DISTRIBUTED LAGS AND BARLEY ACREAGE RESPONSE ANALYSIS

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The need to incorporate production response lags in agricultural supply models is established, and two such lags are considered: the familiar adaptive expectations geometric lag, and a more general polynomial lag. These distributed lag supply response models are applied to Australian barley data for the period 1946-47 to 1968-69. A number of statistical problems associated with the adaptive expectations model are discussed, and in particular it is concluded that lags both in the formation of price expectations and in acreage adjustment should be considered when using geometric lag models. While the polynomial lag model does not provide useful results in the present study, its simplicity and flexibility suggest it may be useful in other studies requiring distributed lag models. The short run and long run price elasticity of barley supply estimates are compared with Gruen et al. [14] supply elasticities for the other major rural commodities, from which it appears that barley has a higher short run elasticity but a lower long run elasticity than wheat, wool and meat.

The need for quantitative aggregate agricultural supply response studies has been well established in the literature. Yet there have been relatively few such studies undertaken,[1] not because they are unimportant but mainly because of a number of estimation difficulties. Not least of these problems is the difficulty in formulating the lags in production responses to price changes. It is this problem as applied to the Australian barley industry which is the concern of the present paper.

Supply Response Models

An agricultural supply response model typically has the form

(1) $$Q_t^* = \alpha_0 + \alpha_1 P_t^* + \delta Z_t$$

where Q_t^* = desired output at time t,
P_t^* = expected price level[2] at time t,
Z_t = a surrogate for non-price variables, and
α_0, α_1, and δ = the regression coefficients to be estimated.

The traditional short run supply response model assumes $Q_t^* = Q_t$ and $P_t^* = P_{t-1}$, that is, it assumes farmers fully adjust to their desired output each season according to the price level in the preceding season.

However, the traditional model is often not satisfactory in explaining farmers' supply responses, for two reasons. Firstly, farm product prices

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With the usual *caveat*, thanks are due to Professor Frank Jarrett, Mr Ron Hefford, Mrs Margaret Atkinson and to the referees for helpful comments on an earlier draft.

[1] Among the few aggregate agricultural supply studies undertaken for Australia are Gruen *et al.* [14], Watson and Duloy [33—wheat], the Bureau of Agricultural Economics [4—sheep and wool], White [36—beef] and Mules [25—dairy products].

[2] Conceptually the price level refers to the price of the commodity in question relative to the price of all other products that compete for the same resources and relative to the price of all the inputs used to produce that commodity.

fluctuate considerably from year to year around a longer term trend. Farmers' expectations of future prices are therefore likely to depend not just on immediate past prices but on a number of past seasons' prices,[3] from which the farmers would arrive at an expected price level, P_t^*. Secondly, farming is characterized by near-perfect competition on the output side and 'asset fixity' on the input side. Thus, while farmers are price takers, they cannot always afford to readily adjust in the short term to price changes. This is because the difference between the acquisition and salvage values of many of their capital assets tend to be too great to warrant moving into or out of an enterprise immediately unless substantial and long term price changes occur (Johnson [18]).

It may be argued that the problem of 'asset fixity' is not substantial in the case of barley production in Australia. Most barley growers are primarily wheat growers who already own cereal cropping equipment, and the decision to buy or sell this equipment depends mainly on the returns to wheat. It may thus be a reasonable approximation to say $Q_t^* = Q_t$, that is, that farmers fully adjust their barley output each season to their desired level. The validity of this assumption is considered in the second part of this paper.

Assuming then that $Q_t^* = Q_t$ and ignoring non-price variables for the moment, the supply model (1) can be expressed as the general distributed lag model

$$(2) \qquad Q_t = \sum_{r=o}^{k} \phi_r P_{t-r-1}$$

where k is the number of past seasons' prices which affect output.

Model (2) implies there are $k + 1$ coefficients to be estimated. Often in supply studies k is of such an order that the coefficients of the equation cannot be directly estimated by least squares regression, because (a) too many degrees of freedom are eroded in the estimation from a limited number of seasons' data, and (b) the lagged price variables are likely to be mutually correlated, so making it difficult to estimate their respective parameters (Johnston [19, pp. 201-207]).

Fortunately this estimation problem can be overcome if we are prepared to restrict the form of distribution the lag might take. In his early work on investment Kyock [21] assumed that ϕ has the special form

$$\phi = \beta(1 - \beta)^r \text{ where } 0 < \beta \leqslant 1, \ \beta \text{ constant}$$

Among those who first used this geometrically declining distributed lag structure are Cagan [5], Nerlove [26] and Friedman [11]. Of relevance to the present study is the adaptive expectations model first formulated for agricultural supply analysis by Nerlove, who suggested that

$$P_t^* = \sum_{r=o}^{\infty} \beta(1 - \beta)^r P_{t-r-1},$$

which is equivalent to

$$(3) \qquad P_t^* - P_{t-1}^* = \beta(P_{t-1} - P_{t-1}^*),$$

[3] Farmers' price expectations are also likely to depend on the available market outlook information, but this factor has not been explicitly included in the model.

has the economic interpretation that each year farmers revise the price they expect to prevail in the coming season in proportion to the error they made in predicting price in the preceding season (Nerlove [26, p. 500]. Nerlove called β the 'coefficient of expectation'.

Assuming $Q_t^* = Q_t$, relation (3) can be substituted in (1) to obtain

$$Q_t = \alpha_0\beta + \alpha_1\beta P_{t-1} + (1-\beta)Q_{t-1} + \delta Z_t + (\beta - 1)\,\delta Z_{t-1}$$

or

$$(4) \qquad Q_t = \pi_0 + \pi_1 P_{t-1} + \pi_2 Q_{t-1} + \pi_3 Z_t + \pi_4 Z_{t-1}.$$

This adaptive expectations model has been widely used in agricultural supply studies in the last two decades, mainly because its coefficients are very simple to estimate. Also it is able to provide simultaneous estimates for the short run and long run price elasticities of supply.[4]

There are, however, a number of statistical problems associated with model (4), some of which are discussed below. Furthermore, this specification is rather restrictive. It may be, for example, that following a relative price fall the farmer does not immediately reduce his output of that commodity because he initially considers the price change to be temporary. He may even increase his output in the approaching season to help maintain his farm income (Campbell [6, p. 25]). In other words, output response to a given price change may not decline geometrically through time. A more general distributed lag specification may therefore be desirable.

To obtain a more general distributed lag specification, de Leeuw [8] used a finite inverted V lag as well as the sum of two finite geometric lags. These have different rates of decline and coefficients of opposite sign. Solow [30] suggested that the points on the lag structure lie along a Pascal probability distribution. Later, Jorgenson [20] extended Solow's work by using a class of lag functions described as rational because they could be expressed as the ratio of two finite polynomials in the lag operation. However, Jorgenson's approach still has several limitations (Mackrell [23, p. 11]). In particular, it is not useful if more than one independent variable is to be included in the supply relationship.

Another alternative type of specification is a finite distributed lag whose coefficients are restricted to be on a polynomial of low order. This was first suggested by Almon [1] and modifications have been made by Bischoff [3], Modigliani and Sutch [24] and Tinsley [31]. Hall and Sutch [16] suggested an even more general structure which is both a polynomial and a rational function. Their suggestion provides a more direct way of producing Almon's results, as it avoids using Lagrange interpolation polynomials. Chen, Courtney and Schmitz [7] used this latter model to analyse milk production response in California. They showed that by restricting the lag shape to lie on a quadratic, for example, model (2) can be simply expressed as

$$(5) \qquad Q_t = \theta_1 \sum_{r=o}^{k} (r-k)\, P_{t-r-1} + \theta_2 \sum_{r=o}^{k} (r^2 - k^2) P_{t-r-1},$$

[4] From the estimate of π_1 in model (4) it is possible to estimate the short run elasticity, and from the estimate of π_2 it is possible to estimate β, the 'coefficient of expectations'. Hence it is possible to obtain an estimate of α_1 of model (1), from which a long run elasticity estimate can be obtained. Also, Griliches [13, p. 19] has shown that the mean lag is given by $(1-\beta)/\beta$.

which has only two weighted price variables for which coefficients are to be estimated, namely

$$W_1 = \sum_{r=o}^{k} (r - k) P_{t-r-1} \quad \text{and} \quad W_2 = \sum_{r=o}^{k} (r^2 - k^2) P_{t-r-1}.$$

This quadratic formulation can be readily extended to an n^{th} order polynomial. For estimation purposes it is also possible to add non-price variables such as Z_t. Moreover a price elasticity of supply can be estimated for each time period as well as for the entire response period considered. In other words, not only do these polynomial lag models provide short run and long run elasticity estimates, but also elasticity estimates for desired lengths of 'intermediate run' (Chen, Courtney and Schmitz [7]).

Empirical Results

Both the geometric and the polynomial lag models were fitted to aggregate data relating to the Australian barley industry. The time series chosen for analysis is the post-war period 1946-47 to 1968-69, prior to the introduction of wheat delivery quotas in Australia. The response variable chosen was barley acreage rather than production, because production statistics include seasonal influences which cloud the land-use response to price change.[5] Numerous exogenous variables were experimented with in a preliminary analysis, as detailed in Anderson [2]. Eventually it was decided that the most significant price variable is either (a) barley price alone or (b) barley price relative to wheat price, while the most significant surrogate for technological and institutional factors encouraging land development in Australia is the area of land used for crops, fallow and sown pastures and clovers.[6]

Geometric lag results

When the adaptive expectations model (4) was applied to the data, it was found that the ordinary least squares regression estimates of the coefficients of Z_t and Z_{t-1} were insignificantly different from zero, and their inclusion led to poorer representations of the data than those obtained from the simpler model

$$Q_t = \pi_0 + \pi_1 P_{t-1} + \pi_2 Q_{t-1},$$

[5] One implication of using acreage as a response variable is that the resulting estimated price elasticities of acreage response are likely to understate the output responsiveness of growers to price changes, because the elasticity of response of yield per acre to price changes is likely to be positive. This is empirically supported by the results of a study of New Zealand wheat yield response by Guise [15]. Moreover, Tweeten and Quance [32] have suggested from their empirical findings for the United States that the yield elasticity may be even greater than the acreage elasticity.

[6] Prices are not deflated. The barley price variable used was the first advance paid on delivery by the Australian Barley Board, net of freight for No. 1 two-row malting barley. The wheat price variable used was the average total return to growers per bushel f.o.r. for deliveries to the Australian Wheat Board. This was considered more appropriate than the first advance since, unlike for barley, the first advance for wheat has not reflected the average return to growers, at least since the late 1950s when it remained unchanged for 16 years. The previous Australian Government's taxation concessions and investment incentives for farmers, together with improved agricultural technology and the wheat price stabilization scheme, have encouraged rapid and widespread post-war development and improvement of arable land throughout the temperate and higher rainfall areas of Australia.

the results for which are reported in the first five columns of Table 1. The last four columns of Table 1 show the derived estimates of the 'coefficient of expectation' β, the mean lag, and the short run and long run elasticity estimates at the mean price and acreage.

The results of Table 1 appear to be quite significant. Before they are further interpreted, however, it is necessary to consider a number of statistical problems inherent in the adaptive expectations model. Two possible misspecification problems in particular are considered here, relating to (a) lags in the formation of price expectations and (b) lags in acreage adjustment.[7]

(a) *Lags in the formation of price expectations*

The apparently significant results of Table 1 suggest that farmers do base their price expectations on a number of previous seasons' prices. The much less significant results obtained in estimating the static model lend further support to the suggestion of lags in the formation of farmers' price expectations. Using barley price alone, for example, the static model provided the following result, which is highly serially correlated according to the d-statistic even though the time-trending technology surrogate is included:

$$Q_t = -206{\cdot}1 + \underset{(1{\cdot}18)}{7{\cdot}554\, P_{t-1}} + \underset{(5{\cdot}03)^{a}}{2{\cdot}399\, Z_t} \qquad \begin{array}{l} R^2 = 0{\cdot}713 \\ d = 0{\cdot}39 \end{array}$$

However, Griliches [12, p. 70] has shown that if the true equation is of the simpler form immediately above, which can be reduced without loss of generality to

$$(6) \qquad Q_t = \alpha_1 P_{t-1} + u_t,$$

and if the disturbance term u_t follows a first autoregressive structure such that

$$u_t = \rho\, u_{t-1} + e_t,$$

and the distributed lag model

$$(7) \qquad Q_t = \pi_1 P_{t-1} + \pi_2 Q_{t-1} + v_t$$

is estimated, introducing the irrelevant Q_{t-1}, then significant and sensible coefficients usually result and reduce the serial correlation in the estimated residuals of (7). But this may be because Q_{t-1} in (7) is acting as a surrogate for u_{t-1} in what may be the truer model (6). And in highly positively autocorrelated cases, ρ will be a significant coefficient and so the estimated coefficient of Q_{t-1} may appear to be positive and significant even though model (7) is wrong. Furthermore, it is for this reason that the usual Durbin-Watson test for serial correlation is inappropriate for models including a lagged dependent variable as an

[7] Another very important statistical problem associated with the geometric lag model is that its estimation using ordinary least squares regression may lead to biased and inconsistent estimates unless the disturbance term u_t is positively serially correlated, with the correlation between u_t and u_{t-1} being $1-\beta$ (Nerlove [27, p. 193]). Liviatan [22] suggested an estimation method which does not depend on any specific assumption about the structure of the disturbance term. This method was tried in the present study, but the estimates were statistically insignificant (Anderson [2]). Some alternative estimation methods not tried in the present study are detailed in a recent book by Dhrymes [9].

TABLE 1

Adaptive Expectations Model Estimates of Barley Acreage Response, Australia, 1946-47 to 1968-69

	Regression coefficients							Elasticities at the means	
	Intercept	Lagged price	Lagged acreage	R^2	d	β	Mean lag (years)	Short run	Long run
(ii) Barley price	—210·2	7·704 (2·15)[a]	0·8880 (10·42)[a]	0·899	1·60	0·112	7·9	0·276	2·465
(ii) Barley price/ Wheat price	—434·4	1254 (1·81)[a]	0·9401 (11·85)[a]	0·893	1·71	0·060	15·7	0·345	5·757

[a] Statistically significant at the 5 per cent level (t values in parentheses).

explanatory variable; there is always a greater likelihood of autocorrelation in autogressive models than the d-statistic test would suggest (Nerlove and Wallis [28]).[8]

It is therefore necessary to test against the possibility of price lag misspecification, even though there are strong *a priori* reasons for expecting lags.

If model (6) does have a first order positively autocorrelated error structure, then by substituting this structure and

$$u_{t-1} = Q_{t-1} - \alpha_1 Pt_{-2}$$

into (6), the following is obtained:

$$(8) \qquad Q_t = \alpha_1 P_{t-1} + \rho Q_{t-1} - \alpha_1 \rho P_{t-2} + e_t,$$

To test which of (6) and (7) is the truer model, relation (8) was estimated to see if the estimated coefficient of P_{t-2} is negative and significant and approximately equal to $-\alpha_1\rho$. The results obtained were as follows:

(i) Using barley price alone:

$$Q_t = -199{\cdot}4 + \underset{(1{\cdot}79)}{8{\cdot}313P_{t-1}} + \underset{(9{\cdot}18)^a}{0{\cdot}8974Q_{t-1}} - \underset{(0{\cdot}22)}{1{\cdot}048P_{t-2}}, \quad R^2 = 0{\cdot}899, \quad d = 1{\cdot}59$$

where $\hat{\alpha}_1\hat{\rho} = 7{\cdot}46$, which does not approximate $\hat{\alpha_1\rho} = 1{\cdot}048$, and

(ii) Using barley price relative to wheat price:

$$Q_t = -383{\cdot}7 + \underset{(1{\cdot}69)}{1380P_{t-1}} + \underset{(11{\cdot}55)^a}{0{\cdot}9388Q_{t-1}} - \underset{(0{\cdot}31)}{215{\cdot}8P_{t-2}}, \quad R^2 = 0{\cdot}893, \quad d = 1{\cdot}69$$

where $\hat{\alpha}_1\hat{\rho} = 1296$, which does not approximate $\hat{\alpha_1\rho} = 215{\cdot}8$.
Therefore the traditional static model is rejected in preference to the distributed lag specification implicit in the adaptive expectations model.

(b) *Lags in acreage adjustment*

The results of Table 1 are based on the assumption that $Q_t^* = Q_t$, that is, that farmers fully adjust their barley acreages each season to their desired level. This assumption is unlikely to be completely realistic, however. A farmer may, for example, not be able to expand his grain acreage as much as he would like to during the present period of high grain prices, perhaps because he cannot afford to buy the bigger machinery necessary. Next year, however, his wheat and wool cheques may be sufficient to overcome this capital constraint, and he could then expand his grain acreage further. These lags in acreage adjustment may be large enough to require inclusion in the supply response model. Nerlove [27] suggested the adjustment lag might have the following nature:

$$(9) \qquad Q_t - Q_{t-1} = \gamma(Q_t^* - Q_{t-1}) \;\; 0 < \gamma \leqslant 1, \; \gamma \text{ constant},$$

which implies that a change in actual output from one year to the next

[8] Recently Durbin [10] suggested a more appropriate test for serial correlation in autoregressive models, but it is only valid in the large sample case. As well as providing biased and inconsistent estimates, autocorrelated results also underestimate the sampling errors of the coefficient estimates. This leads to overestimated t-values, so the usual t-test indicates a greater degree of significance than is actually present (Johnson [19, p. 179]).

is only a proportion of the difference between desired output and last year's actual output. Nerlove called γ the 'coefficient of adjustment'.

If (9) is substituted into model (1) and it is assumed that the previous year's price level is the expected level this year ($P_t^* = P_{t-1}$) then a model similar to the adaptive expectations model (4) is obtained, except with Z_{t-1} excluded. This has come to be known as the 'partial adjustment' model. Thus the autoregressive model (4) with Z_t and Z_{t-1} omitted is open to a dual interpretation, depending on whether it is assumed that $0 < \beta \leqslant 1$ and $Q_t^* = Q_t$, so that $\gamma = 1$ (adaptive expectations), or $0 < \gamma \leqslant 1$ and $P_t^* = P_{t-1}$, so that $\beta = 1$ (partial adjustment).

Generally both sources of lag exist. When both are incorporated in model (1) and Z is omitted for simplicity, the following 'expectations and adjustment' model is obtained:

$$(10) \qquad Q_t = \mu_0 + \mu_1 P_{t-1} + \mu_2 Q_{t-1}, + \mu_3 Q_{t-2},$$

from which it can be shown that

$$\beta, \gamma = (2 - \mu_2 \pm \sqrt{\mu_2^2 - 4\,\mu_3})/2$$

Since β and γ enter symmetrically, it is only possible to distinguish between them on *a priori* grounds. In this study β is chosen as the smaller of the two because, as explained above, lags in the formation of barley price expectations are considered to be larger than lags in acreage adjustment.

Waud [34, 35] discusses the implications of using the adaptive expectations model (or the partial adjustment model) when in fact the expanded expectations and adjustment model is the correct formulation. He has shown that for the large sample case, the use of the former model when the latter is the truer model leads to: (a) serious bias in the least squares estimates of the regression coefficients; (b) a noticeable increase in the size of the estimated standard errors relative to the estimated regression coefficients as the coefficient of adjustment, γ (or the coefficient of expectation, β) gets further away from its erroneously assumed value of 1; and (c) a very serious downward bias in the estimate for β (or γ) and hence an upward bias in the estimate of the mean lag, which becomes extremely severe as γ (or β) gets smaller. The situation would be even less satisfactory for small sample cases such as in the present study.

For these reasons it is necessary when using either the adaptive expectations or partial adjustment model to be confident that the expanded expectations and adjustment model is not more appropriate. In the present case when the latter model was used, Z_t and Z_{t-1} were again insignificant, so the truncated model (10) was estimated and the results are reported in Table 2.

It would appear from Table 2 that the acreage variable lagged two seasons is insignificantly different from zero at the 5 per cent level, and the fit of the regressions as measured by R^2 has not improved over the results of Table 1. Also, the significance of the regression coefficients of all other variables in Table 2 is less than in Table 1. However, as Waud has warned, the estimates of β from the expectations and adjustment model are greater than from the adaptive expectations model, and the mean

TABLE 2

Expectations and Adjustment Model Estimates of Barley Acreage Response, Australia, 1946-47 to 1968-69

	Regression coefficients				R^2	d	β	γ	Mean lag (years)	Elasticities at the means	
	Intercept	Lagged price	Acreage lagged 1 year	Acreage lagged 2 years						Short run	Long run
(i) Barley price	—213·0	7·718 (2·10)[a]	0·9341 (3·69)[a]	—0·04738 (0·19)	0·899	1·68	0·191	0·875	4·4	0·277	1·450
(ii) Barley price/ Wheat price	—434·0	1252 (1·76)[a]	0·9515 (3·66)[a]	—0·1160 (0·05)	0·893	1·73	0·192	0·856	4·4	0·341	2·096

[a] Statistically significant at the 5 per cent level (t values in parentheses).

lags[9] are correspondingly shorter. Moreover, the long run elasticity estimates are considerably lower in the expectations and adjustment case, because they are specified to be inversely proportional to β.[10]

These results illustrate the need to use the expanded expectations and adjustment model even when there are strong *a priori* grounds for assuming $\gamma = 1$. In the present case, for example, even though the estimates for γ from the expanded model are greater than 0·85, the long run elasticity estimates are about half those obtained from the adaptive expectations models.

The above results have all been based on the assumption that the lags in acreage adjustment to price changes follow a geometrically declining pattern. The more general polynomial lag model does not make such a restrictive assumption about the shape of the lag distribution.

Polynomial lag results

Both the quadratic and the cubic polynomial lag models were applied to the barley data. However, the problems of autocorrelated results could not be satisfactorily overcome, so the estimates are not detailed here.[11] The results suggested two points which are relevant to this discussion. Firstly, none of the polynomial elasticity estimates approximated anything like a geometric decline through time. While this provides no statistical grounds for rejecting the hypothesis that acreage response to price changes declines geometrically through time, it does cast some doubt on the validity of this hypothesis. Secondly, because the polynomial lag model is relatively simple to estimate and interpret, and because it allows a flexible shape to the lag distribution, it is worthy of consideration in other studies involving distributed lag models where the problems of autocorrelated residuals can be better overcome than in the present study. It is likely to be particularly appropriate in models using quarterly or monthly data for which the restrictive assumption of a geometrically declining lag structure does not conform with *a priori* reasoning.

Discussion of Results

Since the polynomial lag models have not provided useful results for the purposes of this study we revert back to the expectations and adjustment geometric lag model results of Table 2.

The results using the barley price variable are only slightly more significant than those using the barley price relative to wheat price variable, and the estimates of β (about 0·19), γ (about 0·86) and the mean lag (4·4 years) are almost the same whichever variable is used.

The elasticity estimates differ substantially, however, because the use of a ratio variable in a supply response function has at least two implications. Firstly, the supply elasticity evaluated at given values of the ratio variable is the same with respect to the ratio as with respect

[9] Griliches [13, p. 38] has shown the mean lag for the expectations and adjustment model to be $1/\beta + 1/\gamma - 2$.

[10] Since the short run elasticity is obtained from μ, and the long run elasticity is obtained from $\alpha_1 = \mu_1/\beta$, then the long run elasticity is given by the short run elasticity divided by β.

[11] A detailed discussion of the polynomial results is given in Anderson [2, pp. 54-64].

to the numerator. But in that the ratio variable includes in effect two variables, it would be likely to provide more realistic estimates than would a model using only the barley price variable. This is because the *ceterus paribus* assumptions implicit in the estimation of elasticities are less restrictive in the ratio case. Secondly, the use of a ratio assumes that the elasticity of supply with respect to equi-proportional changes in the prices of both products is zero. This assumption is quite sound for general price changes caused by phenomena such as inflation. It is not so sound for more specific price changes. For example, a world shortage of grains could cause the prices of both barley and wheat to increase in Australia. If farmers were previously cropping less than their maximum arable acreages, then they may increase their areas sown to grains in response to the high grain prices. Yet the ratio of barley price to wheat price would not have altered. For this reason the price ratio series understates the extent of price changes to which growers have responded. Thus the estimated price ratio regression coefficients and hence the elasticity estimates obtained using a price ratio would tend to be biased upwards.

Thus while on the one hand the ratio variable results are based on less restrictive assumptions, on the other hand they tend to be biased. The true values of the elasticities are likely to be between the two sets of estimates, that is, between 0·28 and 0·35 in the short run and between 1·5 and 2·1 in the long run.

These estimates are not inconsistent with the only other comparable estimates known to the author, namely those by Gruen *et al.* [14][12]. Gruen's elasticity estimates for the aggregate coarse grains group were 0·21 for the short run and 1·5 for the long run. An earlier short run estimate was reported as 0·28, following which it was stated that 'one can speculate with reasonable safety that the individual aggregands —oats, barley and maize—would possess even higher own price elasticities' (Powell and Gruen [29, p. 199]). The basis for such speculation is that there are substitution possibilities between the different coarse grains; while a small drop in the price of barley may cause growers to sow less barley, the resulting unutilized resources may be put to oats, for example, so leaving the total output of coarse grains unaltered.

The present study's elasticity estimates for barley can be compared with Gruen *et al.*'s elasticity estimates for the major Australian rural commodities [14, p. 178]. Their short run price elasticity of supply estimates for the major commodities wheat, wool and meat are considerably lower than for the relatively minor barley industry. This is to be expected since it is more difficult for farmers to switch from one form of animal production to another or from animal production to crop production in the short run. Also, Australian conditions are generally well suited to wheat and livestock production, whereas the more exacting climatic conditions required for barley restrict its production to fewer areas. Furthermore, the areas well suited to barley are also well suited to wheat, so that small changes in relative prices induce comparatively large barley acreage changes from season to season.

[12] Gruen *et al.*'s study made use of Nerlove's geometric lag model, but modified it for use in a 6-sector simultaneous equations approach to Australian agriculture. In it they parametrically specified various values for β, and implicitly estimated γ. This differed from the present approach where both β and γ are implicitly estimated when obtaining the elasticity estimates for barley.

Gruen's long run elasticity estimates, on the other hand, are larger for the major commodities than for barley.[13] These estimates suggest that growers adjust their barley acreages more rapidly than they adjust their wheat and livestock production in response to price changes. Certainly one would expect slower adjustment in aggregate wool and meat production, because of the large capital requirements of livestock production (shearing sheds, fences, water) and the slowness with which livestock numbers can be increased through breeding. The larger long run elasticity for wheat compared with barley can be explained by the fact that many barley growers are primarily wheat growers. They therefore base their decisions to buy or sell their cereal cropping equipment such as a harvester mainly on their price expectations for wheat. In this sense the capital requirements for wheat production may be considered by farmers to be larger than the capital requirements for barley production, so making for a larger long run wheat supply elasticity.

Summary and Conclusions

The need to use distributed lags in agricultural supply response models has been established in the first part of the paper. It has been shown empirically that the familiar adaptive expectations geometric lag model can provide long run elasticity estimates which are biased upwards. Therefore, even when there are strong *a priori* reasons for expecting lags only in price expectations and not in acreage adjustment, as is the case for barley, the expanded expectations and adjustment model is to be preferred to the simpler adaptive expectations model.

However, both these models implicitly assume the lags follow a geometric decline through time. While this may be a reasonable assumption for annual crops such as barley, a more general lag specification may be desirable. The polynomial lag model provides one such structure, although it does not yield useful results for the purposes of the present study. It does, however, deserve consideration in other studies involving distributed lags, especially where quarterly or monthly data are used, for which the restrictive assumption of a geometrically declining lag structure may not conform with *a priori* reasoning.

The elasticity estimates obtained from the expectations and adjustment model suggest that barley acreages in Australia are quite responsive to the relative prices of barley and wheat, especially in the short run. The estimated short run price elasticity of supply for barley is higher than for wheat, wool and meat, while the long run elasticity estimate for barley would appear to be lower than for the other major commodities.

[13] However, Powell and Gruen [29] have expressed considerable doubt as to the validity of their long run elasticity estimates, and have shown them to be extremely sensitive to model specification. For example. a change in the specified value of β from 0·4 to 0·7 caused the long run wool supply elasticity estimate to change from 1·4 to 3·6. Also, Gruen *et al.*'s long run estimates are considerably higher than those obtained from other agricultural supply studies of industrialized countries (see, for example, Johnson [17, pp. 112-113]).

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