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by

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Integrating Econometric Models Of Australia's Livestock Industries: Implications For Forecasting And Other Economic Analyses

D.T. Vere and G.R. Griffith∗∗

Abstract

The perceived value of integrating small partial-equilibrium structural models of individual livestock industries into a comprehensive single-sector model is to take advantage of the interrelationships that are usually expressed by cross elasticities on both the supply and demand sides of these industries. Model integration should provide a more realistic representation of the livestock industries and an improved mechanism for industry analyses. However, model integration could also lead to increased error in model simulation that could reduce the value of the larger model for those purposes. Using forecasting as an example application, this paper investigates how the increased endogenisation of cross-commodity relationships in alternative structural econometric models of the Australian livestock industries affects the simulation performance of the larger model. Forecast accuracy and encompassing tests were used to investigate the value of model integration by comparing the accuracy of the models' forecasts and by testing for differences in the information contained in those forecasts. The general result was that combining the models did not adversely affect the forecasts from the integrated model and the encompassing tests indicated that the forecasts of the integrated and single models contained different information. Because the forecasts of the integrated model were not impaired relative to the single model forecasts, model integration was considered to be useful for forecasting and other types of economic analysis in the livestock industries.

Keywords: Structural econometric models; Model integration; Forecasting; Economic analysis.

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1. Introduction

Strong variation in supply and demand is a feature of Australia's extensive livestock industries. Regular cycles in livestock production result from the biological constraints that are associated with animal breeding decisions and seasonal and pasture growth cycles. Cyclical regularity in production influences the patterns of commodity prices and demand over the year. Other sources of variation are irregularly occurring events and policies that periodically have major impacts on these industries. Examples of such issues are the recent drought in eastern Australia that is regarded as being the worst in the past 100 years, threats to meat export markets from pesticide contamination in feedlots, bacterial infections in Japanese meat products, domestic over-supply in the USA, and policy changes such as the deregulation of the Australian wool industry.

The importance of all types of variation in determining activity in the livestock industries gives rise to the need for detailed and timely knowledge of their economic behaviour. One means of fulfilling this need has been to develop and apply quantitative economic models of the individual industries. In Australia, the structural econometric type of industry model has been a focus of such modelling because it is considered that this model best provides a systematic basis for forecasting industry behaviour and for analysing the impacts of events and policies in industries where internal variability and external factors are important (Vere *et al.*, 2000). The structural model's purpose is to explain the industry processes of supply, demand and price formation following the theories of economic behaviour, and to accurately simulate the values of the endogenous variables that are involved in those processes. The simultaneous-equations methodology on which structural modelling is based is recognised as being a logical approach to estimating economic relationships where the values of two or more variables are jointly dependent (Ezekiel and Fox, 1967).

A practical problem with the application of a structural livestock industry model is that many existing models have a single industry focus and can only be used for analyses within those industries. It has not been possible to undertake cross-industry analyses except in simplistic ways such as including the farm and retail prices of competing commodities as explanatory variables in the supply and demand functions for individual commodities. This approach is unsatisfactory because the Australian livestock industries feature strong joint relationships in both supply and demand, which are necessarily treated as being exogenous in the single industry models. However, while model integration potentially offers a solution to this problem, it also raises the risk of additional error being introduced into the larger model's simulation process. This could arise because the larger model has many more endogenous variables that have to be represented by separate equations. The estimation process for these equations could lead to the transfer of additional error into the integrated model's simulation.

Investigating that possibility is the theme of this paper. The objective is to determine whether the combination of several single structural models of Australian livestock industries into a composite livestock sector model reduces the ability of the integrated model to accurately predict the values of the larger set of endogenous variables and so diminishes the value of that model for livestock industry analysis. A forecasting focus is adopted because this activity is a foremost application of structural modelling in the Australian livestock industries. Forecasting involves model simulation and provides a direct comparison of the simulated and actual values of the endogenous forecast variables. Model simulation errors become readily apparent and a model that reduces such error and produces forecasts that approximate the actual data can be expected to be similarly useful in other industry analyses that involve simulating changes to the model's equilibrium conditions. Here, the specifications of the structural equations in the single and the integrated models are the same. This means that differences in the information available to the model simulation routine and in this instance, forecasting, and the effects of these differences on relative simulation/forecast accuracy are more likely to be caused by the model integration process introducing additional measurement error into the larger model, rather than by differences and errors in model specification. This possibility is validated by first determining the root mean squared errors (RMSEs) of each model's forecasts of 15 important livestock series, and second by determining whether the additional information provided by model integration is detrimental to the forecasts from the larger model, using the forecast encompassing test proposed by Fair and Schiller (1990). The results of this forecasting analysis is considered to be a primary indicator of the benefits or otherwise of structural model integration.

2. Background to the model integration issue in a forecasting context

The question of how agricultural forecasts are best produced has been examined in numerous studies, many of which are discussed in the review by Allen (1994). Forecasts have been produced from a variety of formal and informal methods as well as combinations of these methods. A common finding of reviews of forecasting methods has been that no one method is consistently superior to others and that formal forecasting models do not always outperform non-quantitative methods. Most of the 60 structural model-type forecasting applications reviewed by Allen (1994) involved the use of single sector models that did not have endogenous links to a more comprehensive system. There were no studies in that review (or in a larger unpublished appendix) that examined the issue of the forecasting performance of models containing different degrees of aggregation of the single commodity industries. This has been the case in relation to the Australian livestock industries in which single models have been typically been used for historical explanation, impact analysis and forecasting. This practice has permitted only partial cross-industry analyses to be undertaken since the activities of the other industries were assumed to be exogenous. In reality, these industries are closely interrelated in both supply and demand and cross-industry issues cannot be adequately analysed using a model that does not allow for the simultaneous adjustment of quantities and prices between the industries

In a forecasting context, the model integration issue concerns the relative benefits of producing forecasts using structural models containing different degrees of 'partialness' in the model's equilibrium-generating process. This means comparing the forecasts of a single industry structural model where the cross-commodity prices are exogenous with those of a larger integrated system structural model where most of these prices are endogenous. For example, it is known that meat demand in Australia is best modelled as a system that jointly explains beef, lamb, pork and chicken consumption, and that retail meat prices are highly collinear (Piggott *et al*., 1996). In explaining the retail demand for one type of meat (eg., beef) in a model of the beef industry, the prices of competing meats (lamb, pork and chicken) are assumed to be exogenous. In reality, these price effects are not truly exogenous and important feedback effects are ignored. Similar arguments apply on the supply side where Australia's beef, wool and sheepmeats products are mainly derived from mixed grazing systems that may also be associated with cropping enterprises.

The single industry model does not have the mechanism to allow for quantity and price adjustments between the industries with the result being that important cross-industry issues are not able to be accurately analysed. In a larger livestock sector model which includes lamb and pork prices and quantities endogenously, all of the estimated cross-price effects are allowed to have an impact, and the own-price effect of a change in the price of beef is partially offset by the cross-price effects from the related commodities. Demand response would be much less and forecasts of actual industry responses should be more accurate. These considerations suggest that endogenising such cross-price effects through combining single industry models should provide a more realistic livestock sector model that can be used for more accurate forecasting and other types of analyses.

Combining livestock industry models offers the potential advantage of providing more information to the forecasting process since each industry has its own distinguishing features, including differences in the demographic and seasonal aspects of production and in the structures of the domestic and export markets. Model combination also makes available to the forecasting process a much greater volume of information on other exogenous variables. However, a greater level of endogeneity between the major industry variables might also result in less accurate forecasts because of the increased risk of estimation error in the model simulation-forecasting process and of greater measurement errors in the wider range of data required. The effects of model integration on forecasting performance and the wider implications of this practice for the use of the integrated model for industry analysis is the central issue that is investigated in this paper.

3. Methods

Labys and Pollak (1984) defined a structural model to be a quantitative representation of a commodity market or industry with empirical relationships that represent supply, demand and price determination. The main objective in developing this type of model is to identify the sequences of decision making and to quantify the relative importance of the factors that underlie them. For a livestock industry, the structural model seeks to explain basic industry activities such as animal breeding, meat and wool production, the domestic and export demand for livestock products and the formation of farm, retail and export prices. To fulfil this purpose, the model must incorporate the economic theories that describe production and consumption behaviour from which the specified behavioural relationships can be estimated empirically from series of known industry data.

The construction and validation sequences of the structural models used in this study involve the specification and estimation of the economic relationships and the model's solution using dynamic simulation. As previously indicated, the single models represent the separate livestock industries, and the integrated model is an amalgamation of the single models. The main outcome of this integration process is that many variables that were exogenous in the single models become endogenous variables in the integrated model, eg., lamb and pork retail prices are exogenous variables in the beef industry model's beef consumption equation, and these variables become endogenous in the beef industry component of the integrated model.

In the integrated model, the single models have a similar structure which initially specifies the breeding inventories in terms of the lagged values of the explanatory variables to represent the time involved between breeding decisions and outputs. In each model, the lag structure was specified following testing of alternative structures of the lags that are imposed on livestock production by the biological constraints of the breeding process and pasture growth and seasonal cycles (Vere *et al.*, 1993). Livestock production decisions are recursive in that current breeding intentions reflect previous breeding decisions and, together, these influence future output. In this structure, the breeding inventory recursively enters the simultaneously determined production, consumption, trade and price blocks.

The endogenous variables that constitute the supply, demand and price formation processes for each commodity are represented by either a behavioural or a definitional equation (see Table 1). The numbers of endogenous variables in each model are 35 (wool), 30 (beef), 14 (pigs) and 15 (lamb), giving 94 in the integrated model. Of the 94 equations and identities that describe the endogenous variables, nine have endogenous cross-price effects. These include four ewe breeding equations, four per capita meat demand equations and one equation explaining mutton price determination. The behavioural equations were estimated by OLS or by 2SLS where the right hand side variables included current period endogenous variables, using quarterly data between 1972:1 to 1996:4. The main elasticity values calculated from these estimates are given in Table 2. Each model was validated over the full sample period under a dynamic simulation routine in which the solved values for the lagged dependent variables are used to predict the current values of the endogenous variables. The values of the main validation criterion (the simulation R^2) are given in Table 1. These are taken from the full estimation and validation results reported in Vere *et al.* (2000)[1]. The principal feature of these results is that the simulations of most of the endogenous variables in the single models are not adversely affected when they are dynamically simulated in the integrated model. This indicates that model integration has introduced little additional measurement error.

The usefulness of the model to produce forecasts depends on the extent to which the data from which the economic relationships are estimated represent actual past values. Using the notation of Intriligator (1978), the general forecasting form of the structural model is given as;

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

where Y_t is a row vector of the endogenous variables to be forecast, Z_t is a row vector of exogenous variables, Y_{t-1} is a row vector of the lagged endogenous variables, μ_t is a row vector of disturbances, and Π_1 and Π_2 are the matrices of coefficients. This model generates single period forecasts for the endogenous variables as follows;

$$(2)\quad \hat{Y}_{T+1} = Y_T\hat{\Pi}_1 + \hat{Z}_{T+1}\hat{\Pi}_2 + \hat{\mu}_{T+1}$$

where $Y_T\hat{\Pi}_1$ indicates the dependence on current values of the endogenous variables which are weighted by the coefficients in $\hat{\Pi}_1$, $\hat{Z}_{T+1}\hat{\Pi}_2$ is a vector of predicted values of the

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[1] In a dynamic simulation, the squared correlation coefficient (R^2) is a measure of the model's ability to explain changes in the endogenous variables when all the current and lagged period interactions are formally incorporated in the simulation routine.

exogenous variables $\hat{Z}_{T+1}$ and the estimated coefficients $\hat{\Pi}_2$, and $\hat{\mu}_{T+1}$ is a vector of predicted values of the disturbances.

Each model was used to produce within-sample forecasts of 15 major livestock industry series over the full sample period 1972:1 to 1996:4. The series were the total production of and total demand for beef, pork, lamb, mutton and wool, and their real farm prices. All of the information for the forecasting was therefore known and this is consistent with the main data requirement of the Fair and Schiller (1990) procedure (also known as a forecast encompassing test). The first part of this procedure was to calculate the RMSEs to test the relative absolute accuracy of each model's forecasts. RMSE was also expected to indicate whether additional measurement error had been introduced into the forecasting model by model integration. RMSE ratios were also calculated where the numerators and denominators were the RMSEs of the single and the integrated models respectively. A ratio greater than one indicated that the integrated model produced more accurate forecasts than the single model since the former had a lower RMSE (Longbottom and Holly, 1985).

However, the use of RMSE might not provide an adequate forecast evaluation. Fair and Schiller (1990) argued that if the RMSEs of two models were similar, little could be concluded about their relative forecasting merits. Even if the RMSEs were significantly different, the forecasts with the highest RMSE might contain information useful to the forecast that is not in the other model. This cannot be established using RMSE. They proposed the use of a forecast encompassing test as a means of determining the relative value of the information that is contained in the forecasts of the alternative forecasting models. Fang (2003) noted that the forecast encompassing test was complementary to the RMSE forecast evaluation criterion since it can often discriminate between two models even when their forecasts have similar RMSEs. This test can also determine whether the forecast with the higher RMSE contains information that is not in the other forecast.

This approach has been followed in this paper. The potential value of the additional information provided by model integration is first determined by the regression of the forecast errors for each of the series on a constant term to determine the forecast bias of each model. A significant estimate of the constant term indicates either positive or negative bias since the forecast error has a mean value that is other than zero. Lower bias indicates a preferable forecasting model[2]. The second part of this approach involves the regression of the actual change in the forecast series on the changes in the series that were forecast by each of the models. For a one-period-ahead forecast (or one-quarter-ahead in this instance), this regression is given by:

$$(3) \quad Y_t - Y_{t-1} = \alpha + \beta(\hat{Y}_{1t} - Y_{t-1}) + \gamma(\hat{Y}_{2t} - Y_{t-1}) + \mu_t$$

where the right-hand side explanatory variables are the forecast errors of the integrated and single models for each of the 15 series. Equation (3) enables the information contained in the

[2] This is the regression:

$$Y_t - Y_{t-1} = \alpha + (\hat{Y}_{1t} - Y_{t-1})$$

where the dependent variable is the first difference of the actual data, α is the constant term and the explanatory variable is calculated as the difference between the current period forecast and the previous period's actual data.

forecasts of the two models to be compared from the regression of the actual on the predicted changes from each of the models. Using the terminology of Fang (2003), when $\beta = 0$ and $\gamma \neq 0$, the forecast of the second model encompasses the first. The converse applies if $\beta \neq 0$ and $\gamma = 0$. When the forecasts of both models contain independent information for the one-quarter-ahead forecast of Y_t both β and γ should be non-zero, and the null hypotheses ($H1_0$ and/or $H2_0$) are not rejected. The alternate hypotheses ($H1_1$ and $H2_1$) in each forecast comparison are that β and γ equal zero, ie., that neither model's forecasts contain information relevant to a forecast for the next period that is not in both the constant term and the other model.

4. Results

The RMSE estimates indicate a general similarity in the forecasts from the integrated and the single models of most of the 15 series over the full sample period (Table 3). Seven series have identical RMSEs while the RMSE differences in four other forecast series are within 5% of both values. The single models have lower RMSEs in five instances while the integrated model produces three forecast series with lower RMSEs. The RMSEs confirm that in most instances, the larger forecasting model has not been disadvantaged from extra measurement error through model integration, but also that the relative forecasting merits of the two models cannot be adequately distinguished on this (RMSE) basis.

Estimates of the constant terms (Table 3) are also consistent between the models when evaluated at the 10% significance level. Significant bias is evident in both models' forecasts of six of the series (beef, wool and mutton production, mutton demand and farm beef and wool prices) but the forecast error regressions for most of the series have insignificant constants and the forecasts are thus unbiased. The major bias differences are that the beef demand forecasts from the single model are strongly biased relative to the forecasts from the integrated model, and that this relativity is reversed in the lamb farm price forecasts.

Some additional RMSE calculations are given in Table 4 for the forecasts of each model over a later period (1992:1 to 1996:4) of the full sample. By restricting the forecast accuracy comparisons to the last 20 values of the full series, any errors should be highlighted since the dynamic routine in which the models are simulated utilises the successive solved values over the forecast period rather than the actual data. Simulation errors therefore compound and will be most evident in the forecasts of the later periods. These results are consistent with the full-period error comparisons. Eight forecast series had identical RMSEs, six series favoured the single model forecasts and the remaining beef demand series was most accurately forecast by the integrated model. The shorter period results further confirmed that model integration did not increase the simulation error of the larger model.

The value of the independent information contained in the forecasting models is indicated by the results of the forecast encompassing tests in Table 5. For the production variables, forecasts of lamb production from both models are significant in equation (3) at the 1% level (β and γ significant, cannot reject $H1_0$ and $H2_0$) while the wool and mutton production equation forecasts from the integrated model are significant at the 10% level (β significant, cannot reject $H1_0$ and $H2_1$). Neither model contains independent information that is useful in forecasting pork and beef production (cannot reject $H1_1$ and $H2_1$). Both models produce significant forecasts of lamb, beef and mutton demand at the 10% level (β and γ significant) while forecasts of pork and wool demand are not significant in either model (neither β nor γ significant).

The relative information value of the models' forecasts is more apparent in the real farm price forecasts. The beef, lamb, wool and mutton price equations contain significant β and γ estimates (cannot reject $H1_0$ and $H2_0$ in each case). The integrated model's forecasts of farm pork price are also significant. This is an important result because farm prices, which are determined by the coincidence of the endogenous supply and demand schedules, are the variables that are most likely to be adversely affected by additional measurement error through model integration.

The main result is that in eight instances, both models have non-zero coefficients and thus contain independent information that is useful in forecasting the respective series. In each of these instances, the null hypothesis that both models contain independent forecast information is not rejected (the alternative hypotheses are not rejected in four instances). Significant β coefficients but insignificant γ coefficients were estimated in three other instances and together with the former, this indicates that the forecasts from the integrated model provide more information than the forecasts of the single models. Fair and Schiller (1990) stated that this would arise either if the models used different data sets (which is not the case here) or if different restrictions were placed on the models, as has occurred here by endogenising many of the relationships between the forecasting variables through model integration. These results are comparable to those obtained by Fair and Schiller (1990). In comparing the full forecast period results in Tables 3 and 5, the RMSEs for the two models are identical for eight of the forecast series and are reasonably close for the others. The earlier conclusion of Fair and Schiller that their models were similar on an RMSE basis also applies here. However, unlike their finding that their main (Fair) model dominated the others, these livestock models are more evenly balanced in terms of forecasting dominance. The integrated model has 11 significant β coefficients compared to eight significant γ coefficients for the single models. Again, it is worth noting that the integrated model dominates the single models in predicting prices, which is a primary requirement of Australian livestock industry forecasting.

5. Discussion

This paper has investigated the implications for livestock industry analysis of combining five stand-alone structural models of notionally separate Australian livestock industries into an integrated livestock sector model. The latter model contains all the endogenous variables that are in the single models and is solved using a dynamic simulation routine. Potentially, there are several important advantages in integrating single industry models. Using a single model in areas such as forecasting and impact analysis implies that the interactions between the major variables across the separate industries are exogenous. However, it is known that the Australian livestock industries operate with a high level of interdependence on the supply and demand sides and are therefore not exogenous. Endogenising these relationships through model integration should thus offer an improved mechanism to the single industry model for forecasting and other economic analysis.

Using forecasting as an example application, the validity of this expectation was investigated by examining whether there were differences in the forecasts of the major livestock industry variables (supply, demand and farm prices) generated by the single and the integrated models. This was done by using the RMSE absolute forecast accuracy measure, and the encompassing test of Fair and Schiller (1990) that compares the forecast information produced by alternative econometric models. While both models used the same data, model integration was expected to change the information available for forecasting since it allowed many more endogenous cross-relationships to be included in the larger model's simulation and thus provide a more realistic representation of the known interdependencies across these industries. However, this process also raised the possibility of further simulation error being introduced that could be detrimental to the larger model's forecasts.

The general result was that combining the models was not detrimental to the integrated model's forecasts in comparison to the single model forecasts. The RMSEs of both models were similar for most of the 15 forecast series and the RMSE ratios indicated that there were slight improvements in using the integrated model in forecasting two of the series. The results support the observations of Fair and Schiller (1990) and Fang (2003) that RMSE provides an inadequate assessment of the relative forecasting merits of alternative econometric models in some instances. Also consistent with those studies were the results of the encompassing tests. Because both models produced significant coefficients for most of the series, they could not be said to be have been based on the same information. There are therefore meaningful differences between the information contained in the models. But overall, the integrated model contributed more significant coefficients than the single models.

This analysis has shown that endogenising the strong cross-commodity relationships of the Australian livestock industries into a single integrated model can benefit industry forecasting. Rather than adversely affecting forecasts by additional error introduction, model integration improved the forecasts in several instances and provided independent information that could be of value to the forecast user. The integration process enables a more realistic representation of mixed livestock production and marketing systems. In a practical sense, this outcome is most important and enhances the benefits of using the larger structural model for industry analysis since that model better captures the operations of these industries that feature strong cross-industry interrelationships in supply and demand. While these results demonstrate the usefulness of the larger model in livestock forecasting, it is considered that the results also indicate that the model would be similarly useful in other economic applications that require the simulation of and changes to the model's equilibrium conditions. For example, in evaluating policy proposals or the adoption of R&D programs in the Australian livestock industries, it is important to be able to measure the impacts across all affected industries over the medium to long term, so that winners and losers can be identified. In this instance, an integrated modelling system is crucial (Griffith and Vere, 2000). The use of single structural models, in which important economic relationships between industries are necessarily treated as being exogenous, is a less satisfactory approach to such analyses.

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Table 1. Specification and dynamic validation of the Australian livestock industries model: 1972:1 to 1996:4

Dependent variables	Equation [a]	Explanatory variables ($_L$ denotes lag length)	R^2 of estimates	R^2 of dynamic validation	
1. Breeding and capacity inventories				SM [b]	IM [b]
Cows and heifers (CH)	DE	$0.975 \times CH_{L1}$ + (promotions/2) $\times VL_{L1}$ - CHS		0.92	0.92
Steers and bulls (SB)	DE	$0.975 \times SB_{L1}$ + (promotions/2) $\times VL_{L1}$ - SBS		0.70	0.70
Vealers (VL)	DE	CB - SVL + (0.975 - promotions) $\times VL_{L1}$		0.76	0.76
Calves born (CB)	DE	calving ratio $\times CH_{L3}$		0.91	0.91
Short wool breeding ewes (SWE)	BE (OLS)	SWE_{L4}**, (FLP_{L4}/FWP_{L4}), (FLP_{L4}/wheat $price_{L4}$), $season_{L4}$	0.99	0.97	0.97
Long wool breeding ewes (LWE)	BE (OLS)	LWE_{L4}**, (FLP_{L4}/FWP_{L4}), (FLP_{L4}/wheat $price_{L4}$)*	0.98	0.91	0.89
Corriedale-Polwarth breeding ewes (CPE)	BE (OLS)	CPE_{L4}**, (FLP_{L4}/FWP_{L4}), (FLP_{L4}/wheat $price_{L4}$)*, season $_{L4}$	0.99	0.95	0.94
Merino breeding ewes (ME)	BE (OLS)	SM_{L4}**, (FWP_{L4}/wheat $price_{L4}$)**, $(FWP_{L4}/FMP_{L4})^{-}$**, season $_{L4}$**	0.99	0.87	0.86
Lamb breeding inventory 1 (ABI1)	DE	$\delta^{SW}SWE + \delta^{LW}LWE + \delta^{CP}CPE + 1\text{-}\delta^{LW}LWE_{L8} + 1\text{-}\delta^{CP}CPE_{L8}$		0.75	0.58
Lamb breeding inventory 2 (ABI2)	DE	$(ABI1_{L1} + ABI1_{L2} + ABI1_{L3} + ABI1_{L4})/4$		0.97	0.96
Lambs marked (LM)	BE (2SLS)	LM_{L1}**, ABI1**, pasture area**	0.98	0.97	0.95
Lambs not slaughtered (LNS)	DE	LM - SL		0.97	0.96
Sows (SO)	BE (OLS)	SO_{L1}**, FPP_{L2}*, wheat $price_{L2}$	0.76	0.61	0.59
Total breeding ewes (TBE)	DE	ME + SWE + LWE + CPE		0.94	0.92
Total sheep (TS)	DE	TS_{L1} + LNS - deaths - slaughter - live exports		0.99	0.99
Wethers (WT)	BE (OLS)	WT_{L4}**, (FWP_{L4}/wheat $price_{L4}$)**	0.99	0.90	0.90
Fine wool breeding ewes (FWE)	DE	ME $\times$ 0.21		0.87	0.86
Medium wool breeding ewes (MWE)	DE	ME $\times$ 0.79		0.87	0.86
Broad wool breeding ewes (BWE)	DE	SWE + LWE + CPE		0.96	0.96

Source; Vere et al. (2000); dummy variables omitted, [a] definitional equation (DE), behavioural equation (BE); [b] single industry model (SM), integrated industry model (IM); ** and * denotes significance at the 1% and 5% levels, respectively (- sign denotes negative significance).

Table 1 (cont.)

Dependent variables	Equation	Explanatory variables ($_L$ denotes lag length)	R^2 of estimates	R^2 of dynamic validation	
2. Production				SM	IM
Cow and heifer slaughter (CHS)	BE (OLS)	CH_{L1}**, CHS_{L1}**, pasture $area_{L1}$	0.86	0.51	0.51
Steer and bull slaughter (SBS)	BE (OLS)	SB_{L1}**, SBS_{L1}**, FBP_{L1} -*	0.53	0.51	0.51
Vealer slaughter (VLS)	BE (2SLS)	VL_{L1}**, VLS_{L1}**, FBP, pasture area*	0.93	0.90	0.90
Lamb slaughter (LS)	BE (OLS)	LM_{L1}*, LS_{L4}**	0.56	0.54	0.34
Sheep slaughter (SS)	BE (OLS)	TS_{L1}**, SS_{L1}**, FWP_{L1} -**	0.81	0.74	0.74
Pig slaughter (PS)	BE (OLS)	SO_{L2}**, time trend**	0.84	0.76	0.76
Average beef slaughter weight (BW)	BE (OLS)	pasture area**, time trend**	0.47	0.57	0.57
Average vealer slaughter weight (VLW)	BE (OLS)	pasture area*, time trend	0.33	0.33	0.33
Average pig slaughter weight (PW)	BE (OLS)	average pig slaughter $weight_{L1}$**, time trend**	0.99	0.97	0.97
Average sheep slaughter weight (SW)	BE (OLS)	pasture area, time trend	0.38	0.17	0.17
Beef production (PDB)	DE	(VLW × LS) + BW × (CHS + SBS)		0.63	0.62
Lamb production (PDL)	DE	LS × average lamb slaughter weight		0.44	0.24
Pig meat production (PDP)	DE	PS × PW		0.92	0.92
Mutton production (PDM)	DE	SS × SW		0.78	0.78
Total wool production (PDW)	DE	PDFW + PDMW + PDBW		0.88	0.85
Fine wool production (PDFW)	BE (OLS)	FWE_{L2}, $PDFW_{L1}$**, $FFWP_{L1}$*, $season_{L3}$**	0.95	0.73	0.73
Medium wool production (PDMW)	BE (OLS)	MWE_{L3}*, $PDMW_{L1}$**, FWP_{L1}**, time trend**	0.96	0.84	0.84
Broad wool production (PDBW)	BE (OLS)	BWE_{L6}**, $PDBW_{L1}$**, FWP_{L4}*, $season_{L4}$	0.97	0.93	0.87
Wool stocks (WSK)	BE (OLS)	WSK_{L1}**, FWP_{L1}**, wool price ratio, time trend	0.85	0.96	0.96

Source; Vere et al. (2000); dummy variables omitted, [a] definitional equation (DE), behavioural equation (BE); [b] single industry model (SM), integrated industry model (IM); ** and * denotes significance at the 1% and 5% levels, respectively (- sign denotes negative significance).

Table 1 (cont.)

Dependent variables	Equation	Explanatory variables ($_L$ denotes lag length)	R^2 of estimates	R^2 of dynamic validation	
3. Disposal				SM	IM
Per capita beef demand (PCB)	BE (2SLS)	RBP^{-}**, RPP, RLP**, income*, time trend	0.79	0.82	0.71
Domestic beef demand (DBF)	DE	PCB × population		0.69	0.51
Per capita lamb demand (PCL)	BE (2SLS)	RLP^{-}**, RBP**, RPP*, chicken price**, income*	0.93	0.67	0.57
Domestic lamb demand (DLB)	DE	PCL × population		0.26	0.11
Per capita pork demand (PCP)	BE (2SLS)	RPP^{-}**, RBP, chicken price*, income	0.57	0.31	0.29
Domestic pork demand (DPK)	DE	PCP × population		0.48	0.47
Per capita bacon and ham demand (PCBH)	BE (2SLS)	PCBH$_{L1}$**, RBHP, RBP**, income**	0.90	0.80	0.80
Domestic bacon and ham demand (DBH)	DE	PCBH × population		0.89	0.88
Domestic mutton demand (DMT)	DE	mutton stocks$_{L1}$ + PDM - mutton stocks - EXMT		0.46	0.46
Aust. beef exports (BX)	DE	(PDB + beef stocks$_{L1}$ - DBF - beef stocks)/1.5		0.49	0.48
Beef exports to US (BXUS)	BE (2SLS)	USBIM**, US-Australia beef price ratio^{-}**, US beef quota**	0.72	0.37	0.37
US beef imports (USBIM)	BE (OLS)	US beef price ratio^{-}**, US incomes^{-}**, US stocks^{-}*, US beef quota	0.55	0.33	0.33
Japanese beef imports (JBIM)	BE (OLS)	PBJF, Japanese incomes**, Japanese beef stocks**	0.91	0.89	0.90
Aust. beef exports to Japan (BXJ)	BE (OLS)	JBIM**, PBJC	0.75	0.88	0.88
Aust. beef exports to rest of world (BXW)	DE	BX - BXUS - BXJ		0.36	0.42
Aust. lamb exports (LX)	BE (OLS)	PDL**, lamb domestic-export price differential, lamb stocks**	0.64	0.25	0.22
Wool exports to the EC (WXEC)	BE (2SLS)	WXEC$_{L1}$**, PFWEC, polyester price*, EC incomes*	0.41	0.20	0.20
Wool exports to Japan (WXJ)	BE (2SLS)	WXJ$_{L1}$**, PFWJ^{-}*, polyester price$_{L1}$*, Japanese incomes*	0.79	0.73	0.73
Wool exports to rest of world (WXW)	BE (2SLS)	WXW$_{L1}$**, PFWW^{-}*, US incomes**	0.55	0.50	0.50
Aust. wool exports (WX)	DE	WXEC + WXJ + WXW		0.37	0.37
Aust. mutton exports (MX)	BE (OLS)	mutton stocks$_{L1}$**, mutton domestic-export price differential**	0.73	0.48	0.48
Live sheep exports (LSX)	BE (OLS)	LSX$_{L1}$**, FMP$_{L1}$, FWP$_{L1}$	0.84	0.59	0.59

Source; Vere et al. (2000); dummy variables omitted, [a] definitional equation (DE), behavioural equation (BE); [b] single industry model (SM), integrated industry model (IM); ** and * denotes significance at the 1% and 5% levels, respectively (- sign denotes negative significance).

Table 1 (cont.)

Dependent variables	Equation	Explanatory variables ($_L$ denotes lag length)	R^2 of estimates	R^2 of dynamic validation	
4. Prices, margins and revenues				SM	IM
Farm beef price (FBP)	BE (2SLS)	PDB, FBP_{L1}**, BXP_{L1}	0.90	0.91	0.91
Farm lamb price (FLP)	DE	PDL + $stocks_{L1}$ - DLB - LX - stocks		0.58	0.50
Farm pork price (FPP)	DE	DPK + DBH + exports - stocks - pig meat imports - PDP		0.29	0.30
Average farm wool price (FWP)	BE (2SLS)	expected wool export price**, FWP_{L1}**	0.74	0.73	0.73
Fine wool price (FFWP)	BE (2SLS)	FWP, $FFWP_{L1}$**	0.70	0.61	0.61
Farm mutton price (FMP)	BE (2SLS)	FWP*, FLP	0.23	0.16	0.17
Retail beef price (RBP)	DE	FBP + MMBF		0.86	0.86
Retail lamb price (RLP)	DE	FLP + MMLB		0.63	0.47
Retail pork price (RPP)	DE	FPP + MMPK		0.52	0.42
Retail bacon and ham price (RBHP)	DE	FPP + MMBH		0.50	0.42
Beef price spread (MMBF)	BE (OLS)	FBP_{L1}**, wages*	0.71	0.63	0.62
Lamb price spread (MMLB)	BE (2SLS)	RLP*, wages, $MMLB_{L1}$**	0.71	0.39	0.33
Pork price spread (MMPK)	BE (2SLS)	FPP_{L1}**, wages, $MMPK_{L1}$**	0.85	0.40	0.53
Bacon and ham price spread (MMBH)	BE (2SLS)	FPP_{L1}**, wages*	0.87	0.31	0.21
Beef industry revenue (BREV)	DE	PDB × FBP		0.66	0.70
Lamb industry revenue (LREV)	DE	PDL × FLP		0.71	0.69
Pig industry revenue (PREV)	DE	PDP × FPP		0.07	0.04
Wool industry revenue (WREV)	DE	(PDW × FWP + PDM × FMP + LSX × live sheep price)		0.82	0.81

Source; Vere et al. (2000); dummy variables omitted, [a] definitional equation (DE), behavioural equation (BE); [b] single industry model (SM), integrated industry model (IM); ** and * denotes significance at the 1% and 5% levels, respectively (- sign denotes negative significance).

Table 1 (cont.)

Dependent variables	Equation	Explanatory variables ($_{L}$ denotes lag length)	R^2 of estimates	R^2 of dynamic validation	
4. Prices, margins and revenues (cont.)				SM	IM
Average beef export price (BXP)	DE	(BXUS × PBUSF + BXJ × PBJF + BXW × PBWF)/BX		0.89	0.90
Aust. CIF beef price, US (PBUSC)	BE (OLS)	US manufacturing beef price**	0.83	0.84	0.84
Aust. FOB beef price, US (PBUSF)	DE	(1.03) × (PBUSC/exchange rate) × (CPIUS/CPIAU) - freight rate		0.82	0.82
Aust. CIF beef price, Japan (PBJC)	DE	(1.03) × (PBJF + freight rate) × (exchange rate) × (CPIAU/CPIJP)		0.94	0.94
Aust. FOB beef price, Japan (PBJF)	BE (OLS)	FBP_{L1}**, $PBJF_{L1}$**	0.93	0.69	0.70
Aust. CIF beef price, rest of world (PBWC)	DE	(1+0.03) × (PBWF + freight rate) × (exchange rate) × (CPIAU/CPIUS)		0.79	0.80
Aust. FOB beef price, rest of world (PBWF)	BE (OLS)	FBP_{L1}**, $PBWF_{L1}$**	0.91	0.76	0.79
US-New Zealand CIF beef price (PBNZC)	BE (OLS)	US manufacturing beef price**	0.60	0.76	0.76
Average wool export price (PWXP)	DE	(WXEC × PFWEC + WXJ × PFWJ + WXW × PFWW)/WX		0.66	0.66
Aust. CIF wool price, EC (PCWEC)	DE	((1.03 × (PFWEC + freight rate)) × exchange rate × (CPIAU/CPIEC)		0.68	0.68
Aust. FOB wool price, EC (PFWEC)	BE (OLS)	FWP_{L2}**, $PFWEC_{L1}$**	0.83	0.43	0.43
Aust. CIF wool price, Japan (PCWJ)	DE	((1.03 × (PFWJ + freight rate)) × exchange rate × (CPIAU/CPIJP)		0.76	0.76
Aust. FOB wool price, Japan (PFWJ)	BE (OLS)	FWP_{L2}**, $PFWJ_{L1}$**	0.85	0.49	0.49
Aust. CIF wool price, rest of world (PCWW)	DE	((1.03 × (PFWW + freight rate)) × exchange rate × (CPIAU/CPIUS)		0.67	0.67
Aust. FOB wool price, rest of world (PFWW)	BE (OLS)	FWP_{L2}**, $PFWW_{L1}$**	0.81	0.78	0.78
Average mutton export price (PMX)	BE (2SLS)	FMP**, stocks^{-}*	0.43	0.30	0.29

Source; Vere et al. (2000); dummy variables omitted, [a] definitional equation (DE), behavioural equation (BE); [b] single industry model (SM), integrated industry model (IM); ** and * denotes significance at the 1% and 5% levels, respectively (- sign denotes negative significance).

Table 2. Elasticity values in the Australian livestock industries model: 1972:1 to 1996:4

Dependent variables	Elasticity values for selected explanatory variables ($_L$ denotes lag length)
1. Breeding and capacity inventories	
Short wool breeding ewes (SWE)	(FLP_{L4}/FWP_{L4}) = -0.02/-1.30, $(FLP_{L4}/\text{wheat price}_{L4})$ = 0.06/3.34
Long wool breeding ewes (LWE)	(FLP_{L4}/FWP_{L4}) = -0.06/-1.68, $(FLP_{L4}/\text{wheat price}_{L4})$* = 0.09/2.52
Corriedale-Polwarth breeding ewes (CPE)	(FLP_{L4}/FWP_{L4}) = -0.06/-1.15, $(FLP_{L4}/\text{wheat price}_{L4})$* = 0.13/2.65
Merino breeding ewes (ME)	$(FWP_{L4}/\text{wheat price}_{L4})$** = 0.10/6.21, $(FWP_{L4}/FMP_{L4})^{-}$** = -0.07/-4.42
Lambs marked (LM)	ABI1** = 0.32/0.61
Sows (SO)	FPP_{L2}* = 0.03/0.18, wheat price_{L2} = -0.02/-0.13
Wethers (WT)	$(FWP_{L4}/\text{wheat price}_{L4})$** = 0.10/5.15
2. Production	
Cow and heifer slaughter (CHS)	CH_{L1}** = 0.22/2.09
Steer and bull slaughter (SBS)	SB_{L1}** = 0.38/0.59, FBP_{L1}^{-}* = -0.10/-0.15
Vealer slaughter (VLS)	VL_{L1}** = 0.29/0.89, FBP = -1.35/-4.14
Lamb slaughter (LS)	LM_{L1}* = 0.17/0.32
Sheep slaughter (SS)	TS_{L1}** = 0.49/1.97, FWP_{L1}^{-}** = -0.17/-0.71
Pig slaughter (PS)	SO_{L2}** = 0.68
Fine wool production (PDFW)	$FFWP_{L1}$* = 0.03/0.23
Medium wool production (PDMW)	FWP_{L1}** = 0.07/0.35
Broad wool production (PDBW)	FWP_{L4}* = 0.04/0.14
Wool stocks (WSK)	FWP_{L1}** = 0.08/0.61

Source; Vere et al. (2000); ** and * denotes significance at the 1% and 5% levels, respectively; the short run and long run elasticities are given as $\in 1/\in 2$, respectively.

Table 2 (cont.)

Dependent variables	Elasticity values for selected explanatory variables ($_{L}$ denotes lag length)
3. Disposal	
Per capita beef demand (PCB)	RBP^{-}** = -1.38, RPP = 0.37, RLP** = 0.64, income* = 0.33
Per capita lamb demand (PCL)	RLP^{-}** = -1.54, RBP** = 0.87, RPP* = 0.38, chicken price** = 0.74, income* = 0.22
Per capita pork demand (PCP)	RPP^{-}** = -1.59, RBP = 0.41, chicken price* = 0.65, income = 0.12
Per capita bacon and ham demand (PCBH)	RBHP = -0.07/-0.13, RBP** = 0.19/0.34, income** = 1.43/2.65
Beef exports to US (BXUS)	US-Australia beef price ratio^{-}** = -0.99
US beef imports (USBIM)	US beef price ratio^{-}** = -0.70, US stocks^{-}* = -0.69
Japanese beef imports (JBIM)	PBJF = 0.25, Japanese incomes** = 1.77
Aust. beef exports to Japan (BXJ)	PBJC = -0.05
Aust. lamb exports (LX)	lamb domestic-export price differential = -0.01
Wool exports to the EC (WXEC)	PFWEC = -0.12/-0.24, EC incomes* = 0.98/2.02
Wool exports to Japan (WXJ)	PFWJ^{-}* = -0.39/-0.97, Japanese incomes* = 1.01/2.52
Wool exports to rest of world (WXW)	PFWW^{-}* = -0.20/-0.35, US incomes** = 1.18/2.05
Aust. mutton exports (MX)	mutton domestic-export price differential** = -0.31
Live sheep exports (LSX)	FMP$_{L1}$ = 0.03/0.28

Source; Vere et al. (2000); ** and * denotes significance at the 1% and 5% levels, respectively; the short run and long run elasticities are given as $\in 1/\in 2$, respectively.

Table 2 (cont.)

Dependent variables	Elasticity values for selected explanatory variables ($_L$ denotes lag length)
4. Prices, margins and revenues	
Farm beef price (FBP)	BXP_{L1} = 0.25/1.29
Fine wool price (FFWP)	FWP = 0.59/1.19
Farm mutton price (FMP)	FWP* = 0.14/0.60
Beef price spread (MMBF)	FBP_{L1}** = 0.22
Lamb price spread (MMLB)	RLP* = 0.10/0.28
Pork price spread (MMPK)	FPP_{L1}** = 0.08/0.46
Bacon and ham price spread (MMBH)	FPP_{L1}** = 0.09/1.12
Aust. CIF beef price, US (PBUSC)	US manufacturing beef price** = 0.92
Aust. FOB beef price, Japan (PBJF)	FBP_{L1}** = 0.14/0.77
Aust. FOB beef price, rest of world (PBWF)	FBP_{L1}** = 0.29/0.82
US-New Zealand CIF beef price (PBNZC)	US manufacturing beef price** = 0.72
Aust. FOB wool price, EC (PFWEC)	FWP_{L2}** = 0.11/0.52
Aust. FOB wool price, Japan (PFWJ)	FWP_{L2}** = 0.13/0.63
Aust. FOB wool price, rest of world (PFWW)	FWP_{L2}** = 0.38/0.63
Average mutton export price (PMX)	FMP** = 0.50

Source; Vere et al. (2000); ** and * denotes significance at the 1% and 5% levels, respectively; the short run and long run elasticities are given as $\in 1/\in 2$, respectively.

Table 3. Estimates of forecast bias and RMSE: 1972:1 to 1996:4

	Integrated model		Single model		RMSE ratio
Forecast variable	Estimate of constant [a]	RMSE	Estimate of constant [a]	RMSE	
Production					
Lamb	1.19 (1.47)	8.3	0.67 (0.98)	7.0	0.84
Pork	0.15 (0.34)	4.3	0.25 (0.58)	4.3	1.00
Beef	7.11 (1.70)	42.8	7.14 (1.71)	42.9	1.00
Wool	-8.25 (-6.18)	15.8	-8.25 (-6.18)	15.8	1.00
Mutton	-2.55 (-2.04)	12.8	-2.82 (-2.52)	13.0	1.02
Demand					
Lamb	0.58 (0.75)	7.8	0.15 (0.22)	6.9	0.88
Pork	0.47 (0.89)	5.4	0.30 (0.57)	5.4	1.00
Beef	0.80 (0.36)	22.6	4.41 (2.46)	18.7	0.83
Wool	-0.42 (-0.17)	25.3	-0.43 (-0.17)	25.3	1.00
Mutton	11.58 (9.22)	17.2	11.28 (9.13)	16.8	0.98
Real farm price					
Lamb	-3.52 (-1.49)	24.1	0.78 (0.34)	22.8	0.95
Pork	-1.62 (-0.47)	34.9	0.17 (0.03)	37.1	1.06
Beef	-1.65 (-1.72)	10.7	-1.72 (-1.65)	10.7	1.00
Wool	7.74 (7.74)	42.7	7.74 (1.86)	42.7	1.00
Mutton	1.05 (0.77)	23.2	0.77 (0.36)	23.7	1.02

[a] derived from the regression of the forecast error on a constant; t-statistics are in brackets.

Table 4. Short period RMSE comparisons: 1992:1 to 1996:4

	RMSE of forecast series		
Forecast variable	Integrated model	Individual models	RMSE ratio
Production			
Lamb	4.3	3.4	0.79
Pork	2.0	2.0	1.00
Beef	19.4	19.4	1.00
Wool	4.1	4.1	1.00
Mutton	3.4	3.4	1.00
Demand			
Lamb	4.9	4.1	0.84
Pork	2.6	2.6	1.00
Beef	7.0	7.8	1.11
Wool	9.9	9.9	1.00
Mutton	11.2	10.8	0.96
Real farm price			
Lamb	16.0	12.9	0.81
Pork	10.6	10.5	0.99
Beef	2.7	2.7	1.00
Wool	10.3	10.3	1.00
Mutton	7.6	6.8	0.89

Table 5. Forecast encompassing tests: integrated and single models: 1972:1 to 1996:4 [a]

Forecast variable	Estimates of equation (4) for dependent variable $Y_t - Y_{t-1}$		
	Constant	Integrated model (β estimate)	Single model (γ estimate)
Production			
Lamb	-0.22 (-0.36)	-0.76 (-3.07)	1.58 (5.81)
Pork	-0.001 (-0.02)	-0.05 (-0.04)	0.65 (0.46)
Beef	-3.33 (-0.95)	-5.10 (-0.15)	5.61 (0.16)
Wool	7.91 (1.07)	20.90 (1.65)	-19.96 (-1.57)
Mutton	0.89 (0.67)	4.17 (1.65)	-3.32 (-1.31)
Demand			
Lamb	0.04 (0.08)	-0.62 (-2.17)	1.20 (3.80)
Pork	-0.21 (-0.42)	-0.03 (-0.03)	0.65 (0.76)
Beef	-1.70 (-1.02)	0.19 (1.80)	0.38 (2.71)
Wool	0.26 (0.10)	-75.11 (-0.38)	75.96 (0.38)
Mutton	-2.57 (-2.53)	-3.51 (-2.35)	3.81 (2.52)
Real farm price			
Lamb	0.07 (-0.05)	0.41 (4.48)	0.21 (3.06)
Pork	-0.55 (-0.59)	0.05 (1.90)	0.02 (0.78)
Beef	1.31 (1.25)	0.41 (3.96)	0.72 (4.88)
Wool	-1.97 (-0.81)	0.89 (8.76)	0.19 (3.35)
Mutton	-0.25 (-0.35)	0.73 (4.95)	0.05 (1.69)

[a] estimates of equation (3) for one-quarter-ahead forecasts; t-statistics are in brackets; N = 103.