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Broadacre farm productivity and profitability in south-western Australia*

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This paper examines broadacre farm performance in south-western Australia. This region has experienced pronounced climate variability and volatile commodity prices since the late 1990s. Relationships between productivity and profitability are explored using panel data from 47 farms in the study region. The data are analysed using nonparametric methods. By applying the Fare-Primont index method, components of farm productivity and profitability are measured over the period 1998–2008. Growth in productivity is found to be the main contributor of profitability. Gains in efficiency and technical change are identified as jointly and similarly important in their contribution to total factor productivity for the farm sample in the region from 1998 to 2008. However, across environments, efficiency gains play an increasingly important role in influencing productivity as growing season rainfall increases. We conclude that R,D&E that delivers further improvement in technical efficiency and technical change is needed to support the profitability of farms across the study region.

Key words: productivity, profitability, technical change.

1. Introduction

It is often stated that Australian farming's international competitiveness relies on ongoing gains in productivity. Limitations to Australia's agricultural resources of arable land and water suggest future growth in agricultural production will increasingly depend on productivity growth (Zhao *et al.* 2008; Nossal and Sheng 2010). Empirical findings show that from 1977–78 to 2007–08, Australia's largest agricultural sector, known as broadacre agriculture, achieved total factor productivity (TFP) growth of 1.4 per cent per annum (Nossal and Sheng 2010). However, over the last 10 years from 1997–98 to 2007–08, the TFP declined – a decline attributed mainly to drought effects (Sheng *et al.* 2010).

In recent decades, the annual average temperature across Australia has increased and average rainfall in some key grain-growing regions has decreased (Nicholls *et al.* 2003). These changes in temperature and rainfall,

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when combined with farm commodity price volatility (Kimura and Antón 2011), have implications for the management of complex broadacre farm businesses (Kingwell 2011) and ensure farming remains risky (Quiggin *et al.* 2010). Under different scenarios, CSIRO (2007) has projected the average annual temperature in south-west region of Australia to rise between 0.8 and 4°C and the average annual precipitation to decrease between 2 per cent to 10 per cent by 2050 relative to 1990. If the projected climate change does unfold, then in some regions farm profitability and viability could be threatened (Kingwell 2006; Garnaut 2010; Quiggin *et al.* 2010). Uncertainty over the future state of nature, combined with some farmers' inability to easily change input mixes/output mixes, is likely to exacerbate the variation in annual productivity. The adverse impacts of climate risk and other sources of business risk can be partially addressed through greater productivity growth derived from management (technical) efficiency (TE) and technical change.

In Australia, much effort has been devoted to measuring the productivity performance of different sectors and agricultural regions of Australia (Knopke *et al.* 2000; Mullen 2007; Nossal *et al.* 2009). Some authors (e.g. Salim and Islam 2010; Sheng *et al.* 2010, 2011) posit plausible explanations for the observed rates of productivity change. Jackson (2010) points to technological advances such as seed varieties, herbicides, tillage practices and improved machinery. So far, no study has decomposed profitability and productivity of mixed farms in Australia using farm-level panel data to explore the management (technical) efficiency components of individual farms operating under varying climatic and business conditions.

By employing the total factor productivity (TFP) approach, this paper fills this gap by decomposing the profitability and productivity components of Australian mixed enterprise farms, using a case study region of Australia's south-west where in the last decade significant weather variability has been experienced. A better understanding of the components of farm productivity and profitability may help policy makers, innovation funders and product developers to better serve farm businesses.

This paper comprises four sections. Section 2 describes the methodology and data, Section 3 presents the results and discussion, and then, a summary and conclusions are presented in Section 4.

2. Methodology and data

2.1. Method

Farm productivity variations exist as farms face different production opportunities due to differences in factors such as: (i) physical resource endowments (e.g. quality of soils and climate), (ii) technology, capital and infrastructure and (iii) levels of costs and prices (Hayami 1969; Lau and Yotopoulos 1989; Battese *et al.* 2004) and (iv) efficiency variations. Efficiency variations exist as a result of management decisions, that is, slack inputs and misallocation of inputs and outputs. Assessment of efficiency is complicated due to the inability to properly measure the quality of inputs and outputs. In this context, measurement of efficiency has been a controversial tool as it is a residual and thus is likely to involve measurement errors when functional forms or distributions are misspecified. There is substantial evidence in the literature, however, that inefficiency does exist and that it can be measured effectively using either data envelopment analysis (DEA) or parametric methods (O'Donnell *et al.* 2008; O'Donnell 2010a).

To measure farm productivity and efficiency, increasingly sophisticated methodologies have been developed to deal with issues such as data discrepancies, functional forms and behavioural assumption restrictions, *inter alia*. Ozkan *et al.* (2009) reviewed literature on measuring efficiency in agricultural production and classed approaches as parametric or nonparametric. The modified least-squares econometric production and stochastic frontier production function models (a maximum likelihood procedure based on a nonlinear model) are examples of the first, while the traditional Tornqvist-Theil or Christensen and Jorgenson total factor productivity index and DEA are examples of the second. Detailed reviews of the various productivity estimation methods can be found in Van Beveren (2010) and Van Biesebroeck (2007). Most of these studies deal with productivity and efficiency issues – not with profitability to which farm business viability is closely linked (Lovell 2001). Productivity and profitability, however, are related in the sense that a more productive business typically is also more profitable, and a faster growth in productivity often translates into faster growth in profitability, *ceteris paribus* (O'Donnell 2010a).

Economists have used a number of methods to demonstrate a relationship between profitability and productivity changes. Althin *et al.* (1996) show that the index of profitability is approximately equal to the efficiency change component of productivity change, which implies improvements in productivity are accompanied by improvements in profitability. Grifell-Tatjé and Lovell (1999) show that sources of change in profit are driven by changes in quantities and prices. The changes in quantities can be further decomposed as illustrated in Figure 1 into five categories that affect quantities produced. Hadley and Irz (2008) have applied the hierarchy in Figure 1 to farm-level production data for England and Wales.

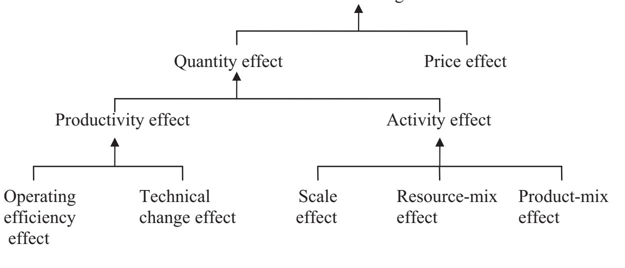

Figure 1 Profit decomposition (adapted from Grifell-Tatjé and Lovell 1999).

Advancing this decomposition approach, O'Donnell (2010a) distinguishes a difference between 'profitability change' and 'profit change' and shows that the sources of profitability change are driven by the changes in terms of trade, productivity and various measures of efficiency indexes. The distinction between 'profit change' and 'profitability change' is that the former is the change in revenue minus cost while the latter is the change in the ratio of revenue to cost in period t compared with period 0. According to O'Donnell (2010a), the sources of profitability change can be decomposed into three stages provided that (i) the output and input quantity aggregates are associated with input and output price aggregates; (ii) the quantity and price aggregates are non-negative and linear homogeneous in prices; and (iii) any quantity-price aggregator function pair satisfies the product rules. The formulae for decomposing these profitability and productivity drivers are presented in simplified forms in Equations (1–6).

Firstly, the profitability index change (dPROF) between firms or periods, 0 and t, can be decomposed into the indexes of changes in the terms of trade (dTT) and total factor productivity (dTFP):

$$d\mathrm{PROF} = d\mathrm{TT} * d\mathrm{TFP} \tag{1}$$

Following O'Donnell (2010a), we used a multiplicatively complete Färe-Primont index number. We computed the change in index numbers in Equations (1–6) between firms for periods 0 to t, using firm or period 0 as a base. For example, the change in profitability (dPROF) in Equation (1) can be computed as the ratio of profitability in time t over profitability in time 0 for firm n. This can be expressed as: $d\mathrm{PROF} = \mathrm{PROF}_{nt}/\mathrm{PROF}_{n0}$ where, $\mathrm{PROF}_{nt} = P_{nt}\, Q_{nt}/\mathrm{W}_{nt}\, X_{nt}$; $\mathrm{PROF}_{n0} = P_{n0}\, Q_{n0}/\mathrm{W}_{n0}\, X_{n0}$; P and Q are the price and quantity of outputs; and W and X are the price and quantity of inputs.

Similarly, the change in terms of trade (dTT) and the change in total factor productivity (dTFP) in Equation (1) can be expressed respectively as: $TT_{n0,nt} = P_{n0,nt}/W_{n0,nt}$ and $TFT_{n0,nt} = Q_{n0,nt}/X_{n0,nt}$.

Secondly, the total factor productivity change (dTFP) index in Equation (1) can be further decomposed into the indexes of technical change (dTECH) and technical efficiency change (dEFF):

$$d\mathrm{TFP} = d\mathrm{TECH} * d\mathrm{EFF} \tag{2}$$

where, $d\mathrm{TFP} = \mathrm{TFP}_{n0,nt} = \frac{\mathrm{TFP}_{nt}}{\mathrm{TFP}_{n0}}$ or $d\mathrm{TFP} = \mathrm{TFP}_{n0,nt} = \left(\frac{\mathrm{TFP}^*_t}{\mathrm{TFP}^*_0}\right) \times \left(\frac{\mathrm{EFF}^*_t}{\mathrm{EFF}^*_0}\right)$. The term $\left(\frac{\mathrm{TFP}^*_t}{\mathrm{TFP}^*_0}\right)$ is the dTECH, which measures the difference between the maximum TFP that is possible using the technology available in period t and the maximum TFP that is possible using the technology available in period 0 and the term $\left(\frac{\mathrm{EFF}^*_t}{\mathrm{EFF}^*_0}\right)$ is the dEFF, which measures technical efficiency change in period t compared with period 0.

Finally, the index of efficiency change (dEFF) can be decomposed into various indexes of efficiency change components as specified in Equations (3–6) (for simplicity, the subscripts are omitted):

$$d\mathrm{Eff} = d\mathrm{OTE} * d\mathrm{OME}*d\mathrm{ROSE} \tag{3}$$

$$d\mathrm{Eff} = dO\mathrm{TE} * d\mathrm{OSE}*d\mathrm{RME} \tag{4}$$

$$d\mathrm{Eff} = d\mathrm{ITE} * d\mathrm{IME}*d\mathrm{RISE} \tag{5}$$

$$d\mathrm{Eff} = d\mathrm{ITE} * d\mathrm{ISE}*d\mathrm{RME} \tag{6}$$

The above indexes are briefly defined below.

- OTE (ITE) is output-oriented (input-oriented) technical efficiency that captures the potential change in TFP for an input (output) level by best practice use of existing technology. It is measured by the difference between observed TFP and the maximum TFP possible with existing technology, while holding the output (input) mix fixed and the input (output) level fixed.
- OSE (ISE) is output-oriented (input-oriented) scale efficiency that captures the potential change in TFP, if output (input) level is changed to achieve the maximum TFP with existing technology. It is measured by the difference between TFP at a technically efficient point and the maximum TFP based on existing technology, while holding the input and output mixes fixed but allowing the levels to vary.
- OME (IME) is output-oriented (input-oriented) mix efficiency that captures the potential change in TFP if output (input) level is changed by altering the mix of enterprises in such a way that output is increased for a given set of inputs (output). It is measured by the difference between TFP at a technically efficient point for use of existing technology or enterprise mix and the TFP that is possible holding the input (output) level fixed but allowing the output (input) level and mix to vary.
- ROSE (RISE) is residual output-oriented (input-oriented) scale efficiency that measures the difference between TFP at a technically and mix efficient point and the maximum TFP that is possible through altering both input and output with existing technology.
- RME is residual mix efficiency that measures the difference between TFP at a technically and scale-efficient point and the maximum TFP that is possible through altering input and output mixes with existing technology.

More detail about the definitions and graphic illustrations of the index numbers specified in Equations (1–6) can be found in O'Donnell (2010a, 2011).

2.2. Study region and farm data

The study region is in the south-west of Western Australia. It comprises around one million hectares and has experienced marked climate variability since the mid-1970s (IOCI 2005; Carmody *et al.* 2010). The data for this study were supplied by two farm management consulting firms whose clients are farmers in this region. The set of panel data came from 67 farms, some with incomplete data series for the period 1998–2008. The data comprise over 209 descriptors of each farm, including detailed information on physical inputs and outputs of crops grown; livestock types, livestock numbers, purchases and sales (including wool sales); financial items and aggregates such as expenditure on casual labour, fertilisers, fuel, chemicals, plant depreciation, repairs, commodity income, assets, liabilities and equity.

After initial scrutiny, 47 farms were found to have complete data series for the 11-year period. Since cropping practices of this region are influenced by rainfall (Garlinge 2005) and noting that this study aims to find explanations for profitability and productivity variations under varying climatic and business conditions, the data accordingly were split into three groups by clustering the sample farms based on their 11-year average growing season rainfall (GSR) with respect to their 11-year average arable land area. The clustering indicated that larger farms had lower annual rainfall and on average were expected to have different farming systems in terms of crops and livestock production mixes. Based on this clustering, the farms were grouped into the following three 11-year average GSR ranges: (i) less than 275 mm (the low rainfall group), (ii) between 276 and 325 mm (the medium rainfall group) and (iii) more than 325 mm (the high rainfall group). Of the selected 47 farms, 13, 22 and 12 farms were split, respectively, into low, medium and high GSR groups. Note that some farms in a group may have experienced rainfall beyond its GSR range in a season in the 11-year study period. The distribution of GSR and farm income per hectare of arable land of these three groups is shown in Figure 2. It indicates that the GSR distribution is different across the groups, and the farm income distribution more or less follows each group's GSR distribution.

2.3. Index of variables construction

Out of the 209 descriptors in the raw data, we selected a subset of variables to describe farm production. The output variables were grouped as crop and animal outputs, and input variables were expressed as land, labour, capital, and materials and services and growing season rainfall (GSR). Below are the details of the model variables.

Crop output (q1) was constructed as the sum of production (tonnes) of all crops (wheat, barley, oats, lupin, canola and other) for each farm, noting that cereals (wheat in particular) were by far the dominant crop type.

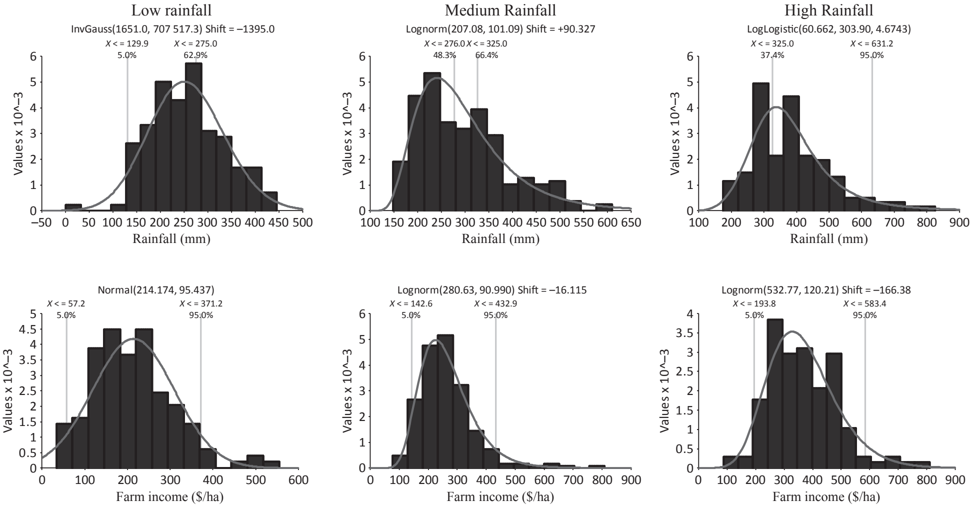

Figure 2 The distribution of growing season rainfall and farm income per hectare of arable land for three farm groups.

Crop price index (p1) was generated by dividing the sum of all revenue from crop production by crop output *(q1)*, using 1998 as the base year.

Animal output (q2) was constructed by dividing the sum of all revenue from cattle, sheep and wool sales by the animal price index (*p2*).

Animal price index (p2) was generated as a revenue share weighted average of sale prices of cattle, sheep and wool, using 1998 as the base year.

Labour input (x1) was in person weeks and was constructed as the annual sum of family, managerial and hired labour.

Labour wage index (w1) was constructed using ABARES's online farm survey data of costs and quantities for average WA farms because no labour payment data for family members existed in the sample data set. We assumed that all farms in the sample faced the same per unit labour cost.

Land input (x2) was effective land area utilised for crop and animal production (in hectares).

Rental price of land (w2) was estimated by multiplying the per hectare land asset value with the 10-year real rate of Australian government bonds. The base year 1998 was used to construct the price series index.

Capital input (x3) was constructed using asset values (livestock, machinery and equipment) divided by their share weighted average price indices from ABARES (2010).

Price of capital (w3) is the user cost of capital per unit and was estimated using the same method used to derive *w2*.

Materials and services (M&S) inputs (x4) was constructed by summing annual farm expenditures over five input categories: fertilisers, chemicals, livestock materials, fuel and lubricants, and repairs and maintenance, and dividing by its price index *(w4)* from ABARES (2010).

Price index of M&S inputs (w4) was constructed as a weighted average price of five items: fertilisers, chemicals, livestock materials, fuel and lubricants, and repairs and maintenance.

Growing Season Rainfall (GSR) input (x5) was the millimetres of actual rainfall recorded for each farm in each growing season of the data period.

Descriptive statistics for these variables for the three sample groups are presented in Table 1. Comparison of these statistics across the three rainfall groups suggests that average effective land input per farm is largest for the low rainfall group, and this group and the medium rainfall group have more crop dominated farming systems than the high rainfall group. On the other hand, as illustrated in Figures 2 and 3, the growing season rainfall (GSR) distribution across the farms in the three groups is also different over the study period. Each box-plot's vertical bar in Figure 3 shows the smallest observation, lower quartile (25th), median (50th), upper quartile (75th) and largest observation. Figure 3 shows that over the period, the GSR fluctuated greatly for all the groups with the year-to-year variation being relatively higher for the medium and high GSR groups. In general, in 2003 and 2005, the GSR was relatively higher but in those years the dispersion was also larger. On the contrary, when GSR was very low in 2000 and 2004, the dispersion was also very small in all three groups.

2.4. Model estimation

Following O'Donnell (2008, 2010b, 2011), the Färe-Primont indexes were computed for productivity and profitability changes using the DPIN 3.0 (O'Donnell 2011). DPIN estimates the production technology and associated measures of efficiency using DEA linear programming. DPIN was applied to measure and decompose profitability and productivity indexes and to estimate the sources of their changes as specified in Equations (1–6). In the software settings, we allowed technical regress and assumed that farms operated under variable returns to scale. We restricted all farms to face the same technical change and allowed for shifts in the enterprise mix of farms in a GSR group if rainfall varied. This also allowed intertemporal shifts in production. The estimated results were then sorted for the three rainfall groups of farms and presented separately as annual farm averages. Other results are presented for the annual average of all 47 farms.

Table 1 Summary statistics (average per farm from 1998 to 2008) of the model's variables by rainfall group

Variables	Unit	Low rainfall group (<275 mm GSR*)					Medium rainfall group (275–325 mm GSR*)					High rainfall group (>325 mm GSR*)				
		Observation	Mean	SD	Min	Max	Observation	Mean	SD	Min	Max	Observation	Mean	SD	Min	Max
Crop (q1)	Tonnes	143	2825	1578	1027	7506	242	2683	1952	203	10,193	132	2586	2175	290	12,939
Animal (q2)	Quantity	143	789	403	523	1821	242	1361	1388	497	9519	132	1906	937	426	5311
Labour (x1)	Person-week	143	93	34	40	168	242	99	46	42	284	132	127	64	48	332
Land (x2)	Hectare	143	2828	1015	1250	5206	242	2373	1422	934	8444	132	2190	1387	598	6532
Capital (x3)	Quantity	143	6546	2568	2200	14,146	242	5529	3499	1727	20,895	132	7700	4746	1395	30,340
M&S (x4)	Quantity	143	8354	3161	2644	17,233	242	7423	4532	1842	24,546	132	8471	4900	1622	29,350
GSR (x5)	Millimetre	143	255	80	111	445	242	296	96	148	610	132	387	123	175	825
Crop price (*P*1)	Index	143	146	51	100	306	242	138	47	65	310	132	148	91	86	673
Animal price (*P*2)	Index	143	163	92	90	430	242	149	53	70	365	132	161	66	54	545
Wage (*w*1)	Index	143	118	12	100	138	242	118	12	100	138	132	118	12	100	138
Land price (w2)	Index	143	128	58	37	445	242	119	42	51	282	132	101	45	31	459
Capital price (w3)	Index	143	113	17	81	186	242	120	25	72	228	132	113	25	46	176
M&S price (w4)	Index	143	120	16	100	179	242	119	16	100	167	132	119	16	100	168

Note: *GSR is growing season rainfall.

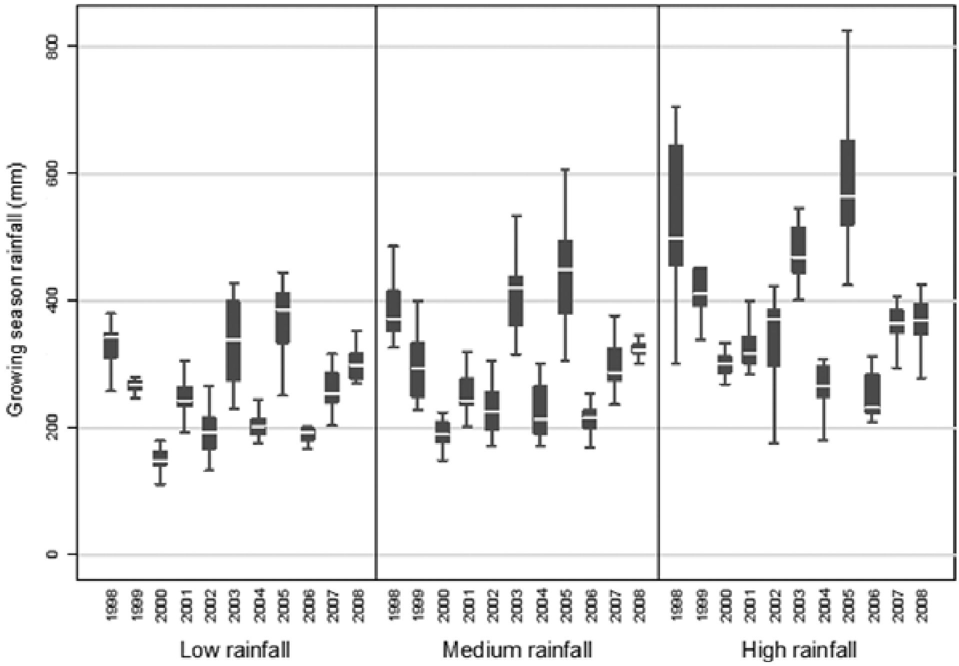

Figure 3 Variations in growing season rainfall for sample farms in the three rainfall groups.

3. Results and discussion

3.1. Profitability and productivity decomposition

The indexes of profitability (*d*PROF), total factor productivity (*d*TFP) and their components are presented in Table 2. These measures were recorded as geometric means for average farms in each rainfall group and for all the farms for each data period using 1998 as the base year. The *d*PROF, terms of trade (*d*TT) and other indexes were computed directly by the DPIN 3.0 program using both quantity and price data for the selected variables as specified in Section 2. The first three columns of Table 2 show the changes in profitability (*d*PROF), terms of trade (*d*TT) and total factor productivity (*d*TFP) of average farms for low, medium, high rainfall groups and for all farms. These results are illustrated in panels A, B, C and D of Figure 4, respectively, and the supporting data summary is presented in Appendix A online to save space.

Profitability growth (*d*PROF) is observed in all groups but varied from 0.63 to 1.71, 0.64 to 1.71, and 0.85 to 1.44 for the low, medium and high GSR groups, respectively, and from 0.69 to 1.63 for all farms compared with the base year 1998. A comparison of these results indicates that profitability growth is higher and less variable for the higher rainfall group. By contrast, the variation is greater for the low and medium rainfall groups. For all the groups, the lowest profitability is observed in 2000 (an extreme drought) and the highest profitability is observed in 2007. Lower rainfall (Figure 3), lower outputs

Table 2 Indexes of changes in profitability and productivity components

Year	*d*PROF index	*d*TT index	*d*TFP index	*d*TECH index	*d*EFF index	*d*OTE index	*d*OSE index	*d*OME index	*d*ROSE index
(a) Low rainfall group									
1998	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
1999	1.017	0.926	1.099	1.000	1.099	1.087	0.951	0.989	1.023
2000	0.625	0.858	0.728	1.000	0.728	0.979	0.680	0.996	0.747
2001	1.203	1.157	1.040	1.024	1.015	0.904	0.996	0.951	1.181
2002	0.810	1.243	0.651	1.024	0.636	0.892	0.636	0.990	0.720
2003	1.493	1.161	1.286	1.207	1.065	1.052	0.997	1.010	1.002
2004	0.820	0.811	1.012	1.207	0.838	1.004	0.772	0.980	0.852
2005	0.995	0.947	1.051	1.100	0.955	0.899	0.986	0.983	1.081
2006	0.862	0.937	0.919	0.986	0.932	1.026	0.822	1.000	0.909
2007	1.714	1.501	1.142	1.017	1.123	1.061	0.958	1.012	1.046
2008	1.436	1.248	1.151	1.086	1.060	1.013	0.947	0.978	1.070
G-mean	1.044	1.054	0.990	1.057	0.937	0.990	0.876	0.990	0.956
(b) Medium rainfall group									
1998	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
1999	0.988	0.783	1.262	1.000	1.262	1.144	0.975	1.019	1.082
2000	0.642	0.716	0.896	1.000	0.896	0.967	0.811	0.995	0.932
2001	1.162	0.989	1.174	1.024	1.146	0.982	0.936	0.978	1.194
2002	1.245	1.165	1.069	1.024	1.043	0.939	0.938	1.022	1.087
2003	1.345	1.128	1.193	1.207	0.988	0.985	0.988	1.022	0.981
2004	0.975	0.783	1.246	1.207	1.032	1.023	0.859	1.014	0.994
2005	0.952	0.969	0.983	1.100	0.893	0.856	0.946	1.004	1.039
2006	0.957	0.848	1.128	0.986	1.144	1.051	0.854	1.008	1.080
2007	1.706	1.287	1.326	1.017	1.304	1.007	0.957	1.023	1.266
2008	1.210	1.032	1.173	1.086	1.080	0.902	0.934	1.013	1.182
G-mean	1.077	0.958	1.125	1.057	1.064	0.984	0.925	1.009	1.072

Table 2 (*Continued*)

Year	*d*PROF index	*d*TT index	*d*TFP index	*d*TECH index	*d*EFF index	*d*OTE index	*d*OSE index	*d*OME index	*d*ROSE index
(c) High rainfall group									
1998	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
1999	0.865	0.698	1.239	1.000	1.239	1.059	1.036	1.065	1.098
2000	0.852	0.735	1.159	1.000	1.159	0.955	0.938	1.084	1.119
2001	1.269	0.951	1.334	1.024	1.302	0.975	0.997	1.053	1.268
2002	1.362	1.142	1.192	1.024	1.164	0.914	0.976	0.973	1.309
2003	1.211	1.065	1.138	1.207	0.942	0.849	1.028	0.999	1.111
2004	1.020	0.719	1.419	1.207	1.175	1.003	0.935	1.016	1.153
2005	0.984	0.946	1.041	1.100	0.946	0.827	0.991	1.067	1.072
2006	1.113	0.760	1.465	0.986	1.486	1.011	0.990	1.065	1.379
2007	1.435	0.950	1.510	1.017	1.486	0.918	0.997	1.066	1.519
2008	1.291	0.846	1.526	1.086	1.405	0.910	1.020	1.043	1.480
G-mean	1.111	0.881	1.262	1.057	1.195	0.945	0.991	1.039	1.217
(d) All farms									
1998	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
1999	0.963	0.796	1.209	1.000	1.209	1.106	0.983	1.022	1.069
2000	0.685	0.758	0.904	1.000	0.904	0.967	0.802	1.017	0.918
2001	1.200	1.023	1.173	1.024	1.145	0.958	0.968	0.989	1.209
2002	1.131	1.180	0.958	1.024	0.935	0.919	0.851	1.001	1.017
2003	1.348	1.120	1.203	1.207	0.997	0.966	1.000	1.013	1.019
2004	0.940	0.773	1.216	1.207	1.007	1.013	0.852	1.005	0.990
2005	0.972	0.957	1.016	1.100	0.923	0.860	0.969	1.014	1.059
2006	0.966	0.848	1.139	0.986	1.156	1.034	0.878	1.020	1.096
2007	1.634	1.243	1.315	1.017	1.294	0.998	0.967	1.030	1.258
2008	1.290	1.034	1.248	1.086	1.149	0.933	0.959	1.011	1.218
G-mean	1.076	0.963	1.118	1.057	1.058	0.976	0.927	1.011	1.073

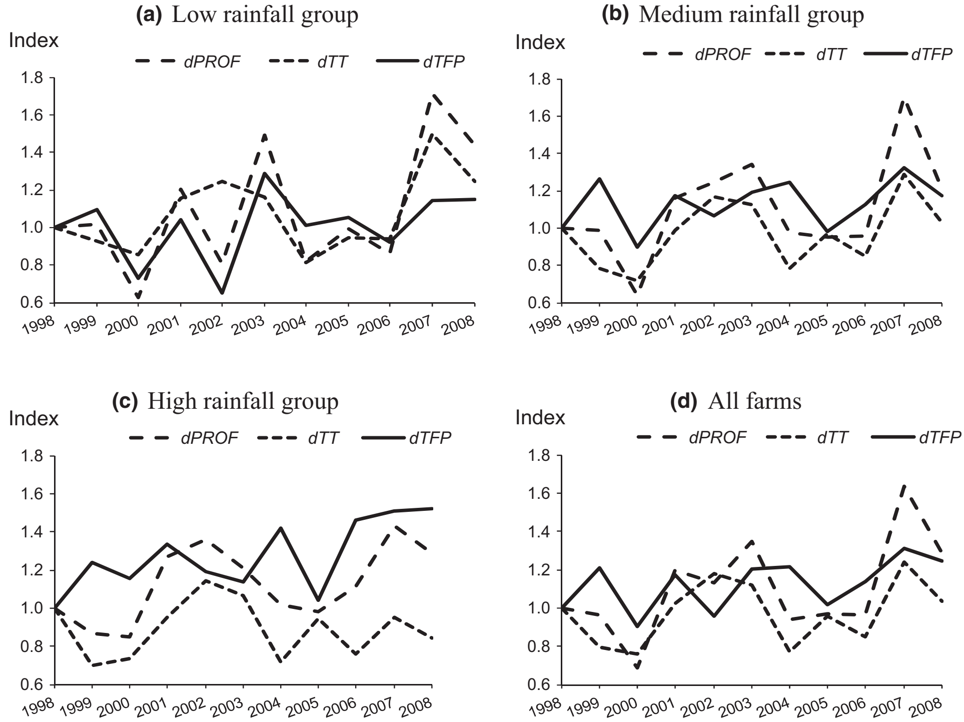

Figure 4 Changes in profitability of farms.

(Panel A, Figure A1) and higher input prices (Panel D, Figure A1) caused the lower profitability in all the groups in 2000. On the other hand, the highest profitability in 2007 appears to be due to higher output prices (Panel B, Figure A1) and favourable rainfall (Figure 3).

For the high and medium rainfall groups, the *d*TFP was the dominant source of profitability growth. For example, for the 11-year period, its 7.7 per cent profitability increase (which equates to 0.73 (*d*lnPROF=ln(1.076)/(2008–1998)*100) per cent growth per annum) was the combined effect of a 4.2 per cent fall in TT (1–0.958) and a 12.5 per cent increase in TFP for the medium group. For the high rainfall group, its 11.1 per cent profitability increase was attributable to a 11.9 per cent fall in TT and a 26.2 per cent increase in TFP. By contrast, for the low rainfall group, its 4.4 per cent profitability increase was due to a 5.4 per cent increase in TT and a 1.0 per cent fall in TFP.

The *d*TT effects on *d*PROF are found to vary more or less in the same pattern across the years within each rainfall group. However, the changes in *d*TT do differ between the rainfall groups with *d*TT responsible for a 5.4 per cent rise for the low rainfall group, contrasting with declines in the other rainfall groups. There are a greater number of the *d*TT falls observed for the high rainfall group (Table 2 and Panel C, Figure 4). The higher rainfall group comprises more livestock dominant farms that experienced increases in their costs of production in the study period due to higher feed grain prices, alongside few favourable movements in wool prices. For example, in 2002, the greasy wool price was around 680 c/kg and in 2008 the price had declined to around 500 c/kg (see Panels B and D, Figure A1).

We observe that in 2000 (an extreme drought), the *d*TFPs for both the low and medium rainfall groups were the lowest (Table 2). On the other hand, the *d*TFP growth remained higher for the high rainfall group but with a higher variation, ranging between 4 per cent in 2005 and 53 per cent in 2008. An examination of the data reveals that the output quantity did not increase much in 2005 while input quantity increased greatly in that year for the high rainfall group, causing its *d*TFP to be the lowest (Panel A and B Figure A1). In 2008, the output increase was relatively higher for this group. We also observe that output quantity did not exactly follow the movement of output price, and in some years, it moved inversely (Panels A and B, Figure A1). In rain-fed farming systems often output quantity is liable to be more influenced by GSR rather than output price. For all farms, the profitability growth (*d*PROF) followed the pattern of the medium group. The *d*TFP growth for the all farm groups remained higher than 1998 except in 2000 and 2002 and varied between two per cent in 2005 and 32 per cent in 2007.

We analysed the above results from two perspectives: examining the *d*TT effect and the rainfall effect on productivity and profitability. We observed that the *d*TT effect moderated the movement of *d*PROF caused by *d*TFP effect, except in the years when all three indexes moved in the same direction (Figure 4). The decomposition of *d*TFP to its efficiency components is examined in the next subsection.

3.2. Efficiency changes

Relative to 1998, the total factor productivity changes (*d*TFP) were decomposed into technical change (*d*TECH), output-oriented technical efficiency change (*d*OTE), output-oriented mix efficiency change (*d*OME) and residual output-oriented scale efficiency change (*d*ROSE). These indexes are presented in Figure 5 for the three rainfall groups of farms in panels A, B and C and also for all farms in panel D. The fourth and the last column in Table 2, respectively, show the technical change (*d*TECH) and residual output-oriented scale efficiency (*d*ROSE). For the high rainfall group, the *d*TFP over the period is estimated at 1.262, which equates to 2.33 ($d\ln TFP = \ln(1.262)/(2008–1998)*100$) per cent per annum growth, compared with that of −0.1 ($d\ln TFP = \ln(0.990)/(2008–1998)*100$) and 1.18 ($d\ln TFP = \ln(1.125)/(2008–1998)*100$) per cent per annum, respectively, for the low and medium rainfall groups. For all groups, per annum TFP growth is 1.12 ($d\ln TFP = \ln(1.118)/(2008–1998)*100$) per cent. In 2007 and 2008, the observed high levels of TFP coincided with a big swing into cropping (see panel A in Figure A1 in online Appendix A) in those years, triggered by a spike in cereal prices (panel B in Figure A1) and some favourable rainfall distributions across the farm groups (see Figure 3). On the other hand, the *d*TFP was the lowest in 2000

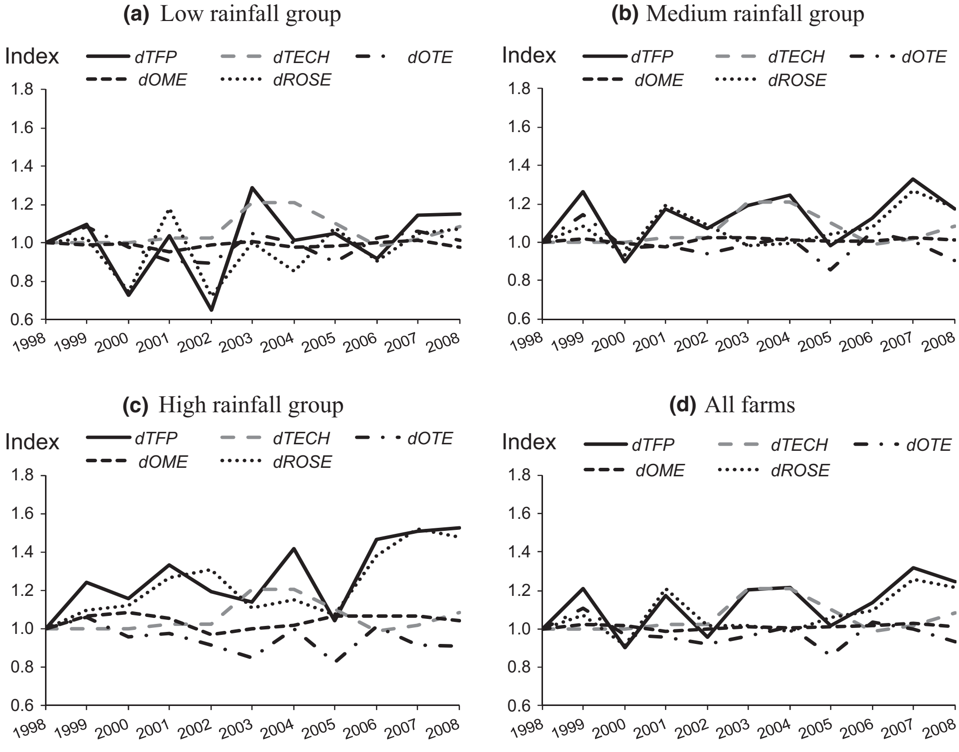

Figure 5 Changes in total factor productivity (TFP) components of farms.

(an extreme drought). However, there was an exception in 2005 when the mean rainfall was higher than in 2003 and 2007 (Figure 3) but the *d*TFP was lower for all groups (Table 2). This is principally due to farms reducing crop areas in that season (see panels A&B in Figure A2) and additionally there being lower values of efficiency (*d*EFF) in that year due to lower values of output-oriented technical efficiency (OTE).

The *d*TECH index shows the difference between the maximum possible TFP achieved by some farmers operating on the new production possibility frontier and the maximum possible TFP achieved by some farmers operating on the old production possibility frontier. Note that the technical change (*d*TECH) index is the same for all groups and it fluctuates because we assumed that all sample farms practise the same technology, and we allowed technical regress for the study period. From 1998 to 2000, the index remained more or less flat then increased in 2003–2005. After dropping in 2006, it increased again slightly in 2007 and 2008. It appears that the peak technical progress did not coincide with the year of favourable GSRs. This would perhaps suggest that the rainfall effects on the technical change and *d*TFP are minimised because of including GSR as an input variable in the model estimation.

We observe that the *d*OME and *d*ROSE are the main sources of TFP growth, but the *d*ROSE appears to be the main source of variation in *d*TFP in all groups. This could indicate that farmers in the study area are efficient in their enterprise mix for a given level of input, and at the same time, given the technology, farmers are even more efficient in altering the levels of both inputs and outputs to maximise TFP. However, the output-oriented technical efficiency (*d*OTE) that involves best practice use of existing technology has declining trends. This suggests the best practice use of existing technology is not contributing much to the TFP growth as compared to the contribution by best practice enterprise mix and alterations of input and output levels.

For the high rainfall group, the *d*OME is higher relative to the other groups, indicating that this group has better options for relaxing restrictions on its output mix as evident in Table 1 and Figure A2. Note that the high rainfall group has relatively more emphasis on crop-animal mixed production compared with the other two groups. In this group, all 132 observations have animal production activities with lowest standard deviation compared with the other two groups (Table A1). An examination of the changes in outputs and changes in the proportion of the crop area and income in the online Appendix A (Figures A1 and A2) reveals that total output growth is higher for the high rainfall group (Panel A, Figure A1) and the proportion of crop area to effective area varies widely compared with the low and medium groups (Panel B, Figure A2).

These results suggest that especially in low rainfall environments, farmers may have less flexibility in altering their enterprise mix away from cropping into alternative profitable enterprises. By contrast, in high rainfall environments where farmers already have a mix of livestock and crop alternatives and have maintained their sheep infrastructure, they can more easily alter their enterprise mixes in response to rainfall and commodity price relativities.

To economise on space, detailed results regarding efficiency scores are not presented here but are available as the online Appendix B.

3.3. Importance of technical change and efficiency gains

Gains in efficiency and technical change are identified as jointly and similarly important in their contribution to total factor productivity across the entire farm sample in the region from 1998 to 2008 (Table 2). However, for the high rainfall group, gain in efficiency is the more important contributor to productivity and profitability (Panel C, Figure 6).

The important role played by scale efficiency (*d*ROSE) has previously been reported for studies of Australian broadacre agriculture (O'Donnell 2010a). He found that during periods of significant declines in the terms of trade that scale (and mix) efficiency increased. In this current study of broadacre farming in south-western Australia, during a period of reducing terms of trade, at least for the medium and high rainfall groups, we also find that scale efficiency and technical efficiency (mix) play important roles in boosting change in total factor productivity (*d*TFP).

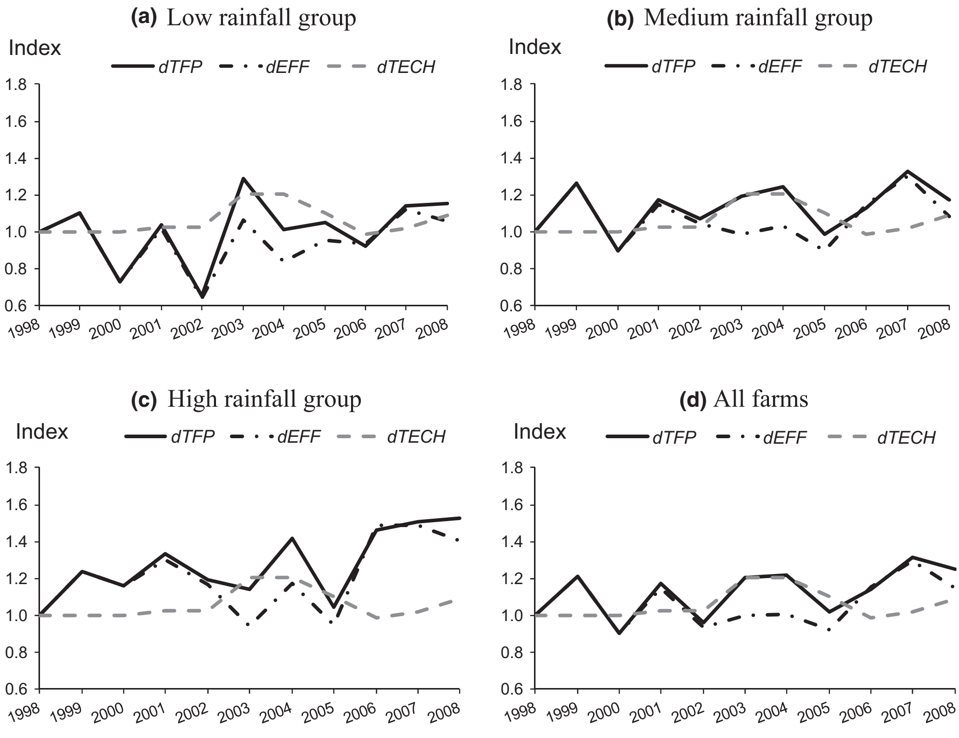

Figure 6 Comparison of productivity change (*d*TFP) and efficiency changes (*d*EFF).

Hughes *et al*. (2011) and the current study both find that scale efficiency and technical efficiency (mix), together with technical change, play important roles in generating productivity gains in south-western Australia. The business and adaptation strategy that many farms have employed is to increase farm size and/or the size of cropping programs, and thereby reap the benefits of scale economies (Kingwell *et al*. 2013). In undertaking this often successful expansion strategy, farms have tended to rely on existing technologies and to improve their use of best practice methods. Underpinning this strategy often has seen a greater reliance on crop (mainly wheat) production, and wheat growing has supported the growth and resilience of many farm businesses during the study period. However, as shown by the results for the high rainfall group, enterprise mix efficiencies can also play an important role in supporting farm productivity. The benefits from scale economies can be reduced if they incur a loss of flexibility in adjusting a farm's enterprise mix.

Asseng and Pannell (2012) recognise farmers' current sound use of best practice methods, yet they stress the need to develop technologies that will boost technical change (*d*TECH). Future productivity enhancement cannot solely rely on improvements in technical efficiency (*d*EFF). Technical change is also essential to shift farmers' production frontiers outwards. R, D & E that offers farmers affordable beneficial technical change is required, especially given the current parlous financial situations of some broadacre farm businesses (Kingwell *et al.* 2013).

4. Summary and conclusion

This paper explores farm businesses' profitability and productivity in the south-west of Western Australia using farm panel data. The effect on farm profitability and productivity, under varying rainfall conditions, of changes in technology, technical, mix and scale efficiencies and the farmer's terms of trade is examined. The sample of farms was split into three rainfall groups, although using other groupings such as farm size may have revealed additional insights regarding the heterogeneity of farm productivity and profitability.

Farms in the higher rainfall group had highest profitability growth with less year-to-year variation. For the low rainfall group, year-to-year fluctuations in productivity growth were higher and coincided with fluctuations in growing season rainfall. The terms of trade was positive for the low rainfall group. By contrast, due to higher input costs (particularly supplementary feed) and less favourable movements in output prices, the medium and high rainfall groups had a declining trend in their terms of trade.

For the medium and high rainfall groups, their productivity growth was found to be the dominant source of their profitability growth. By contrast, favourable terms of trade due to higher crop prices supported the profitability growth of the low rainfall group. Farms in the low rainfall group also extracted further advantage from their favourable terms of trade by operating crop-dominant farming systems.

Decomposing the productivity growth indicated that efficiency gains were equally important to technical change in affecting productivity growth across the entire farm sample. However, for farms in the medium and high rainfall groups, their output-oriented technical efficiencies declined, while their scale and mix efficiency components remained more important as contributors to productivity growth. In other words, for farms in the medium and high rainfall groups, their productivity growth was mostly due to greater efficiency gains rather than technical change.

Overall, our results indicate that productivity growth is similarly supported by technical change and efficiency gains. Hence, to support farm profitability, priority should be placed on R,D&E that delivers a combination of efficiency gains and further technical change.

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Appendix A

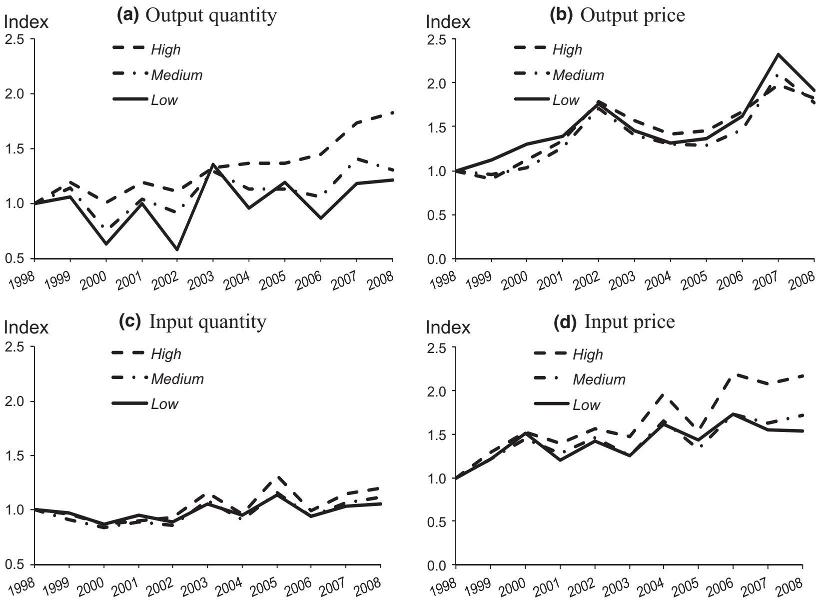

Figure A1 Changes in aggregate output–input quantities and prices.

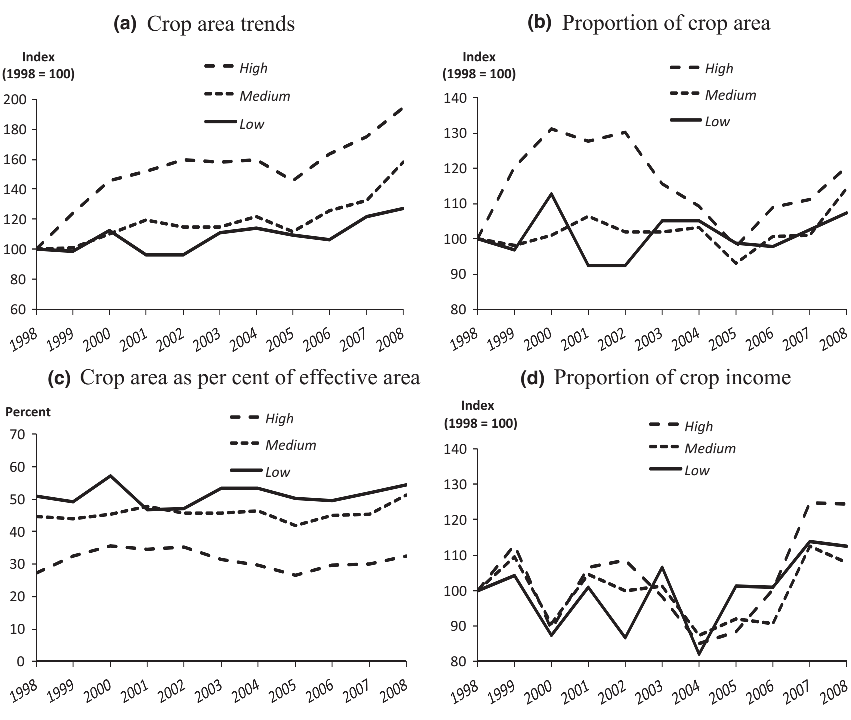

Figure A2 Changes in crop area and income.

Table A1 Summary statistics of outputs per unit of inputs (average per farm over 1998–2008)

Variables	Low rainfall (<275 mm GSR*)					Medium rainfall (275–325 mm GSR*)					High rainfall (>325 mm GSR*)				
	Observation	Mean	SD	Min	Max	Observation	Mean	SD	Min	Max	Observation	Mean	SD	Min	Max
Crop output/labour	143	32.67	19.95	4.60	102.39	242	26.65	11.82	4.83	55.11	132	20.11	13.81	3.48	93.13
Crop output/area	143	1.01	0.46	0.15	2.28	242	1.10	0.50	0.22	2.26	132	1.12	0.44	0.28	2.78
Crop output/capital	143	0.46	0.30	0.08	2.40	242	0.50	0.17	0.12	1.18	132	0.32	0.25	0.12	1.57
Animal output/labour	143	8.84	4.37	3.88	20.42	242	13.70	8.84	4.15	49.75	132	17.08	8.47	8.88	46.93
Animal output/area	143	0.31	0.16	0.12	0.80	242	0.58	0.57	0.19	3.78	132	1.04	0.30	0.71	1.52
Animal output/capital	143	0.14	0.09	0.07	0.50	242	0.27	0.24	0.10	1.33	132	0.32	0.19	0.31	1.05

Note: *GSR is growing season rainfall.

Appendix B

Efficiency scores

The output- and input-oriented measures of the changes in efficiency categories (technical, scale, and mix) are presented in Figure 1B for low, medium and high rainfall groups in panels A, B and C, respectively, and for all farms in panel D. Figure 1B shows that farms in all three groups are highly input-oriented mix efficient (IME). These scores are close to unity and mostly invariant over the data period. This finding is different from that reported by O'Donnell (2010a). He found that Australian farms are more output-oriented mix efficient (OME) and attributed this finding to the farming characteristics of having high ratios of land-to-labour and land-to-capital. We looked into these ratios for our sample data and found that while land-to-labour ratios were high, land-to-capital ratios were low for all the groups (Table A1, Appendix A).

Comparison among the groups shows that OME was higher for the high rainfall group. This result suggests that farms in the high rainfall group are more efficient in output mix compared with other groups in achieving maximum productivity. This finding reconfirms that high rainfall farms have flexibility advantages due to their retention of a mix of crop and animal enterprises compared with the low and medium rainfall groups as evidenced

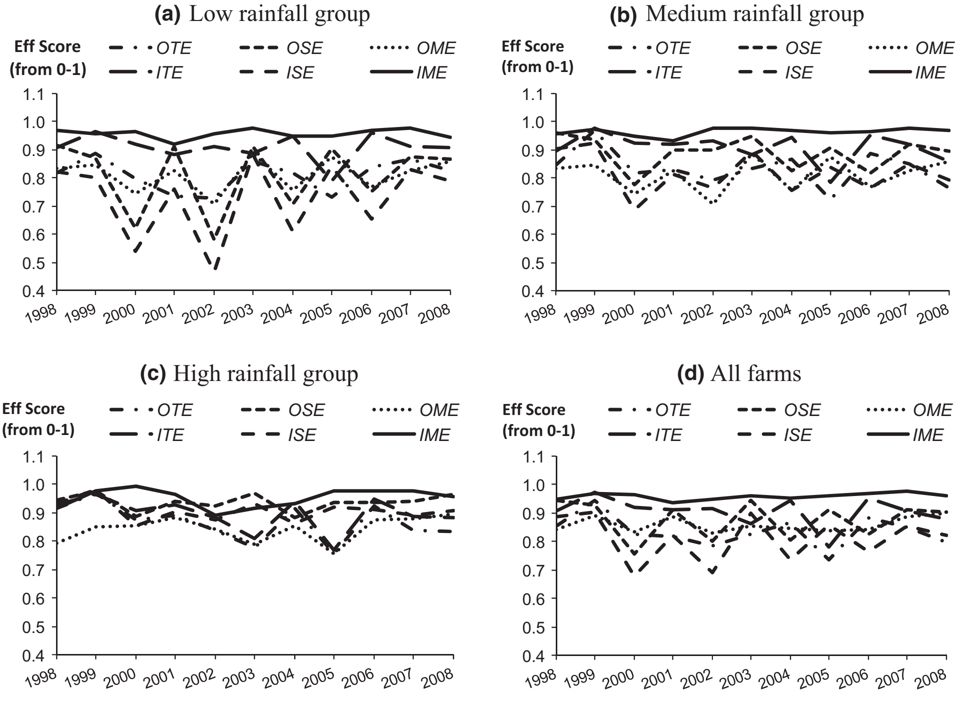

Figure B1 Output- and input-oriented efficiency scores of farms.

by their allocation of land varying widely between crops and sheep over the data period (Panel B, Figure A2).

For all groups, the ITE score was higher over the study period. On the other hand, the OTE score remained lower and had a declining trend until 2006. For the medium and high rainfall groups, however, both the ITE and OTE declined except until 2006 for OTE. This indicates that there remains scope for these farmers to increase efficiency in input use and output production by adopting better management practices.