real saleyard lamb price (this is a price-dependent version of the lamb slaughterings function given in equation 1).

$$\underset{(OLS)}{(2)\ PALBNW} = \underset{(7.7)}{29.7} + \underset{(1.0)}{2.88\ NABI} + \underset{(9.5)}{6.89\ AFNW} - \underset{(-4.8)}{18.5\ SLLBNW} + \underset{(2.2)}{0.03\ PFWLAU(-1)}$$
$$+ \underset{(1.3)}{1.76\ DUMQ1} + \underset{(2.8)}{3.59\ DUMQ2} + \underset{(3.8)}{4.84\ DUMQ3} - \underset{(-3.1)}{11.83\ DUM74}$$
$$- \underset{(-1.9)}{7.32\ DUM74(-1)}$$

Adjusted $R^2 = 0.83$; $DW = 1.96$; $N = 64$

Per capita lamb consumption

$$\underset{(OLS)}{(3)\ DCLBAU} = \underset{(2.8)}{3.75} + \underset{(3.8)}{0.4\ DCLBAU(-1)} - \underset{(-2.1)}{0.003\ RINCAU} + \underset{(3.3)}{0.11\ PRBFCH}$$
$$+ \underset{(1.6)}{0.01\ PRPKNW} - \underset{(-4.7)}{0.2\ PRLBNW} - \underset{(-3.9)}{0.71\ DUMQ1} - \underset{(-2.6)}{0.55\ DUMQ2}$$
$$- \underset{(-0.1)}{0.02\ DUMQ3} + \underset{(1.8)}{0.73\ DUM74}$$

Adjusted $R^2 = 0.82$; $h = -0.66$; $N = 64$ Time-series ARIMA models;

(ii) ARIMA Estimates;

Lamb slaughterings

$$(4)\ SLLBNW\ \Delta Y_t;\ (1 - \underset{(-2.4)}{0.473B}) = (1 - \underset{(-6.8)}{0.846B})\ (1 - \underset{(-3.0)}{0.422B} - \underset{(-2.7)}{0.337B})^4\ e_t$$

ARIMA(1,1,1)
(0,1,2)

Adjusted $R^2 = 0.39$; $DW = 2.04$; $Q\ \chi^2(4,21) = 15.8$; $N = 64$

Real saleyard lamb price

$$\text{(5) PALBNW } \Delta Y_t = \underset{(-1.0)}{(1 - 0.135B)} \; (1 - \underset{(-8.5)}{1.111B} + \underset{(-1.6)}{0.194B})^4 \, a_t$$

ARIMA(0,1,1)
(0,1,2)

Adjusted R^2 = 0.48; DW = 1.99; Q $\chi^2(3,22)$ = 30.1; N = 64

Per capita lamb consumption

$$\text{(6) DCLBAU } \Delta Y_t = (1 - \underset{(-4.0)}{0.503B} - \underset{(2.9)}{0.364B^2}) \; (1 - \underset{(-5.5)}{0.602B} - \underset{(5.5)}{0.611B})^4 \, a_t$$

ARIMA(2,1,0)
(2,1,0)

Adjusted R^2 = 0.51; DW = 1.93; Q $\chi^2(4,21)$ = 28.4; N = 64

Variable Definitions and Sources

AFNW = area of improved pastures fertilised, New South Wales (m ha), ABS,

DCLBAU = Australian per capita lamb consumption (kg/head),

DUMDRT = drought dummy variable (1 = below average quarterly rainfall, zero otherwise), ABARE series,

DUM74 = impact dummy variable for the 1974 beef export market to US crash (1 = 1974:4, zero otherwise),

DUMQ1, DUMQ2, DUMQ3 = quarterly dummy variables,

NABI = New South Wales adjusted inventory of intended matings to British breed rams at March 31; (m), constructed (Vere and Griffith 1988),

PALBNW = real saleyard lamb price, dressed carcase weight, Homebush (c/kg), NSW Agriculture & Fisheries,

PRBFCH = weighted average of real retail beef and chicken prices, (c/kg), calculated,

PRLBNW = real retail lamb price, Sydney (c/kg), NSW Agriculture & Fisheries,

PRPKNW = real retail pork price, Sydney (c/kg), NSW Agriculture & Fisheries,

PFWLAU = real average Australian greasy price for all wools (c/kg), AWC,

RINCAU = real household disposable income ($'000), ABS,

SLLBNW = New South Wales lamb slaughterings (m), AMLC.