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COMPARATIVE FORECAST ACCURACY IN THE NEW SOUTH WALES PRIME LAMB MARKET

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The market for Australian prime lamb is characterised by high production seasonality and a highly competitive retail demand. Because these factors often translate into substantial market variability, regular forecasts of supply and demand are important requirements of lamb market participants. There has been some forecasting activity in the state and national lamb markets but it has been a somewhat controversial activity. This paper assesses the comparative forecast accuracy of a range of methods in the New South Wales lamb market. The results indicate that no single method is clearly superior in all situations and the greatest scope for improving forecast accuracy in the New South Wales lamb market is through the use of combined econometric and naive approaches.

The need for market forecast information arises because of delays between production decisions and their outcomes. As many agricultural production decisions are made under uncertainty, forecasts of the factors influencing market supply and demand offer opportunities for improved decision making. Australia's extensive livestock enterprises display significant seasonal instability in production and prices. These conditions are characteristic of prime lamb production. Lamb also faces a relatively unfavourable position in the retail meat market with a price- and income-inelastic demand and strong competition from other meats. These factors emphasise the importance of lamb market forecasts to producers in output and market planning, to processors when assessing abattoir capacities, to retailers and industry organisations in planning promotion and to exporters in determining forward contracts.

There has been regular lamb market forecasting in some Australian states but the overall effort remains low. For some years, the New South Wales Meat Production Forecasting Committee (NSWMPFC) made quarterly judgemental forecasts of lamb slaughterings and production. In 1986, the Australian Meat and Live-stock Corporation (AMLC) initiated lamb producer surveys to enable the quarterly forecasting of breeding intentions and live lamb numbers in Victoria, New South Wales and South Australia. This activity has since been restricted to forecasts of lamb turnoffs. Nationally, the Australian Bureau of Agricultural and Resource Economics makes annual forecasts of lamb slaughterings, production, consumption, and saleyard and retail prices.

One reason for the low level of forecasting activity in the New South Wales lamb market is the complexity of lamb production systems relative to other livestock enterprises. These systems are based on various British-breed ram types which are mated to ewes of the same breed or, predominantly, to cross-bred ewes. Ram breed proportions and seasonal mating patterns vary according to differing environments throughout the state with most lamb being produced under cross-breeding systems. These demographic constraints and commodity

price relativities strongly influence lamb production decisions but they are often modified by exogenous factors such as pasture availability and quality. It is desirable that a lamb market forecasting mechanism explicitly incorporates these factors but, in practice, they have been largely ignored in previous state-level market forecasts. The strong subjective element in the past New South Wales lamb market forecasts was a factor in their sceptical view by industry.

This paper compares the application and accuracy of a range of *ex post* forecasting methods in the New South Wales prime lamb market. The methods include econometric models (single-equation regressions, a structural model of this lamb market and its restricted reduced form, and time-series models) and a range of composite approaches incorporating the econometric models and other non-quantitative approaches. The methods are applied to forecasting three state lamb market variables, slaughterings, real saleyard prices and per capita consumption. They are compared on the basis of their relative forecast accuracies.

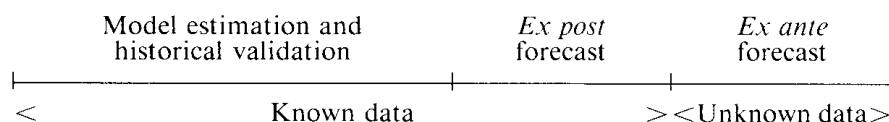
Lamb Market Forecasting Methods: Descriptions and Specifications

A convenient classification of applied forecasting procedures in agricultural markets is into formal and informal methods (Freebairn 1975). The formal category includes the econometric (or explanatory) models which incorporate the economic theory of the market processes, and the time-series (or mechanistic) (hereafter, referred to as autoregressive integrated moving average or ARIMA models) which have no formal economic basis.¹ The informal category includes the naive no-change methods and expert judgements. While formal procedures do not produce forecasts as easily as the simpler methods, they are expected to offer greater benefits in terms of increased forecast accuracy as they provide more detailed analysis of the properties of the series of interest (Newbold and Granger 1974). Several reviews of forecasting methods have emphasised the difficulties in demonstrating the superiority of a particular method or category in applied situations (Freebairn 1975; Gellatly 1979; Brandt and Bessler 1983). A discussion of the relative merits of forecasting procedures in the New South Wales lamb market is provided in Vere and Griffith (1989).

Formal forecasting methods

Formal methods generate two types of forecasts: the point forecast and the confidence interval in which it lies. 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. *Ex ante* forecasts are often conditional due to data uncertainties, but they may also be unconditional. The distinction between these types of forecasts is important and it appears to be confused in parts of the literature [see, for example, Fildes (1979) and Stekler (1968), for conflicting definitions]. It might be illustrated in the econometric model forecasting context as below:

¹While ARIMA models have no formal economic basis, they are included in the formal category because a formal process is used to derive the required forecasts.



Ex post forecasts are derived from known data and 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. Because most formal forecasting methods are based on regression techniques, they offer opportunities to trace forecast errors, and can produce both static and dynamic forecasts. Static forecasts utilise the actual values of the lagged endogenous variables while dynamic forecasts incorporate the solved values of the lagged endogenous or dependent variables.

In the following sections, the methods are compared where applicable, on the basis of their static and dynamic forecasting abilities. The single-equation and ARIMA forecasting models were specified for three variables, lamb slaughterings, the real saleyard price of lamb and per capita lamb consumption (these and all other variables are defined in the Appendix). The structural market model in which these variables are endogenous was previously developed by the authors (Vere and Griffith 1988). These models were estimated from quarterly data between 1969(1) to 1984(4), leaving 12 observations available for *ex post* forecasting with the explanatory models to 1987(4). All estimation was done using the TSP Version 4.1 econometric package (TSP International 1986).

Single-equation regressions. Single-equation regression models produce forecasts of the dependent variable beyond the estimation period using a relationship of the form:

$$(1) \quad Y_{T+1} = \alpha + \beta Z_{T+1} + u_{T+1}$$

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 Z_t , a process which requires separate estimation for each forecast period.

Behavioural equations for the three series were estimated by ordinary least squares (OLS) and used to produce 12 *ex post* static quarterly forecasts to 1987(4). Dynamic *ex post* forecasts were also made from the lamb slaughterings and lamb consumption equations which contained a lagged dependent variable. These equations are numbered (A1) to (A3) in the Appendix (see also Vere and Griffith 1988).

Structural models. The structural market model is the most detailed of the forecasting methods and is usually specified as a system of equations representing the market's relationships and linkages. This model simultaneously generates solution values for a set of endogenous variables under either static or dynamic simulation. The model's structure can be reduced into the following single equation in vector form:

$$(2) \quad Y_j = \beta_j Z_j + \varepsilon_j$$

where Y_j is a column vector of n values assumed by the dependent

variable of the j -th equation, Z_j is a (n times m) matrix of values assumed by the m_j independent variables of the j -th equation, β_j is the corresponding (m times 1) vector of coefficients to be estimated and ε_j is a (n times 1) vector of disturbances.

A structural model can produce both (i) an *ex post* simulation to test the accuracy of the model for forecasting purposes which involves simulating the model over the sample period using known data for the set of exogenous variables and comparing the actual and predicted series for the endogenous variables, and (ii) an *ex ante* forecast which involves projecting values for the exogenous variables (by various methods including simple extrapolation, judgemental adjustments and formal time-series estimation) and simulating the model beyond the sample period. In both instances, the forecast values are determined by the model's estimated relationships.

After Intriligator (1978), the general reduced forecasting form of a structural model can be given as:

$$(3) \quad Y_t = Y_{t-1}\Pi_1 + Z_t\Pi_2 + u_t$$

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 and u_t is a vector of disturbances. Π_1 and Π_2 are the coefficient matrices. This model generates single period ahead forecasts for the endogenous variables as follows:

$$(4) \quad Y_{T+1} = Y_T\Pi_1 + Z_{T+1}\Pi_2 + u_{T+1}$$

The structural model used here is a twelve-equation simultaneous system of the New South Wales prime lamb market (Vere and Griffith 1988). The model 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) and lamb prices (saleyard and retail). An additional equation determines total lamb market revenue. The model's supply and demand sides are linked by an equilibrium market-clearing condition with current prices influencing both production and demand. This model was used to produce 12 *ex post* static and dynamic quarterly forecasts of the three endogenous variables (slaughterings, real saleyard prices and per capita consumption) to 1987(4).

Reduced forms of structural models are also used for forecasting prices and quantities where these variables result from the coincidence of supply and demand. In a strictly defined reduced-form model, a market price or quantity is expressed in terms of all the structural model's predetermined variables and the model is solved in terms of its reduced-form coefficients (these are the coefficients of the predetermined variables in the reduced-form model). For forecasting, the predetermined variables are usually limited to a manageable number and the resulting model is the restricted reduced form which can be estimated by least squares. A restricted reduced form of the model for real lamb saleyard price was estimated by non-linear least squares and is given in equation (A4) in the Appendix (see Vere and Griffith 1989 for further detail).

Time-series ARIMA models. ARIMA models forecast a variable's future values by relating them to the pattern of its past values and their

current and past disturbances. They are most often applied in situations where little is known about the forecast variable's determinants. As ARIMA models are not based on economic theory, they make no assumptions about the relationships affecting the forecast variable. Instead, these models assume that the forecast series has been generated by a stochastic process with a structure that can be characterised and described. This assumption has important forecasting implications because it creates the error component in the forecast on which the forecast confidence intervals are based.

An attraction of the ARIMA forecasting approach is that it allows the data to suggest the eventual form of the chosen forecast function. The ARIMA model is a time-series functional form which is commonly applied to forecasting non-stationary agricultural series. Leuthold, MacCormick, Schmitz and Watts (1970) present a general specification for a non-stationary ARIMA process of order (p, d, q) for a series Y_t as:

$$(5) \quad \text{ARIMA } (p, d, q): \phi_p(B)(1-B)^d Y_t = \theta_0 + \theta_q(B) \varepsilon_t$$

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, θ_0 is defined as $(1 - \phi_1 - \phi_2 - \dots - \phi_p)\mu$, and ε_t is the underlying white noise process. This equation is expanded to represent an ARIMA process of order (p, d, q) times $(P, D, Q)^s$ for a seasonal series Y_t after Box and Jenkins (1970):

$$(6) \quad \text{ARIMA } (p, d, q)(P, D, Q): (1 - \phi_1 B - \dots - \phi_p B^p)(1 - \Phi_1 B^s - \dots - \Phi_P B^{Ps}) Y_t \\ = (1 - \theta_1 B - \dots - \theta_q B^q)(1 - \Theta_1 B^s - \dots - \Theta_Q B^{Qs}) \varepsilon_t$$

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 (5).

The ARIMA models were selected following the standard Box-Jenkins time-series procedures of identification from the autocorrelation and partial autocorrelation functions over 25 lags, estimation and diagnosis until satisfactory descriptions of each of the three series were obtained. Each model was based on first-differences and exhibited white noise residuals at 10 per cent after a Q-test with $k - p - q$ degrees of freedom. The estimated models are given in equations (A5) to (A7) in the Appendix (see Vere and Griffith 1989 for further detail).

Informal forecasting methods

Naive methods. There are a number of variations of this approach to forecasting with the most commonly applied being no-change which holds the previous period's value of the variable as the forecast. Here, the no-change forecast is regarded as being both static and dynamic as it is a component of the Theil relative accuracy measure and several of the composite forecasting models. The no-change forecasts for each of the three series in Table 1 are the actual data lagged one period.

Judgemental method. These are the third intra-quarterly revisions of the NSWMPFC's forecasts for lamb slaughterings between 1985 and

the third quarter of 1987 and are treated here as static forecasts. The Committee has made no forecasts since 1987(3).

Composite methods. Composite approaches to forecasting recognise that alternate methods rarely yield the same results and that their forecasts often contain independent information relevant to the forecast user (Bates and Granger 1969). This information will differ where one forecast embodies variables or data which another does not, and where each forecast makes different assumptions about the nature of the relationships between the variables. An improved forecast will often result where each forecast in the composite contains independent information. It is often the case that both quantitative and qualitative information is available which should be incorporated into the forecasting mechanism (Newbold and Granger 1974). In theory, any two or more methods can be combined to produce a composite forecast and most usually contain both quantitative and qualitative elements, for example, an econometric forecast modified by expert opinion. It is common practice to judgementally adjust econometric forecasts with non-quantitative information (Granger and Newbold 1973) and most agricultural commodity analysts adopt the approach of incorporating econometric forecasts into their final subjective assessments (Jolly and Wong 1987).

Methods of combining forecasts range from complex systems of assigning weights to individual forecasts to simple averages of their absolute values. Bates and Granger (1969) proposed various weighting methods where the main objective was to select a combination of weights which minimised forecast variance. They suggested that weights should be determined according to forecast performance, giving most emphasis to the best-performed recent forecasts. A system in which weights were allowed to vary on the basis of recent forecast error offered the best potential for improving combined forecast performance. The choice of weights was arbitrary where a lack of previous forecasts provided no basis for assigning weights according to forecast performance.

These procedures presented some difficulties when applied to the New South Wales lamb market. Because the forecasts were *ex post* based on known data to 1987(4), subjective modification of the quantitative forecasts (after Brandt and Bessler 1981) was inappropriate. Also, since this market has been subjected to only one continuous forecasting approach over the 1980s (the judgemental forecasts of the NSWMPFC to September 1987), there was no basis for assigning weights based on the past accuracies or otherwise of the forecast methods (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 the farm prices of lamb or lamb consumption.

Following preliminary analysis, four composite forecasting models were determined: (i) a combination of the econometric forecasts using weights of 50 per cent for the regression models and 25 per cent each for the structural and 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 both static and dynamic forecasts of the three series. The single-equation regression model for saleyard price contained no dynamics and was replaced by the ARIMA model in the dynamic forecasting composite model (iii). Accordingly, composite models (i) and (ii) were not used to dynamically forecast this variable. 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 model was to assess whether its forecasts could not be significantly improved through combination with ARIMA model forecasts.

Forecast Accuracy Evaluation

Objectives

The economic value of forecast information depends on the extent to which users benefit from its adoption and its ultimate test is the translation of its predictive accuracy into improved decisions. Previous assessments of applied forecasting methods suggest that relative forecast quality is determined by the situation in which they are applied and the user's requirements (Makridakis and Hibon 1979). These requirements vary from indications of likely future trends such as predicting turning points in a data series, to quantitative estimates of a series' future levels within confidence bounds or a likely distribution. The differing requirements of the users of forecast information prevent any categorical statement of the objectives of forecast evaluation. Because forecasting methods range from the subjective to the highly sophisticated, it is necessary to reconcile the degree of forecast accuracy required with the costs of obtaining it.

It is convenient to consider the requirement for forecast accuracy in terms of a users' loss function which measures the consequences of forecast errors. (This concept is an integral part of decision theory and is well developed in that literature.) A linear function assumes that each forecast inaccuracy is similar to the user and that its marginal loss is constant, while losses are proportional to error size in a quadratic function. While there is some debate as to the actual forms of the loss functions confronting forecast users, quadratic loss is often used in applied situations (Fildes 1979). This 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 loss criteria are central to the forecast accuracy measures discussed below.

Accuracy measures

Gellatly (1979) made the distinction between evaluating the predictive ability of the various forecasting methods and evaluating their individual characteristics. The approach followed in this section was to evaluate the forecasts on the basis of their comparative accuracies, that is, comparing the predictions with the actual data, hence the emphasis on *ex post* forecasts. As most of the forecasts have econometric derivations, their relative accuracies were assessed outside the

modelling estimation samples to emphasise their forecasting rather than explanatory abilities. The accuracy measures adopted to evaluate the forecasts for the three series were:

- (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.
- (ii) Mean absolute percentage error (MAPE) is 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) which 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 1, 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.

Results

Static forecast comparisons

Table 1 summarises the static forecast accuracy analysis for the three series. Overall, 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 of these series resulted from composites of the econometric models and the no-change forecasts, while the structural model and its restricted reduced form were the least accurate. On the same criteria, only the ARIMA model accurately forecast real saleyard lamb prices. The relatively high percentage mean errors for the structural model's lamb price forecasts resulted from its consistent over-estimates of the series in relation to the actual data. This provided for no offsetting effects within the aggregate mean error as no forecast series contained positive and negative error elements. Similarly, the very 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's measure of relative forecast accuracy also indicated the superiority of the single-equation regression and the composite models in forecasting lamb slaughterings and consumption while the ARIMA model provided the most accurate static price

TABLE 1
Static Forecast Accuracy Analysis by Forecast Method

	Single-equation regression	Structural model	Restricted reduced-form model	ARIMA model	Composite models				NSWMPFC forecast	No-change forecast ^a	
					(i)	(ii)	(iii)	(iv)			
<u>Lamb slaughtering</u>											
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		
<u>Real saleyard lamb price</u>											
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			
<u>Per capita lamb consumption</u>											
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	3.5			

^aTurning point analysis not applicable.

^bRatio of turning point errors to the number of turning points in the series.

forecasts.² Analysis of the forecast series turning points 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 errors in failing to predict actual turning points. All methods correctly predicted three or more of the five actual turning points in the saleyard price series and there was a low incidence of forecast error, although each of the three econometric models forecast non-existent turning points. It is noteworthy that these errors were not evident in the forecasts of the composite models. No method correctly predicted more than three of the five turning points in the lamb consumption series and their error ratios were relatively high. Again, the econometric models predicted two or more turning points which were not in the actual series.

Dynamic forecast comparisons

The dynamic forecast accuracy analysis results were generally consistent with those for the static forecasts (Table 2). Again, the single regression and the composite models provided the most accurate forecasts of lamb slaughterings and consumption. The range of dynamic forecasting models for lamb saleyard price was limited to the structural model and its restricted reduced form, and the ARIMA model because there were no dynamics in the single-equation regression model estimates. While neither of the structural models produced satisfactorily accurate dynamic forecasts of this series, combining the ARIMA model and the no-change forecasts [dynamic composite model (iii)] offered significant accuracy gains. 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.

Discussion and Summary

This analysis has indicated 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 more difficult to forecast accurately 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 clearly superior in all situations and the main opportunities for improving forecast accuracy were seen to lie in combining the various econometric and the no-change approaches.

²Confidence intervals for U can also be calculated but Theil (1966, 26–35) only recommends this when U is relatively low (<0.3). Because of the wide range in U values reported in these results, confidence intervals are not calculated.

TABLE 2
Dynamic Forecast Accuracy Analysis by Forecast Method

	Single-equation regression	Structural model	Restricted-reduced-form model	ARIMA model	Composite models			No-change forecast ^a
					(i)	(ii)	(iii)	
<u>Lamb slaughtering</u>								
Mean square error	0.01	0.03		0.03	0.01	0.01	0.04	0.02
Mean absolute % error	0.01	0.11		0.01	0.02	0.0	0.05	0.01
Theil's U_2 statistic	0.76	1.84		1.96	0.74	0.55	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	1.7	1.7
<u>Real saleyard lamb price</u>								
Mean square error		150.26	122.74	38.88			76.93	15.08
Mean absolute % error		0.54	0.52	0.29			0.41	0.04
Theil's U_2 statistic		9.96	8.14	2.58			5.10	1.00
Turning points in series	5							
Turning points correct		4	3	3		2	4	
Turning point error ratio ^b		1.5	2.5	3.5		1.5	1.5	
<u>Per capita lamb consumption</u>								
Mean square error	0.07	0.24		0.22	0.03	0.04	0.05	0.12
Mean absolute % error	0.04	0.12		0.07	0.03	0.01	0.02	0.01
Theil's U_2 statistic	0.64	2.04		1.90	0.42	0.35	0.43	1.00
Turning points in series	5							
Turning points correct	3	3		3	3	3	3	3
Turning point error ratio ^b	2.5	2.5		4.5	2.5	2.5	1.5	1.5

^aTurning point analysis not applicable.

^bRatio of turning point errors to the number of turning points in the series.

The relatively weak forecasting performance of the structural model was not anticipated. The model used to generate the forecasts was considered to accurately represent the causal processes in the New South Wales lamb market and it displayed excellent statistical properties under *ex post* and beyond-sample validation (Vere and Griffith 1988). Further, this model's forecasts were based on known values of the explanatory variables to 1987(4). Freebairn (1975) maintained that the forecast accuracy of a formal model depended *inter alia*, on whether the modelled past behaviour will be repeated in forecast period. There is some evidence that this might not be so in this state lamb market as there were events after 1984 which were atypical to the normal market cycles (for example, the highest wool prices since 1950 and the doubling of 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 (this reality would reduce the model's beyond-sample explanatory and forecasting powers). Accordingly, the possibility of change in the structure of the three series 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.³ 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).

In all situations, the composite models were more accurate in forecasting lamb slaughterings and consumption but not in lamb price forecasting. All four composite models were more accurate than the component methods in static forecasting lamb slaughterings and consumption, but did not improve on the ARIMA model's real saleyard lamb price forecasts. The dynamic forecast accuracy results for lamb slaughterings and consumption were similar while the combination of the ARIMA and the no-change models offered accuracy improvements in lamb price forecasting. These results indicate that the forecasts of the individual models 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.

Granger and Newbold (1973) proposed that the two relevant questions in forecast evaluation were the acceptability of a particular set of forecasts to the user and the extent to which the adopted methods can be modified to improve forecasting performance. To this end, the forecasting procedures reported in this paper are the subject of ongoing

³The 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.

monitoring and evaluation by the AMLC and departmental sheep advisory officers. This analysis has tended to confirm the latter question, that is 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.

APPENDIX

Estimates of the Econometric Forecasting Models (t Values in Parentheses)

Single-equation estimates:

Real saleyard lamb price [this is a price-dependent version of the lamb slaughtering function given in equation (A2)].

$$(A1) \quad PALBNW = 29.7 + 2.88 NABI(-4) + 6.89 AFNW - 18.5 SLLBNW + 0.03 PFWLAU(-1) \\ (OLS) \quad (7.7) (1.0) \quad (9.5) \quad (-4.8) \quad (2.2) \\ + 1.76 DUMQ1 + 3.59 DUMQ2 + 4.84 DUMQ3 - 11.83 DUM74 \\ (1.3) \quad (2.8) \quad (3.8) \quad (-3.1) \\ - 7.32 DUM74(-1) \\ (-1.9)$$

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

Variable Definitions and Sources

PALBNW, Real saleyard lamb price, dressed carcase weight, Homebush (c/kg), NSW Department of Agriculture; *NABI*, New South Wales adjusted inventory of intended matings to British-breed rams at March 31 (m), constructed (Vere and Griffith 1988); *AFNW*, area of improved pastures fertilised, New South Wales (m ha), ABS; *SLLBNW*, New South Wales lamb slaughterings (m), AMLC; *PFWLAU*, real average Australian greasy price for all wools (c/kg), AWC; *DUMQ1*, *DUMQ2*, *DUMQ3*, quarterly dummy variables; *DUM74*, impact dummy variable for the 1974 beef export market to US crash (1 = 1974:4, zero otherwise).

Lamb slaughterings

$$(A2) \quad SLLBNW = 0.56 + 0.24 NABI(-4) + 0.11 AFNW - 0.01 PALBNW - 0.003 PFWLAU(-1) \\ (OLS) \quad (4.6) (3.3) \quad (4.8) \quad (-6.1) \quad (-3.8) \\ - 0.09 DUMDRT(-1) + 0.43 SLLBNW(-4) \\ (-1.2) \quad (4.8)$$

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

Variable Definitions and Sources

SLLBNW, New South Wales lamb slaughterings (m), AMLC; *NABI*, New South Wales adjusted inventory of intended matings to British-breed rams at March 31 (m), constructed (Vere and Griffith 1988); *AFNW*, area of improved pastures fertilised, New South Wales (m ha), ABS; *PALBNW*, real saleyard lamb price, dressed carcase weight, Homebush (c/kg), NSW Department of Agriculture; *PFWLAU*, real average Australian greasy price for all wools (c/kg), AWC; *DUMDRT*, drought dummy variable (1 = below average quarterly rainfall, zero otherwise), ABARE series.

Per capita lamb consumption

$$(A3) \quad DCLBAU = 3.75 + 0.4 DCLBAU(-1) - 0.003 RINCAU + 0.11 PRBFCH \\ (OLS) \quad (2.8) \quad (3.8) \quad (-2.1) \quad (3.3) \\ + 0.01 PRPKNW - 0.2 PRLBNW - 0.71 DUMQ1 - 0.55 DUMQ2 \\ (1.6) \quad (-4.7) \quad (-3.9) \quad (-2.6) \\ - 0.02 DUMQ3 + 0.73 DUM74 \\ (-0.1) \quad (1.8)$$

Adjusted $R^2 = 0.82$; $h = -0.66$; $N = 64$ *Variable Definitions and Sources*

DCLBAU, Australian per capita lamb consumption (kg/head), AMLC; *RINCAU*, real household disposable income (\$'000), ABS; *PRBFCH*, weighted average of real retail beef and chicken prices (c/kg), calculated; *PRPKNW*, real retail pork price, Sydney (c/kg), NSW Department of Agriculture; *PRLBNW*, real retail lamb price, Sydney (c/kg), NSW Department of Agriculture; *DUMQ1*, *DUMQ2*, *DUMQ3*, quarterly dummy variables; *DUM74*, impact dummy variable for the 1974 beef export market to US crash (1 = 1974:4, zero otherwise).

*Restricted reduced-form estimates:**Real saleyard lamb price*

$$(A4) \quad PALBNW = 18.7 + 0.12 PFWLAU + 5.29 AFNW + 0.08 PRBFNW + 0.234 EXLBNW(-1) \\ (LSQ) \quad (4.1) \quad (4.1) \quad (4.9) \quad (2.4) \quad (0.7) \\ - 12.73 PALBNW(-8)/PFWHAU(-8) + 2.92 DUMQ1 + 6.44 DUMQ2 \\ (-2.9) \quad (1.8) \quad (3.9) \\ + 6.93 DUMQ3 - 14.21 DUM74 - 6.69 DUM74(-1) - 12.40 SLLBNW(-4) \\ (4.3) \quad (-3.1) \quad (-1.4) \quad (-4.9)$$

Adjusted $R^2 = 0.75$; $h = na$; $N = 64$ *Variable Definitions and Sources*

PALBNW, Real saleyard lamb price, dressed carcass weight, Homebush (c/kg), NSW Department of Agriculture; *PFWLAU*, real average Australian greasy price for all wools (c/kg), AWC; *AFNW*, area of improved pastures fertilised, New South Wales (m ha), ABS; *PRBFNW*, real retail beef price, Sydney (c/kg), NSW Department of Agriculture; *EXLBNW*, New South Wales lamb exports (kt), AMLC; *PFWHAU*, real average Australian wheat price at silo (\$/tonne), ABARE; *DUMQ1*, *DUMQ2*, *DUMQ3*, quarterly dummy variables; *DUM74*, impact dummy variable for the 1974 beef export market to US crash (1 = 1974:4, zero otherwise); *SLLBNW*, New South Wales lamb slaughterings (m), AMLC.

*Time-series ARIMA models:**Real saleyard lamb price*

$$(A5) \quad PALBNW \Delta Y_t = (1 - 0.135B)(1 - 1.111B + 0.194B^2)^4 \varepsilon_t \\ ARIMA(0, 1, 1) \quad (-1.0) \quad (-8.5) \quad (-1.6) \\ (0, 1, 2)$$

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

$$(A6) \quad SLLBNW \Delta Y_t = (1 - 0.473B)(1 - 0.846B)(1 - 0.422B - 0.337B^2)^4 \varepsilon_t \\ ARIMA(1, 1, 1) \quad (-2.4) \quad (-6.8) \quad (-3.0) \quad (-2.7) \\ (0, 1, 2)$$

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

Per capita lamb consumption

$$(A7) \text{ DCLBAU } \Delta Y_t = (1 - 0.503B - 0.364B^2)(1 - 0.602B - 0.611B^2)^4 \varepsilon_t$$

$$\text{ARIMA } (2, 1, 0) \quad (-4.0) \quad (2.9) \quad (-5.5) \quad (5.5)$$

$$(2, 1, 0)$$

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

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