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Modelling agricultural land use allocation in regional Australia*

Eddie Oczkowski and Yapa Bandara†

An analysis of the drivers of agricultural land use is important for policy makers as the issues of climate change and food security become increasingly prominent in the political landscape. This paper analyses the role of prices, total land holdings and climate on land use in Australia. The analysis relates to a unique comprehensive coverage of commodity types at a regional level. An explicit treatment of missing data and the novel use of cluster analysis is employed within a partial adjustment framework for modelling land allocation. The majority of commodity types across regions exhibit significant degrees of slow partial adjustment for land allocation, the frequency of slow adjustment is greatest with crops and livestock and weakest for vegetables. In general, relative own and cross prices, total land holdings and rainfall only have a minor impact on short-term land allocations, however numerous individual commodity/regional combinations have identified significant short-run impacts.

Key words: horticulture, land use & tenure, livestock, supply analysis.

1. Introduction

A thorough understanding of the use of rural land is becoming increasingly important in both Australia and worldwide as the potential impact of global climate change and issues of food security are given greater attention by policy makers. The issue of what determines the allocation of land among competing uses requires a detailed analysis to facilitate better informed policy making. The objective of this paper is to report on an econometric analysis of the key drivers of agricultural rural use in Australia, at a detailed commodity and regional level. The econometric estimation of acreage response elasticities with regard to prices, land holdings and rainfall, will describe to what extent and how agricultural land allocation is determined by these economic and climatic influences. It transpires that the nature of the involved production processes and institutional characteristics of the Australian context necessitates the use of the partial adjustment model (PAM) of Nerlove (1958) as the principal empirical framework to account for the various adjustment lags which impact on the land allocation process.

In Australia, extensive research into supply response of broadacre agriculture focussing upon a limited number of major livestock and cropping

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† Eddie Oczkowski (email: eoczkowski@csu.edu.au) and Yapa Bandara are at School of Accounting and Finance, Charles Sturt University, Wagga Wagga, NSW, Australia

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categories has been undertaken (Griffith *et al*. 2001), and even though one can identify a number of detailed studies on other individual commodities, no comprehensive systematic study of agricultural supply response at the regional level for other crops, fruits and vegetables has been recently undertaken in Australia. The purpose of the paper is to help fill this gap and provide a broad regional and commodity detailed analysis of land allocation.

The paper considers the analysis of over 50,000 land allocation data points to facilitate the examination of land-use allocation relating to 64 commodity types, 58 Australian regional statistical divisions (SD) and 24 years of annual data. The size and detailed coverage of the data indicates the substantial contribution of the analysis described in this paper. Moreover, the nature of the data requires the explicit recognition of missing data and the novel use of cluster analysis to find a suitable level of aggregation. In the next section, we outline the theoretical and econometric framework for analysing land allocation; section three describes the data development required for the analysis, while the results and discussion follow thereafter.

2. Theoretical and econometric framework

The profit-maximising theoretical framework for agricultural land allocation models (Chambers and Just 1989) employs a multi-output production system which assumes that farmers allocate land to the production of m commodities by maximising a profit function $\pi(.)$ subject to a fixed amount of land $\bar{z}$:

$$\max_{z_i} \pi(p, w, z) : s.t. \sum_{i=1}^{m} z_i = \bar{z} \tag{1}$$

where p and w are vectors of (expected) output and input prices, respectively, z is a vector of land allocations, and π (.) is assumed to be linearly homogenous and convex in p and w, increasing in p, decreasing in w and increasing and concave in z. The first-order conditions for profit maximisation imply that the marginal profit with respect to land allocation should be equal across all commodities:

$$\frac{\partial \pi(p, w, z)}{\partial z_i} = \frac{\partial \pi(p, w, z)}{\partial z_j} \quad i,j = 1, \ldots m \tag{2}$$

These first-order conditions result in optimal land allocation functions of the form:

$$z_i^* = z_i(p, w, \bar{z}) \quad i = 1, \ldots m \tag{3}$$

that is, optimal land allocations (z_i^*) are a function of all (expected) output prices, input prices and the fixed quantity of available land. Equation (3) holds in the general case where there is jointness in production input technology, but it also holds in the case of input nonjointness through the existence of an allocatable fixed factor such as land, see Shumway *et al.* (1984).

Given normal inputs then z_i^* is increasing in own price and given the concavity of $\pi(.)$ with respect to z then z_i^* is increasing in $\bar{z}$. However, the relation with cross-prices depends on the nature of the jointness of production. For normal inputs, z_i^* is complementary for other prices (increasing in p_j) for production jointness and is competing for other prices (decreasing in p_j) for production nonjointness. Intuitively, cross-price complementarity arises in the jointness case given that the increased use of one input tends to increase the marginal productivity of other inputs. While for the case of production nonjointness, if the price of a commodity increases, then the land allocation to that commodity increases and given no production complementary incentives to increase allocation to other commodities, then the land constraint implies that land allocation to other commodities falls.

Following Moore and Negri (1992) if a flexible normalised quadratic profit function is specified for Equation (1), then optimal land allocation functions are linear. If a single input price index is employed to represent all input prices and is used to normalise output prices, then we have for each commodity:

$$z_t^* = \beta_0 + \beta_1' p_{t-1}^r + \beta_2 \bar{z}_t \tag{4}$$

where the βs represent suitably conformed parameters and p^r is a vector of relative (to input) output prices, and consistent with preliminary modelling results and previous agricultural supply response models, one period lags in relative prices are employed for expected prices.

An approach commonly employed for systems of net-output equations, similar to Equation (4), is to impose the regularity restrictions of homogeneity, monotonicity, curvature and symmetry implied by the profit-maximising framework. This approach has been employed for Western Australian broadacre agriculture by Coelli (1996), Ahammad and Islam (2004) and Xayavong *et al.* (2011).[1] We attempted to employ a restricted seemingly unrelated regressions estimator (SURE) for Equation (4) but without success. Our desire to maintain the data richness of small regions and individual commodity types and to permit the exploration of numerous substitution/complementarity possibilities resulted in significant estimation convergence problems, due to the lack of degrees of freedom. As demonstrated by previous studies, to successfully implement a regularity imposed restricted SURE approach, data pooling across regions and commodity types

[1] These previous and other Australian studies estimate systems of net output functions (supply and input demand) and hence use quantity measures as dependent variables, this contrasts to the (our) land allocation functions which use acreage measures as dependent variables. This makes comparison with previous Australian studies and approaches slightly less relevant.

appears to be necessary.[2] As a consequence of our desire to maintain data richness and broad regional/commodity coverage, we shall employ an unrestricted approach in estimating acreage response equations.

3. Data description and development

The primary data source for land allocation and price data is the annual Australian Bureau of Statistics (ABS) Agricultural Survey/Census, see Appendix 1 for precise definitions and data sources. We use and extend the National Land and Water Resources Audit (2001) to access a spatially consistent database of land allocations[3] covering the period 1982/3 to 2005/6. Land allocation data relating to 1970 region/commodity combinations were considered for analysis. Unfortunately, data on the value of agricultural commodities produced are only available on a consistent time series basis at a state-wide level, while input prices are only consistently available at a national level through the Australian Bureau of Agricultural and Resource Economics (ABARE).

Given the survey scope variability, missing data are a natural consequence of developing a consistent time series dataset for land allocations. As a first pass through the data, a time series for a SD/commodity combination was discarded if it contained more than 25 per cent missing observations (Hair *et al.* 2006). This deletion resulted in 1773 region/commodity combinations covering 58 SDs and 46 commodities. It transpired that even with this reduction, numerous reported land allocations were particularly small in size (mean annual land allocations were <1000 m^2) which led to problems with the modelling analysis, that is, the variability of data becomes extreme with very small land allocations. The task was to establish an appropriate level of aggregation through the use of cluster analysis, not too thin to make model estimation problematic and not too thick so as to lose the potential diversity of different regions.

3.1. Cluster analysis and aggregation

The starting point for conducting a cluster analysis is to identify broad geographically similar regions. A natural broad initial division is that

[2] One can point to a number of land allocation studies which do not impose all theoretical restrictions. The use of such restrictions is also not without criticism. Shumway (1995) discusses the experience of North American agriculture and finds some significant variance between the empirics and theory. Babcock (1999) summarises a debate about this conflict and makes the point that 'we should not expect empirical support for straightforward applications of the standard theory of the firm' (Babcock 1999, p. 720). Various reasons are offered for this conflict, including data aggregation, an inappropriate short-run profit maximising objective, incomplete markets and the presence of risk.

[3] For livestock and orchard grown products, a conversion to hectare equivalence was needed. For a very small minority of regions, the need to convert the number of meat cattle to land used together with the associated approximations, resulted in the summed total employed area exceeding the survey reported total holdings, for some years.

provided by state boundaries. As clustering variates, we employ the time series sample means (of nonmissing data) for all commodities. The aim is to combine areas that are similar in their land allocation profiles. A two-step cluster analysis was performed which combines hierarchical and nonhierarchical algorithms (Punj and Stewart 1983), and we employ the Calinski and Harabasz (1974) index to choose the optimal number of clusters for each state.

The analysis suggests the following optimal number of clusters: New South Wales (NSW), six clusters from 12 SDs; Victoria (Vic), five from 11; Queensland (Qld), six from 11; South Australia (SA), six from seven; Western Australia (WA), five from nine; and Tas, two from four. Given the very small size of collected reported land allocations in NT and ACT, each territory combines two SDs into one cluster. The regional clusters are defined in Table 1.

All the regions combined by the clusters represent physically adjacent parcels of land, only three exceptions exist: Qld#3, WA#1 and Tas#1. We shall make comment on the land-use profiles of the clusters in regard to three naturally occurring commodity groupings of, crops & livestock, fruit and vegetables, which are used in modelling. Land use for crops & livestock clearly dominates over fruit and vegetables across the clusters. For crops & livestock, meat cattle and sheep & lambs are the two most dominant users of land in all clusters except a few. For fruit, there is significant variability in dominant land use, in terms of the two largest land uses in each cluster, grapes is important in 23 of the 32 clusters, followed by apples (11), mangoes (6) and oranges (5). Some clear location dominance exists with grapes being dominant in SA, apples in Tas and mangoes and bananas in northern parts of Australia. For vegetables, like fruit there is significant variability, land use for potatoes is the largest being among the two most dominant uses for 21 clusters, followed by pumpkins, etc. (8), carrots (7) and lettuce (4). In terms of location, potatoes clearly dominate in NSW and SA, beans have some importance in the northern half of Qld, and peas are important in Tas.

3.2. Missing data

Given the cluster analysis aggregation, the next task is to account for the remaining missing values in the identified clusters It is generally agreed that 'model-based' approaches rather than ad-hoc approaches such as interpolation or mean imputation are the most suitable for analysing incomplete datasets, see for example Hair *et al*. (2006). These approaches make use of the proposed model specification to either estimate the model directly or impute values for missing observations. We employ the AMOS program (Arbuckle 2008) and regression imputation. Initially, the specified model with missing data is estimated by Full Information Maximum Likelihood, the estimated parameters are used in the model, and regression is employed to predict values for the missing cases.

Table 1 Regional clusters: definitions

Cluster No.	Name	Statistical divisions
New South Wales	NSW	
1	Coastal	Sydney, Hunter, Illawarra, Richmond-Tweed, Mid-North Coast
2	Northern	Northern
3	Central & North Western	North Western, Central West
4	Southern & Eastern	South Eastern, Murrumbidgee
5	Murray	Murray
6	Far West	Far West
Victoria	Vic	
1	Eastern	Melbourne, Ovens & Murray, East Gippsland, Gippsland
2	Central & Southern	Barwon, Central Highlands, Loddon, Goulburn
3	Western District	Western District
4	Wimmera	Wimmera
5	Mallee	Mallee
Queensland	Qld	
1	South East	Brisbane, Moreton
2	North West & Mackay	Mackay, North West
3	North & Wide Bay	Wide Bay-Burnett, Northern, Far North
4	Darling Downs	Darling Downs
5	South & Central West	South West, Central West
6	Fitzroy	Fitzroy
South Australia	SA	
1	Adelaide	Adelaide
2	Outer Adelaide & Murray	Outer Adelaide, Murray Lands
3	Yorke & Lower North	Yorke & Lower North
4	South Eastern	South Eastern
5	Eyre	Eyre
6	Northern	Northern
Western Australia	WA	
1	Perth & Pilbara	Perth, Pilbara
2	South West	South West
3	Southern	Lower Great Southern, Upper Great Southern, Midlands
4	Central & South East	South Eastern, Central
5	Kimberley	Kimberley
Tasmania	Tas	
1	Hobart & North West	Hobart, Mersey-Lyell
2	Northern & Southern	Northern, Southern
Northern Territory	NT	
1	Northern Territory	Darwin, NT – Balance
Australian Capital Territory	ACT	
1	Australian Capital Territory	Canberra, ACT – Balance

Regression imputation is employed using Equation (4) for each individual cluster region/commodity combination. Given that the dataset comprises of 46 commodity types, then to operationalise the imputation, some assumption is needed to limit the number of other relative prices. We broke up the commodities into three natural groups within which cross-price effects are more likely to occur: (i) crops and livestock (17 commodities), (ii) fruit (18 commodities) and (iii) vegetables (11 commodities). Equation (4) is estimated for each individual time series using these subgroups to define the relevant cross-price effects. This approach still leads to the use of numerous regressors which are typically highly correlated. Given that the focus is on imputing missing data, then the emphasis rests with prediction, and hence, high degrees of multicollinearity are not of concern.

The pattern of the missing data was reasonably similar across the sates with the percentage of missing observations ranging from 3.7 per cent for Tasmania to 7.1 per cent for Queensland. For the three major commodity groups, the percentage of missing observations was 2.5 per cent for crops and livestock, 6.8 per cent for fruit and 9.3 per cent for vegetables. The regression imputation resulted in a small number of negative observations, 0.8 per cent of all observations. Experimentation with the Bayesian censored option in AMOS proved to be unsuccessful (nonconvergence) given the smallness of the sample size and the large number of regressors. As a consequence, all imputed negative values were set to zero to ensure some consistency with data theoretical expectations, given the small fraction of these cases, any impact of modelling results is negligible.

3.3. Preliminary modelling

An important exogenous influence outside the structure of the model defined by Equations (1–4) is the impact of climate variability and water availability on land allocation. Unfortunately, no systematic data collection of agricultural water use occurred in Australia over the time period of consideration. As such proxies for the uptake of water such as average temperature and rainfall information were employed in preliminary modelling. More success was achieved with average rainfall data, and a one period lagged form is included as an additional regressor in the final modelling.

Initial diagnostic testing indicated significant problems with standard issues such as specification error and auto-correlation, in part, this may be due to the lack of any dynamics in the proposed model. As a consequence, the PAM is adopted. There are many reasons for expecting partial adjustment in the Australian agricultural land allocation context. In general, as argued by Nerlove (1958), most livestock and perennial crops involve a biologically long production process, where the time between initial land use and ultimate commercial output takes a number of years. The principle also applies to annual crops if long-lived capital equipment or land improvements are required for production. The costs of input adjustment also impact upon the allocation process and involve costs relating search, relocation and reorganisation.

In the Australian horticulture context, Proctor *et al.* (1992) point to the perennial nature of most fruit crops, the lingering impact of former restrictive marketing arrangements and institutional arrangements such as water quotas, restrictions on farm size and the transferability of water rights. Relatedly, the widespread use of long-term contracts in Australian agricultural marketing for crops such as wine grapes (Fraser 2005) implies that there may be less flexibility to adjust inputs quickly in response to unexpected shocks to new optimal levels.

We employ the PAM to specify that actual land allocations may only partially adjust to desired allocations according to:

$$\Delta z_t = \lambda(z_t^* - z_{t-1}) \tag{5}$$

Combining Equations (4) (with an additional rainfall variable (r)) and Equations (5) and adding a classical error term (u) gives:

$$z_t = \alpha_0 + \alpha_1' p_{t-1}^r + \alpha_2 \bar{z}_t + \alpha_3 z_{t-1} + \alpha_4 r_{t-1} + u_t \tag{6}$$

where the adjustment coefficient is given by: $\lambda = 1 - \alpha_3$ and the speed of adjustment given by $1/\lambda$, indicates the fraction of adjustment in one period. The multipliers for p_{t-1}^r, $\bar{z}_t$ and r_{t-1} are α_1', α_2 and α_4 in the short run and α_1'/λ, α_2/λ and α_4/λ in the long run, respectively.

Given the existence of many highly correlated cross-relative price variables, some strategy for reducing the impact of multicollinearity on the estimated models is required. A stepwise procedure which forced the entry of the lagged area, own price, total holdings and rainfall variables, but included cross-price effects only if they were significant at a 5 per cent level proved to be a useful strategy. The use of the PAM and the stepwise procedure significantly reduced the initially identified specification error and auto-correlation problems and substantially improved the goodness of fit of models[4].

4. Modelling results

The results from the 795 estimated models[5] are summarised by focussing upon statistically significant estimates, partial adjustment coefficients and elasticities (evaluated at the means of the data). Table 2 provides an overall summary of the percentage of statistically significant estimates, while Tables 3–5 break down the summary into commodity groupings. In a broad sense Australia wide,

[4] Approximately, only 10 per cent of models have potential significant degrees of auto-correlation and/or specification error, standard error corrections for auto-correlation using a HAC estimator proved be unsuccessful (unrealistically low standard errors) due to smallness of the sample size. The number of statistically significant elasticities and the R_s^2 increased substantially when moving from the static model to the PAM.

[5] The full results are presented in a series of 89 tables specified by commodity groups and clusters and are available from the authors.

Table 2 Overall summary: percentage of statistically significant estimates (5% level)

Commodity/Region	Number of commodities/Regions	Lagged area		Own price		Total holdings		Rainfall		Other prices	
		+	–	+	–	+	–	+	–	+	–
New South Wales	185	44.3	0.5	20.5	7.6	13.5	9.2	6.5	3.2	34.6	30.8
Crops & Livestock	71	50.7	1.4	40.8	14.1	7.0	8.5	2.8	4.2	33.8	38.0
Fruit	75	45.3	0	9.3	5.3	13.3	13.3	6.6	4.0	50.7	21.3
Vegetables	39	30.8	0	5.1	0	25.6	2.6	12.8	0	5.1	35.9
Victoria	140	65.0	0	11.4	2.1	11.4	5.0	3.6	5.0	26.4	24.3
Crops & Livestock	56	76.8	0	21.4	1.8	12.5	1.8	1.8	8.9	23.2	33.9
Fruit	49	61.2	0	4.1	2.0	8.2	4.1	4.1	4.1	34.7	20.4
Vegetables	35	51.4	0	5.7	2.9	14.3	11.4	5.7	0	20	14.3
Queensland	172	44.8	0	10.5	4.7	8.7	12.8	10.5	2.3	28.5	30.8
Crops & Livestock	71	38.0	2.8	18.3	5.6	7.0	4.2	19.7	1.4	22.5	29.6
Fruit	62	54.8	0	6.5	3.2	6.5	17.7	3.2	4.8	27.4	41.9
Vegetables	39	41.0	0	2.6	5.1	15.4	20.5	2.1	0	41.0	15.4
South Australia	116	67.2	0	14.7	2.6	12.9	9.5	5.2	5.2	19.0	30.2
Crops & Livestock	58	70.7	0	19.0	1.7	12.1	13.8	1.7	6.9	15.5	39.7
Fruit	37	64.9	0	13.5	2.7	10.8	5.4	10.8	0	21.6	18.9
Vegetables	21	61.9	0	4.8	4.8	19.0	4.8	4.8	4.8	23.8	23.8
Western Australia	119	54.6	0.8	13.4	4.2	14.3	13.4	10.1	6.7	37.8	19.3
Crops & Livestock	40	60.0	0	25.0	0	22.5	5.0	12.5	5.0	35.0	27.5
Fruit	51	49.0	2.0	7.8	7.8	15.7	19.6	9.8	9.8	54.9	17.6
Vegetables	28	57.1	0	7.1	3.6	0	14.3	7.1	3.6	10.7	10.7
Tasmania	56	60.7	0	5.4	0	7.1	5.4	5.4	0	23.2	25.0
Crops & Livestock	19	73.7	0	10.5	0	5.3	0	5.3	0	42.1	42.1
Fruit	18	72.2	0	5.6	0	11.1	0	5.6	0	16.7	0
Vegetables	19	36.8	0	0	0	5.3	15.8	5.3	0	10.5	31.6
Northern Territory	2	100	0	0	0	50	0	50	0	0	0
Fruit	2	100	0	0	0	50	0	50	0	0	0
Australian Capital Territory	5	40	0	20	0	0	0	0	0	0	20
Crops & Livestock	5	40	0	20	0	0	0	0	0	0	20
Australia	795	54.2	0.5	13.7	4.2	11.7	9.6	7.2	3.8	28.9	27.3
Crops & Livestock	320	58.4	0.9	24.4	5.0	10.6	6.3	7.5	4.7	26.3	34.4
Fruit	294	55.1	0.3	7.8	4.1	11.2	11.9	6.8	4.4	37.8	23.1
Vegetables	181	45.3	0	4.4	4.8	14.4	11.6	7.2	1.1	19.3	21.5

Numbers represent percentage of number of commodities/regions.

Table 3 Crops & livestock: percentage of statistically significant estimates (5% level)

Commodity	Number of regions	Lagged area		Own price		Total holdings		Rainfall		Other prices	
		+	–	+	–	+	–	+	–	+	–
Crops & Livestock	320	58.4	0.9	24.4	5.0	10.6	6.3	7.5	4.7	26.3	34.4
Wheat	30	73.3	0	33.3	0	30.0	0	10.0	0	23.3	40.0
Oats	29	24.1	0	44.8	3.4	17.2	10.3	3.4	0	24.1	17.2
Barley	29	72.4	0	48.3	0	17.2	0	3.4	0	31.0	48.3
Sorghum	13	7.7	0	30.8	30.8	7.7	7.7	7.7	15.4	46.2	0
Maize	15	40.0	0	6.7	6.7	6.7	6.7	33.3	6.7	20.0	20.0
Rice	3	66.7	0	0	0	0	0	33.3	0	0	33.3
Triticale	24	75.0	0	37.5	4.2	12.5	12.5	0	4.2	33.3	37.5
Cotton	12	75.0	8.3	33.3	0	0	16.7	33.3	0	25.0	66.7
Lupins	20	80.0	0	0	5.0	5.0	0	0	5.0	25.0	25.0
Peanuts	6	50.0	0	0	0	0	0	16.7	0	33.3	33.3
Field Peas	22	72.7	0	31.8	0	13.6	9.1	13.6	13.6	9.1	72.7
Canola	20	90.0	0	20.0	5.0	10.0	10.0	10.0	5.0	30.0	35.0
Sugar Cane	5	20.0	20.0	0	0	0	20.0	0	0	60.0	60.0
Tobacco	3	66.6	0	0	0	0	0	0	0	33.3	33.3
Sheep & Lambs	30	53.3	0	0	20.0	0	0	0	3.3	40.0	33.3
Milk Cattle	29	55.2	3.4	20.7	0	6.8	13.8	6.8	10.3	20.7	13.8
Meat Cattle	30	43.3	0	16.6	3.3	6.6	3.3	0	6.6	13.3	33.3

Numbers represent percentage of number of regions.

Table 4 Fruit summary: percentage of statistically significant estimates (5% level)

Commodity	Number of regions	Lagged area		Own price		Total holdings		Rainfall		Other prices	
		+	–	+	–	+	–	+	–	+	–
Fruit	294	55.1	0.3	7.8	4.1	11.2	11.9	6.8	4.4	37.8	23.1
Oranges	20	35.0	0	10.0	10.0	5.0	5.0	0	10.0	55.0	20.0
Lemons & Limes	20	45.0	0	5.0	10.0	5.0	20.0	5.0	10.0	20.0	40.0
Mandarins	20	55.0	0	10.0	5.0	15.0	15.0	0	10.0	60.0	25.0
Apples	20	70.0	0	0	5.0	5.0	15.0	5.0	10.0	35.0	15.0
Pears	17	47.1	0	5.9	5.9	23.5	5.9	11.8	0	47.1	47.1
Apricots	22	50.0	0	9.1	4.5	36.4	9.0	22.7	0	27.3	18.2
Avocados	19	36.8	0	0	5.3	15.8	10.5	0	5.3	52.6	31.6
Cherries	18	50.0	0	16.7	0	11.1	16.7	5.5	5.5	38.9	11.1
Mangoes	12	75.0	8.3	0	0	8.3	8.3	0	8.3	50	0
Nectarines	22	63.7	0	4.5	4.5	4.5	22.7	4.5	0	45.5	27.3
Peaches	22	59.1	0	9.1	0	4.5	9.1	9.1	0	40.9	31.8
Plums & Prunes	12	50.0	0	8.3	8.3	0	0	16.6	0	58.3	16.7
Almonds	8	37.5	0	0	0	12.5	37.5	12.5	0	50.0	37.5
Macadamias	3	0	0	0	0	0	33.3	0	0	33.3	133.3
Strawberries	18	38.9	0	5.6	5.6	22.2	11.1	5.6	5.6	33.3	11.1
Bananas	9	77.8	0	11.1	0	11.1	27.2	22.2	0	0	22.2
Pineapples	4	75.0	0	25.0	0	0	0	0	0	0	0
Grapes	28	85.7	0	17.9	0	3.6	0	3.6	3.6	10.7	7.1

Numbers represent percentage of number of regions.

Table 5 Vegetable summary: percentage of statistically significant estimates (5% level)

Commodity	Number of regions	Lagged area		Own price		Total holdings		Rainfall		Other prices	
		+	–	+	–	+	–	+	–	+	–
Vegetables	181	45.3	0	4.4	4.8	14.4	11.6	7.2	1.1	19.3	21.5
Potatoes	23	60.9	0	17.4	0	13.0	13.0	4.3	4.3	8.7	17.4
Beans	17	29.4	0	5.9	0	11.8	17.7	0	0	23.5	5.9
Cabbages	17	35.3	0	0	5.9	23.5	0	5.9	0	17.6	29.4
Carrots	17	70.6	0	0	0	0	17.6	0	0	29.4	17.6
Cauliflower	17	52.9	0	0	0	11.8	17.6	11.8	0	17.6	17.3
Lettuce	19	52.6	0	5.3	10.5	15.8	5.3	5.3	0	31.6	26.3
Mushrooms	9	33.3	0	0	0	0	11.1	0	0	22.2	11.1
Spring Onions	8	37.5	0	0	12.5	25	0	12.5	0	25.0	25.0
Peas	16	50.0	0	0	6.3	12.5	18.8	6.3	0	18.8	6.3
Pumpkins	26	26.9	0	3.8	0	15.4	15.7	19.2	0	11.5	30.8
Tomatoes	12	41.7	0	8.3	0	33.3	0	8.3	8.3	16.7	50.0

Numbers represent percentage of number of regions.

cross-price effects are significant most often with 56 per cent significant estimates,[6] while in 55 per cent of equations, the lagged area employed variable is significant. The importance of the other three variables is substantially weaker with total holdings being significant 21 per cent of the time, own price 18 per cent and rainfall significant in 11 per cent of the models.

For the lagged area employed variable, SA and Vic exhibit the greatest prevalence of partial adjustment with about two-thirds of significant estimates. In terms of the broad commodity groups, crops & livestock exhibit the greatest prevalence of slow adjustment (58 per cent of cases) and vegetables the smallest (45 per cent of cases). In terms of specific commodity types (Tables 3–5), slow partial adjustment is most prevalent with canola (90 per cent), grapes (86 per cent) and lupins (80 per cent) and least prevalent with macadamias (0 per cent), sorghum (8 per cent) and sugar cane (20 per cent). Table 6 identifies the smallest adjustment coefficients for commodity/region combinations. Very slow partial adjustment occurs most frequently for grapes, triticale and mangoes. The prevalence of very slow adjustment for grapes occurs in all states, but is most widespread in NSW and WA.

For the own-price variable, NSW (28 per cent), WA (18 per cent) and SA (17 per cent) exhibit the greatest prevalence of own-price responsiveness. In terms of the broad commodity groups, crops & livestock exhibit the greatest prevalence of own-price responsiveness with 29 per cent of cases and vegetables the smallest with 9 per cent of cases. In terms of specific

[6] For other prices, the percentages in the tables represent the number of times other prices are significant as a percentage of estimated models. This measure therefore recognises that for some models, two or more cross-price effects may be significant. The 56 per cent of significant estimates for other prices fall to 44 per cent for the percentage of equations which have at least one significant other price variable.

Table 6 Low adjustment coefficients

Commodity	Region/Cluster	Commodity	Region/Cluster
Crops & Livestock		Fruits	
Wheat	VIC#5,TAS#2	Lemons & Limes	QLD#3
Barley	NSW#3, NSW#4,VIC#4,VIC#5,	Mandarins	NSW#3,QLD#6,SA#2
Triticale	NSW#3, NSW#4,NSW#5, VIC#2,VIC#4,VIC#5	Apples	VIC#2,SA#1,SA#4
Lupins	VIC#1,	Apricots	VIC#2,VIC#5
Field Peas	SA#2,WA#4	Avocados	QLD#2
Canola	NSW#5,VIC#1,VIC#3,VIC#5,SA#4	Cherries	VIC#2,QLD#4,TAS#1,TAS#2
Sugar Cane	QLD#3	Mangoes	QLD#1,QLD#2,QLD#3,QLD#6,WA#3,WA#4
Milk Cattle	NSW#1	Nectarines	QLD#1,SA#2,WA#4
Vegetables		Peaches	QLD#1,WA#4
Potatoes	VIC#3,QLD#1,SA#2,TAS#2	Plums & Prunes	VIC#5
Beans	WA#2,	Strawberries	QLD#1
Carrots	VIC#5,WA#1	Bananas	QLD#3
Spring Onions	VIC#1	Grapes	NSW#3,NSW#4,NSW#5,VIC#5,QLD#5,QLD#6, SA#1,SA#6,WA#2,WA#3, WA#4,TAS#1,TAS#2

Statistically significant lagged area with adjustment coefficient <0.10.

commodity types own-price responsiveness is most prevalent with sorghum (61 per cent), oats (48 per cent) and barley (48 per cent) and numerous specific commodities exhibit no significant own-price responsiveness, these include rice, peanuts, sugar cane, tobacco, mangoes, macadamias, almonds, carrots, cauliflower and mushrooms. Table 7 identifies the largest estimated own-price elasticities for commodity/region combinations. Large own-price elasticities are most common with crops & livestock and are very rare with vegetables. The greatest number of large own-price elasticities is associated with triticale, barley, sorghum and canola.

For the total holdings variable, WA (28 per cent), NSW (23 per cent) SA (22 per cent) and Qld (22 per cent) exhibit the greatest prevalence of total holdings responsiveness. In terms of the broad commodity groups, vegetables exhibit the greatest prevalence of total holdings responsiveness with 23 per cent of cases and crops & livestock the smallest with 17 per cent of cases. In terms of specific commodity types, total holdings responsiveness is most prevalent with almonds (50 per cent), apricots (45 per cent) and bananas (38 per cent), and a number of specific commodities exhibit no significant total holdings responsiveness, these include rice, peanuts, tobacco, sheep & lambs and plums & prunes. Table 8 identifies the largest estimated total holdings elasticities for commodity/region combinations. Large total holdings elasticities are most common with fruit and less common with crops & livestock and vegetables. The greatest number of large total holdings price elasticities is associated with apricots, peas and pumpkins.

For the rainfall variable, WA (17 per cent) and Qld (13 per cent) exhibit the greatest prevalence of rainfall responsiveness. In terms of the broad commodity groups, crops & livestock exhibit the greatest prevalence of rainfall respon-

Table 7 Large own-price elasticities

Commodity	Region/Cluster	Commodity	Region/Cluster
Crops & Livestock		Fruits	
Wheat	NSW#1,NSW#6, QLD#1,QLD#3	Oranges	SA#1
Oats	QLD#6(−),ACT	Lemons & Limes	QLD#4(−)
Barley	NSW#2,QLD#1, QLD#3,SA#4,WA#4	Mandarins	QLD#2
Sorghum	NSW#3(−),NSW#4, NSW#5,VIC#5,QLD#1	Pears	NSW#1
Maize	NSW#2(−),NSW#5	Apricots	TAS#2
Triticale	NSW#2(−),QLD#4,SA#4, WA#3,WA#4,TAS#1	Cherries	NSW#4
Cotton	NSW#4	Plums & Prunes	QLD#1(−),SA#2
Lupins	NSW#3(−)	Strawberries	NSW#3(−)
Field Peas	VIC#2	Vegetables	
Canola	NSW#5,QLD#1,QLD#5(−), SA#6,WA#3	Beans	WA#2
Milk Cattle	NSW#2,QLD#5	Lettuce	SA#4,WA#3(−)

Statistically significant own-price coefficients with sample means elasticity >1.0.

Table 8 Large total holdings elasticities

Commodity	Region/Cluster	Commodity	Region/Cluster
Crops & Livestock		Fruit	
Wheat	NSW#2,VIC#2,QLD#3, WA#1	Oranges	NSW#3
Oats	QLD#3	Lemons & Limes	NSW#3(−),QLD#4(−), WA#4(−), WA#5(−)
Barley	VIC#2,QLD#2,WA#1, WA#3	Mandarins	NSW#6,QLD#2, WA#3(−)
Sorghum	NSW#2	Apples	NSW#6(−)
Triticale	NSW#1,SA#1,SA#5(−)	Pears	NSW#1,NSW#2,WA#3
Cotton	NSW#2(−),QLD#5(−)	Apricots	NSW#1,NSW#6,QLD#3(−), SA#5,SA#6,WA#4,TAS#2
Lupins	WA#1	Avocados	NSW#2,VIC#2,QLD#3(−)
Field Peas	WA#2	Cherries	SA#6(−),WA#3
Canola	VIC#3,SA#2(−),SA#3, WA#4(−)	Mangoes	QLD#5(−)
Milk Cattle	NSW#2(−),QLD#5(−)	Nectarines	QLD#6(−),WA#3(−),WA#4(−)
Vegetables		Peaches	WA#3(−)
Potatoes	VIC#4,	Almonds	VIC#5(−)
Beans	QLD#3,QLD#4(−), WA#5(−),TAS#2(−)	Strawberries	NSW#3(−),VIC#4, QLD#3(−),WA#2
Cabbages	TAS#2	Bananas	QLD#6(−)
Carrots	QLD#3(−)	Grapes	QLD#4
Cauliflower	QLD#6(−)		
Lettuce	SA#4		
Peas	NSW#4(−),VIC#2, QLD#3(−), QLD#4,WA#3(−)		
Pumpkins	NSW#3,VIC#4,SA#4(−), WA#3(−), TAS#2(−)		
Tomatoes	NSW#2,NSW#3,VIC#5		

Statistically significant total holdings coefficients with sample means elasticity >3.0.

siveness with 12 per cent of cases and vegetables the smallest with 8 per cent of cases. In terms of specific commodity types, rainfall responsiveness is most prevalent with maize (40 per cent), rice (33 per cent) and cotton (33 per cent), and a number of specific commodities exhibit no significant rainfall responsiveness, these include tobacco, macadamias, pineapples, beans, carrots and mushrooms. Table 9 identifies the largest estimated rainfall elasticities for commodity/region combinations. Large rainfall elasticities are most common with crops & livestock and least common with vegetables. The greatest number of rainfall elasticities is associated with maize, pumpkins, cotton, wheat, field peas, canola and lemons & limes.

The cross-price variables are statistically significant in about 56 per cent of all cases with about an equal division between positive and negative impacts. NSW (65 per cent), Qld (59 per cent) and WA (57 per cent) exhibit the greatest prevalence of cross-price responsiveness. In terms of the broad commodity groups, crops & livestock and fruit equally exhibit the greatest prevalence of cross-price responsiveness with 61 per cent of cases and

Table 9 Large rainfall elasticities

Commodity	Region/Cluster	Commodity	Region/Cluster
Crops & Livestock		Fruits	
Wheat	NSW#1,NSW#2,QLD#1	Oranges	QLD#6(−)
Sorghum	NSW#3(−),NSW#5(−)	Lemons & Limes	QLD#2(−),WA#2(−), WA#5
Maize	QLD#1,QLD#4,QLD#5, QLD#6,WA#5(−)	Mandarins	QLD#1(−),WA#4(−)
Rice	NSW#2	Apples	SA#1,WA#3(−)
Triticale	NSW#4(−)	Pears	NSW#2
Cotton	QLD#2,QLD#3, QLD#4,QLD#5	Apricots	WA#2,WA#4,TAS#2
Lupins	NSW#4(−)	Avocados	NSW#1(−)
Peanuts	QLD#1	Cherries	WA#3(−)
Field Peas	NSW#2(−),WA#3,TAS#2	Mangoes	WA#1(−)
Canola	NSW#3(−),QLD#5,WA#4	Nectarines	NSW#1
Sheep & Lambs	WA#1(−)	Peaches	NSW#4,VIC#4
Milk Cattle	QLD#5,WA#3	Plums & Prunes	NSW#1,QLD#1
Vegetables		Strawberries	VIC#3,VIC#4(−)
Carrots	WA#2	Bananas	NT
Cauliflower	QLD#4,WA#3	Grapes	VIC#1(−),WA#4
Lettuce	VIC#5		
Spring Onions	VIC#1		
Peas	TAS#2		
Pumpkins	NSW#2,NSW#3,NSW#5, SA#1(−),SA#4		
Tomatoes	NSW#3		

Statistically significant rainfall coefficients with sample means elasticity >0.5.

vegetables the smallest with 41 per cent of cases. In terms of specific commodity types, cross-price responsiveness is most prevalent with macadamias (133 per cent), sugar cane (120 per cent), pears (94 per cent) and cotton (92 per cent). Only pineapples exhibit no significant cross-price responsiveness, other commodities which have low cross-price influences include grapes (18 per cent), bananas (22 per cent) and peas (25 per cent). Table 10 identifies the largest estimated cross-price elasticities for commodity/region combinations. Large cross-price elasticities are most common with fruit and crops & livestock with similar magnitudes and rare with vegetables.

A number of estimated elasticities have signs inconsistent with short-run profit-maximising expectations. For example, Table 1 indicates that for all models, significant negative estimates exist for own price in 4.2 per cent of cases. In general, the number of theoretical violations is rather small. Interestingly, the violation of these theoretical expectations is not uncommon in agricultural modelling, for example, Shumway (1995) finds that in 46 studies of North American agriculture, the curvature property was rejected in 36 per cent of cases. Similarly, in three Australian studies (Coelli 1996; Ahammad and Islam 2004; and Xayavong *et al.* 2011), the estimation of unrestricted supply equations led to the violation of curvature conditions. For these cases, the implication is either the data are flawed and/or the

Table 10 Large cross-price elasticities

Commodity	Region/Cluster	Commodity	Region/Cluster
Crops & Livestock		Fruit	
Wheat	NSW#6(−),QLD#3(−), WA#1	Oranges	NSW#2,QLD#4(−)
Barley	WA#1	Lemons & Limes	QLD#4(1 +, 2 −)
Sorghum	VIC#5	Mandarins	QLD#2(−)
Maize	NSW#5(−),QLD#5(−), VIC#2(1+,1−)	Apples	VIC#3
Rice	VIC#2(−)	Pears	NSW#1(1+,1−)
Triticale	NSW#1(1+,1−), VIC#3,QLD#1, SA#4(−),SA#6(−), WA#4(−)	Apricots	NSW#2(−), NSW#6
Cotton	QLD#3(2+,1−)	Avocados	NSW#2,NSW#3(−), VIC#1(−)
Lupins	SA#1	Cherries	VIC#5
Peanuts	NSW#2(1+,1−)	Mangoes	QLD#4
Field Peas	NSW#3(−),WA#2(−)	Nectarines	QLD#1(−),WA#3(1 +,1 −)
Canola	QLD#1(1+,1−), QLD#4(2+), WA#3(−), WA#4(−)	Peaches	NSW#5, NSW#6,QLD#1(−), WA#3
Tobacco	QLD#3(−)	Plums & Prunes	NSW#4
Milk Cattle	VIC#4	Almonds	NSW#5,VIC#5,SA#4
Vegetables		Macadamias	QLD#3(−)
Carrots	NSW#5(−), QLD#3(2+)	Strawberries	NSW#3, VIC#4(2+),QLD#3
Spring Onions	TAS#1(−)	Bananas	QLD#6(−)
Peas	NSW#5(2+),		
Pumpkins	QLD#4		
Tomatoes	QLD#1(−),QLD#4(−)		

Statistically significant cross-price coefficients with sample means elasticity >2.0.

theory is inappropriate (Just and Pope 1999). In our case, both reasons are possibly relevant, some data aggregation and imputation of missing data were necessary, and given the institutional context and the prevalence of partial adjustment, for a very small minority of commodities, short-run profit maximisation may be an inappropriate assumption.

5. Discussion and conclusions

Theoretically, the motivation for the use of the PAM suggests an expectation of slower adjustment and smaller price responsiveness for livestock and perennial crops and fruits, and faster adjustment for annual crops and most vegetables. For the main livestock (beef and sheep) and crop types (wheat) in Australian agriculture, Griffith *et al.* (2001) found a lack of consensus across studies but generally that own-price elasticities are inelastic with wheat elasticities being larger than livestock. The estimates for the Australian

Wheat–Sheep zone tended to be greater than other zones. In general, cross-price elasticities were also found to be inelastic and mostly negative.

Consistent with these expectations, the prevalence of slow adjustment is weakest with vegetables and most widespread with the perennials such as grapes and bananas, but also occurs frequently with some annuals such as canola and lupins. The greater prevalence of slow adjustment occurs in the southern mainland states; the results indicate that location may play an important role in the pace of adjustment of land allocation. To the extent that slow partial adjustment implies that farmers are operating away from desired land allocation levels for prolonged periods, implies that land use may be less efficient than preferred for these commodities.

In terms of livestock and wheat, our results are generally consistent with previous Australian studies[7] of price elasticities (e.g Coelli 1996 and Xayavong *et al.* 2011), as the majority of price elasticities are insignificant or very small. The relative greater price responsiveness of wheat compared with livestock is consistent with previous studies also and is reaffirmed with long-run elasticities as the presence of slow partial adjustment is far greater with wheat than with sheep & lambs and meat cattle. Interestingly, the largest wheat elasticities fall outside the wheat–sheep zone; this is in contrast to some previous findings that the wheat/sheep zones produce larger price elasticities.

A number of cross-price elasticities were identified as significant and point to some important substitution and complementarity relationships. Potential for substitution and complementarity appears to be greatest with triticale, canola, maize, peaches and strawberries. The results for total holdings suggest that the greatest scope for increasing land allocations by increasing land availability exist with apricots, wheat and barley, with no obvious locational advantages.

Unfortunately, the lack of water allocation and other specific climatic data prevented a thorough analysis of the impact of climate on land allocations. However, some scant evidence is available through rainfall elasticities. The commodities likely to benefit most from additional rainfall appear to be wheat, maize, cotton and pumpkins with the bulk of these benefits occurring in NSW and Qld.

In conclusion, this study has reaffirmed the importance of the partial adjustment model in Australian agriculture; the study presents sufficient widespread evidence across numerous commodity types and detailed regional locations to suggest that land allocations in the majority of cases only partially adjust to desired levels. In part, the Australian institutional context in terms of legislative, marketing and contractual arrangements explains the slowness of the adjustment process. Interestingly, price effects, changes in total land holdings and rainfall influences have a relatively minor impact. Overall, these findings suggest that the economic

[7] The comparison of our estimates with previous studies is somewhat problematic as our elasticities relate to acreage response rather than the output responses of previous studies, and over coverage is more spatially disaggregated.

drivers of agricultural land-use allocation have a small short-run impact and will only show significant effects over a substantial time period.

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Appendix 1

Data appendix

Land allocation

Area employed per 1000 hectares (HA). Data collected by the Australian Bureau of Statistics (ABS) annual agricultural survey (census every year up to 1996/7 and a census every 5 years thereafter). ABS Statistical District level data employed. Sources: 1982/3–96/7 National Land and Water Resources Audit (2001) and 1997/8–2005/6 ABS personal communication and ABS Agricultural Commodities: Small Area Data, Australia (cat no. 7125.0). Orchards conversion (no. of trees to HA): Stewart *et al*. (2001), Table 5, p21. Livestock conversion (no. of head to HA), annual state level stocking rates employed for sheep, lambs, milk and meat cattle: 1982/3–89/90 ABS Livestock and Livestock Products, Australia (7221.0), ABS Summary of Crops, Australia (7330.0) and 1990/1–2005/6 ABARE AgSurf (www.abare.gov.au/interactice/agsurf).

Prices

Relative price employed as: average gross value (AGV) of output/total input prices paid index for farmers (1997/8 = 100). AGV measured in *t*, kg, *per head or* 100l depending upon output, AGV = (gross value of production)/(production level). ABS state level data employed for outputs and an Australian wide index for inputs. Output Prices Sources: ABS Livestock and Livestock Products, Australia (7221.0), ABS Summary of Crops, Australia (7333.0), ABS Value of Agricultural Commodities Produced (7503.0), ABS Livestock Products, Australia (7113.0), ABS Agricultural Commodities, Australia (7121.0). Input Prices Sources: ABARE (2009).

Total holdings

Total area allocated per 10,000 hectares (HA). Source: same as land allocation.

Rainfall

Average annual rainfall. State level data employed. Source: Australian Government Bureau of Meteorology (www.bom.gov.au/climate/data).