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Broadacre Farm Productivity Trajectories and Farm Characteristics

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Abstract

Improving farm productivity is touted as essential for the future prospects of Australian agriculture, particularly for the export-oriented broadacre farm sector. Accordingly, this paper examines productivity gain in a large sample of Australian farms over the period 2002 to 2011. The annual components of productivity of the same group of 223 farms are measured each year for a decade by using a multiplicatively complete Färe-Primont index number and applying DEA methods. Results show the variability and trends in these farms' annual productivity. Farms are classed according to the geometric mean of their total factor productivity and the variance of this productivity. This relationship displays convexity, and high growth in productivity is associated with greater volatility in productivity. Only a small proportion of farms over the decade achieved high, stable growth in productivity. Most farms either experienced high growth and high variability in productivity or low growth and low variability in productivity. The characteristics of farm businesses in both categories are examined to ascertain links between farm characteristics and their trend in farm productivity. Key findings are that, overall, most farms experienced growth in their total factor productivity with the principal cause of this growth being greater technical efficiency rather than technical change. Farms that experienced the highest growth in their total factor productivity typically increased their farm size, became more crop dominant, often operated farms in lower-rainfall regions, generated more profit and were less exposed to debt and generated more crop yield and more livestock income per millimetre (mm) of growing season rainfall.

Key words: Productivity, Profitability, Farm characteristics, Volatility

Introduction

It is widely acknowledged that the physical operating environment for broadacre farm businesses in southern Australia has been challenging since the late 1990s (Howden and Hayman, 2005; Garnaut, 2011; Stretch et al., 2012). Many scientists consider the future environment will remain challenging due to continuing climate variability and long-term climate change (Kingwell and Pannell, 2005; Kingwell, 2006; Gunasekera et al., 2007; Sietchiping, 2007; Garnaut, 2011; Addai, 2013). Warming and drying trends, complemented by increasing atmospheric concentrations of carbon dioxide (CO₂), have been observed in southern Australia (Frederiksen et al., 2011; Cai et al., 2012; Asseng and Pannell, 2012; Addai, 2013).

Contemporaneous with the unfolding recent change in climate (Kingwell et al., 2013) has been a period of marked price volatility for many farm and food commodities since the late 1990s (Kingwell, 2012; Martin, 2013). Against this backdrop of price volatility and climate challenge, farm businesses in Australia have also needed to cope with the business pressures arising from a periodic strong Australian dollar, scarce skilled farm labour, ever-changing technologies and the de-regulation of grain marketing; all factors adding to the challenge and complexity of broadacre farming (Kingwell, 2011).

The variable nature of the farm operating environment over the last decade or so would have affected farm productivity and profitability. Exactly how and to what degree is a focus of this paper in which the productivity and profitability of a set of 223 farms in south-western Australia from 2002 to 2011 is examined. The rest of the paper includes four sections. Section 2 presents the study region and its farming system. The data and methodology are described in Section 3 and the results are presented and discussed in Section 4. Concluding comments are presented in Section 5.

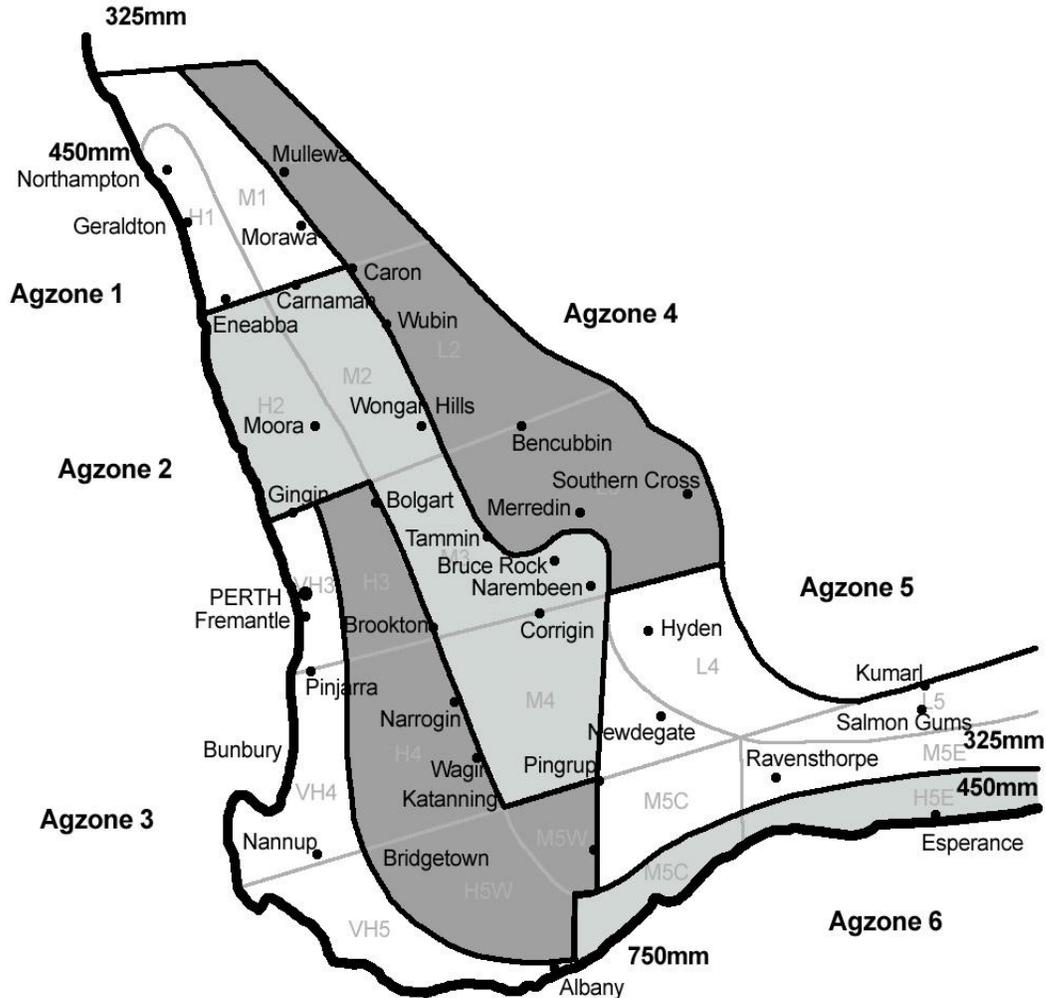
The Study Region

The study region of south-western Australia (Figure 1) has a Mediterranean climate and is characterised by long, hot and dry summers and cool, wet winters. In the northern and central parts of the study region, around three-quarters of the average annual rainfall is received between April and October. Summer rainfall is highly variable, and is more common along the south coast parts of the study region.

The region's farming system is mainly a mixture of grain and livestock enterprises with sheep rather than cattle being the predominant animal enterprise. Only 23 of the 223 farm businesses in the study sample had cattle at the end of the study period. The grains grown are wheat, barley, canola, and lupins, although the area of lupins has decreased substantially during the 2010s due to poor yields and low profitability and the canola area has increased (ABARES, 2017).

Sheep are run on annual pastures during winter and spring. In summer months, livestock feed is mainly pasture residues and crop stubbles. In late summer through to early winter there is often a feed gap and supplements of lupins or barley are fed to maintain animal welfare. The quantity and quality of pasture produced is mainly influenced by the timing of the first winter rains, farm soil type, early spring rainfall and sheep and weed management. The sheep systems mainly involve Merinos and include both wool and meat-dominant systems.

Figure 1. The study region of south-western Australia



During the study period (2002 to 2011) sheep numbers in Western Australia (WA) decreased from 24 million to fewer than 15 million, in response to decreasing profitability. The highest reduction in sheep numbers occurred in the low-rainfall areas (Agzones 4 and 5 in Figure 1) where stocking rates and profitability in the last ten years were low compared to the potential profitability of cropping enterprises. However, despite the high relative profitability of cropping, the vast majority of farmers have continued to maintain mixed enterprise farms (Kingwell et al., 2013). The productivity and profitability of farms and their enterprise mix also vary by rainfall zones (Islam et al., 2014).

Data and Methodology

Data describing the farm businesses in the study region were supplied by three agricultural consultancy firms with farm business clients in the region. Initially, farm business records of 242 farms were obtained for the period 2002 to 2011, with farms being selected from a majority of the zones shown in Figure 1. Zones H2, H3 and L4 were not represented. The longitudinal datasets describe the farm production and financial records of each farm over the decade. Because each consultancy firm provided different sets of physical and financial variables, and some variables are measured differently by each

firm, care was taken to form a consistent unified dataset and, therefore, data from 223 farms were used in calculating productivity trajectories. The sample size in the main zones represents up to 15 per cent of the farm population in those zones.

Farm productivity measures

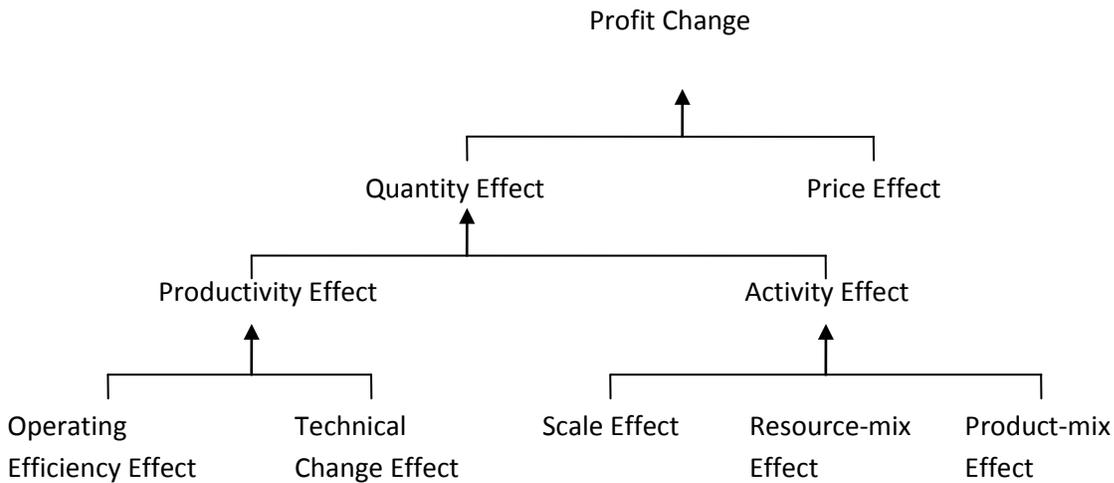
Farm productivity variations in agricultural production exist as farms face different production opportunities due to differences in factors such as: (i) physical resource endowments (e.g. quality of soils and climate), (ii) technology, capital and infrastructure and (iii) levels of costs and prices (Hayami, 1969; Hayami and Ruttan, 1971; Lau and Yotopoulos, 1989; Battese et al., 2004). On the other hand, efficiency variations exist as a result of management decisions where farmers underutilise certain inputs, misallocate inputs, select an inappropriate mix of enterprises or choose a crop type or crop variety that performs poorly. In this context, measurement of efficiency has been a controversial analytical tool, as it is a residual measure, and thus is likely to involve measurement errors when functional forms or distributions are mis-specified. There is substantial evidence in the literature, however, that inefficiency does exist and that it can be measured effectively using either data envelopment analysis or parametric methods (O'Donnell et al., 2008; O'Donnell, 2010).

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) have reviewed the literature on measuring efficiency in agricultural production, classifying existing approaches as parametric or non-parametric. The modified least-squares econometric production and stochastic frontier production function models (a maximum likelihood procedure based on a non-linear model) are examples of the first, and the traditional Tornqvist-Theil or Christensen and Jorgenson total factor productivity index and data envelopment analysis are examples of the second. Detailed reviews of productivity estimation methods can be found in Van Beveren (2012) and Van Biesebroeck (2007). Most of these studies deal with productivity and efficiency issues and not with profitability, to which farm business viability is closely linked (Lovell, 2001). Productivity and profitability, however, are related in the sense that, typically, a more productive business is also more profitable, and faster growth in productivity often translates into faster growth in profitability, *ceteris paribus* (O'Donnell, 2010).

Economists have used numerous 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 that improvements in productivity are accompanied by improvements in profitability. Grifell-Tatjé and Lovell (1999) show that sources of profit change are driven by changes in quantities and prices. The changes in quantities can be further decomposed, as illustrated in Figure 2, into five categories that affect quantities produced. Hadley and Irz (2008) have applied the hierarchy displayed in Figure 2 to farm-level production data for England and Wales.

Advancing this decomposition approach, O'Donnell (2010) distinguished a difference between "profitability change" and "profit change" and showed that the sources of profitability change are driven by the changes in the 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 to period 0 .

Figure 2. Profit decomposition



Source: adapted from Grifell-Tatjé and Lovell (1999)

According to O'Donnell (2010), the sources of profitability change can be decomposed into three stages provided that: (a) the output and input quantity aggregates are associated with input and output price aggregates; (b) the quantity and price aggregates are non-negative and linear homogeneous in prices; and (c) any quantity-price aggregator function pair satisfy the product rules. The formulae for decomposing these profitability and productivity drivers are presented in simplified forms in the following equations (1) to (6).

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 in total factor productivity ($dTFP$):

$$dPROF = dTT * dTFP \quad (1)$$

Following O'Donnell (2010), we used a multiplicatively complete Färe-Primont¹ index number. We computed the change of index numbers in Equations (1) to (6) between firms or 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:

$$dPROF = PROF_{nt} / PROF_{n0} \text{ where,}$$

$$PROF_{nt} = P_{nt}Q_{nt} / W_{nt}X_{nt}$$

$$PROF_{n0} = P_{n0}Q_{n0} / W_{n0}X_{n0}$$

P and Q are the price and quantity of outputs, and W and X are the price and quantity of inputs.

¹ There are several well-known indexes (e.g., the Fisher, Törnqvist, and Malmquist indexes). The Färe-Primont index satisfies a suite of important axioms from index number theory (e.g. identity, transitivity, circularity, weak monotonicity, proportionality, and time space reversal). The Färe-Primont TFP index is a general index in the sense that it nests several other TFP indexes as special cases (O'Donnell, 2016).

Similarly, the change in terms of trade (dTT) and the change in total factor productivity ($dTFP$) in equation (1) can be expressed respectively as:

$$TT_{n0,nt} = P_{n0,nt} / W_{n0,nt} \quad \text{and}$$

$$TFP_{n0,nt} = Q_{n0,nt} / X_{n0,nt}$$

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 ($dEFF$):

$$dTFP = dTECH * dEFF \quad (2)$$

where,

$$dTFP = TFP_{n0,nt} = \frac{TFP_{nt}}{TFP_{n0}} \quad \text{or}$$

$$dTFP = TFP_{n0,nt} = \left(\frac{TFP_t^*}{TFP_0^*} \right) \times \left(\frac{EFF_t^*}{EFF_0^*} \right)$$

The term $\left(\frac{TFP_t^*}{TFP_0^*} \right)$ is $dTECH$ 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 $\left(\frac{EFF_t^*}{EFF_0^*} \right)$ is $dEFF$ which measures technical efficiency change in period t compared to period 0 .

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

$$dEff = dOTE * dOME * dROSE \quad (3)$$

$$dEff = dOTE * dOSE * dRME \quad (4)$$

$$dEff = dITE * dIME * dRISE \quad (5)$$

$$dEff = dITE * dISE * dRME \quad (6)$$

The above indexes are defined briefly below.

OTE (ITE) is output-oriented (input-oriented) technical efficiency that captures the potential change in TFP output (input) 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) to (6) can be found in O'Donnell (2010 and 2011).

Variables and index construction

The following is a list of key variables constructed and used in this study's productivity analyses.

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 the dominant crop type by far.

Crop price index (p1) was generated by dividing the sum of all revenue from crop production by crop output (q1).

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

Animal price index (p2) was generated as an average of cattle, sheep and wool sale prices using revenue share as a weight. Their sale prices were generated by dividing their revenue from quantity sales.

Land input (x1) was effective land area utilised for crop and animal production (in hectares).

Rental price of land (w1) was estimated by multiplying the land asset value that was available in the sample data and the 10-year real rate of Australian government bonds.

Labour input (x2) was in person weeks and was constructed as the annual sum of available family, managerial and hired labour.

Labour wage index (w2) was constructed using ABARE's online farm survey data (DAWR, 2018), as no labour payment data for family members existed in the sample data set. The cost and quantity of labour input from ABARE data were based on the average of the WA farm survey. We assumed that all farms in the sample faced the same per unit labour cost.

Capital input (x3) was constructed using asset values (livestock, machinery and equipment) divided by their average prices index series from ABARES (2011) and using each asset's capital value share as their respective weighting to form the index.

User cost of capital (w3) was estimated using the same method used to derive (w1).

Fertilisers (x4) was constructed by dividing fertiliser expense by its price index (w4).

Fertiliser price (w4) was the fertiliser prices index series from ABARES (2011).

Materials and services (M&S) inputs (x5) was constructed by summing annual farm expenditures over five input categories: chemicals, livestock materials, fuel and lubricants, and repairs and maintenance and dividing each item by the relevant price index from ABARE (2011).

Price of M&S inputs (w5) was constructed as an average of the prices of five items: chemicals, livestock materials, fuel and lubricants, repairs and maintenance, and contract expenses using their expenditure shares as a weight.

Growing Season Rainfall (GSR) input (x6) was actual rainfall recorded in millimetres for each farm in each growing season of the data period.

Results and Discussion

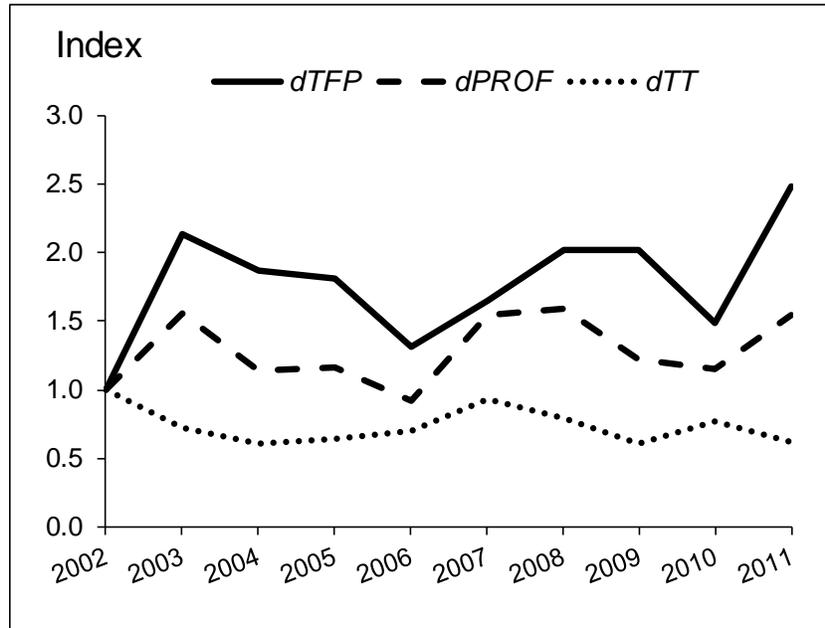
Profitability and productivity measures

The components of profitability and productivity are measured for each sample farm in each year of the study period. As mentioned above, the measure of change in farm profitability ($dPROF$) is the ratio of revenue to cost in each year compared to a previous year and this measure can also be decomposed into its components of change in the terms of trade (dTT), where the terms of trade is the ratio of prices received to prices paid, and change in total factor productivity ($dTFP$) (see equations (1) and (2)).

As shown in equation (1), a positive improvement in the terms of trade will increase the change in farm profitability, if there is no decline in farm productivity. Also, an increase in farm productivity will beneficially influence farm profitability, if there is no adverse movement in the terms of trade.

The results in Figure 3 show, firstly, a slight downwards trend (not significant) in the terms of trade over the years 2002 to 2011, when averaged across the sample of all farms. Favourable peaks in the terms of trade coincided with years in which international grain prices experienced spikes (e.g. 2007 and 2010, see Kingwell (2012)). Secondly, the changes in farm total factor productivity were, overall, strongly positive. Thus, due to the strongly positive effect of productivity and the slight weakening in the terms of trade, an overall positive change in farm profitability occurred, averaged across the entire sample of farms.

These are important results insofar as they show that, in spite of the warming and drying trends observed over those years (Kingwell et al., 2013), farm profitability on average improved, in spite of no lasting improvement in the terms of trade, being supported by productivity growth.

Figure 3. Changes in farm profitability, productivity and terms of trade

Productivity improvement has allowed most farm businesses to prosper during a period of climatic challenge and with a slight worsening in the terms of trade.

The fact that over the study period the terms of trade experienced a very slight decline would have offered a small encouragement to technically-efficient firms to expand their operations into the region of increasing returns to scale (and scope), with the result that increases in profitability would be associated with increases in productivity.

The change in total factor productivity ($dTFP$) in equation (1) can be decomposed into components of technical change ($dTECH$) and technical efficiency change ($dEFF$). As shown in equation (2), $dTECH$ 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. In addition, $dEFF$ measures technical efficiency change in period t compared to period 0.

The results in Figure 4 show that, when the change in total factor productivity among farms is decomposed into technical change and technical efficiency components, the increase in farm productivity is almost solely attributable to increases in technical efficiency. Although the index of technical change ($dTECH$) is slightly positive, the greater contribution to change in productivity ($dTFP$) is via change in technical efficiency ($dEFF$). The practical implication of this finding is that, throughout the study period, farms have improved their productivity, not so much by investing in new technologies that may have shifted outwards their production possibilities, but rather through better use of existing technologies, including some technologies that offer scale economies.

As outlined earlier, the change in efficiency ($dEFF$) also can be decomposed into various indexes of efficiency change components. How all these components of the change in efficiency ($dEFF$) alter over the study period is shown in Figure 5.

Figure 4. The technical change and technical efficiency components of farm productivity

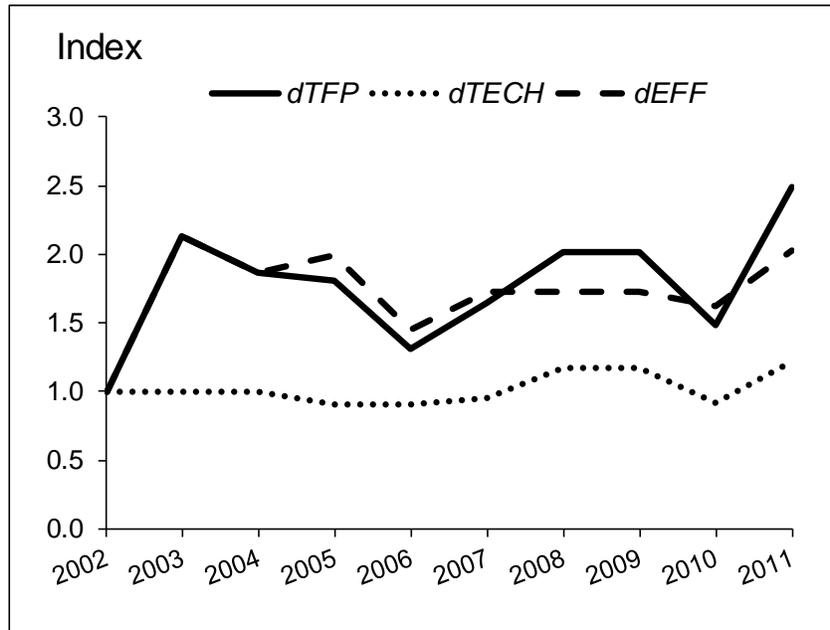
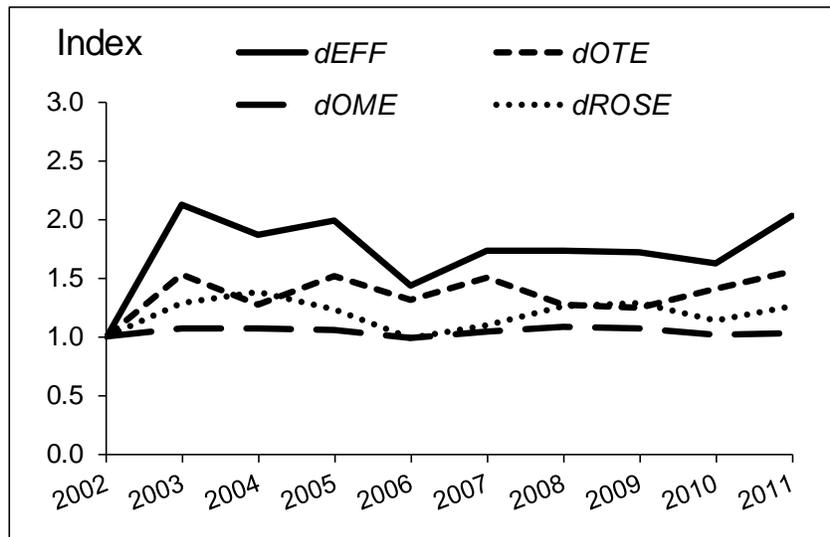
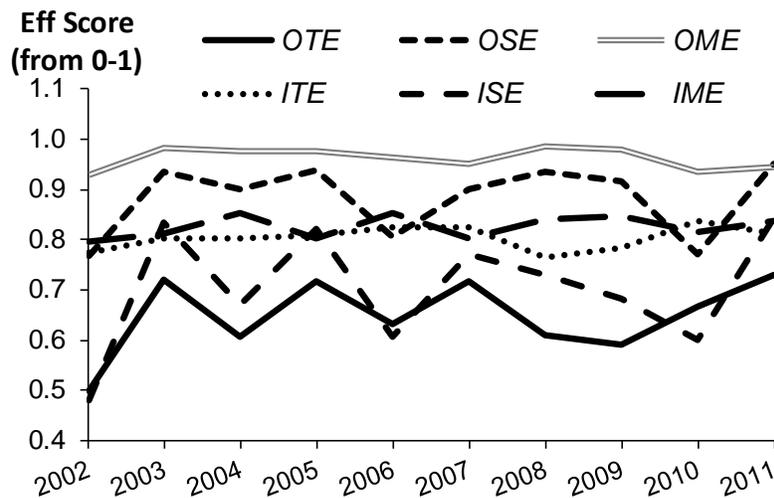


Figure 5. Components of the change in efficiency



The results indicate that changes in output-oriented technical efficiency ($dOTE$) that involve best-practice use of existing technology and scale efficiency ($dROSE$) are the dominant causes for the improved changes in efficiency ($dEFF$) and changes in total factor productivity ($dTFP$).

The output- and input-oriented efficiencies measured in levels, presented in Figure 6, reaffirm that output-oriented scale and mix efficiencies are major contributing factors.

Figure 6. Output- and input-oriented efficiency scores of farms

The improvement in total factor productivity among broadacre farmers (see Figure 4) is not a new finding. Productivity growth has been a key factor driving agricultural output in Australia. Mullen and Crean (2007) identify that more than two-thirds of the current real value of Australian agricultural output can be attributed to productivity growth since the early 1950s. These authors and Sheng et al. (2011) argue that an important source of productivity growth has been new technology from investment in research.

Boult et al. (2018) and Sheng et al. (2011) point out, however, that agricultural productivity growth in Australia has slowed since the 1980s, as it has in some other developed countries. These authors suggest that a significant structural change, or turning point, occurred in the total factor productivity in Australia in the mid-1990s. They argue that the slowdown has been attributable to a combination of adverse seasonal conditions and stagnant public research and development expenditure since the late 1970s.

More particularly, Hughes et al. (2011) observe that a significant slowdown in productivity growth was observed over the previous decade, even after controlling for deteriorating climate conditions. For cropping specialists across Australia, they found that climate-adjusted productivity growth averaged 1.06 per cent a year post-2000, in comparison to 2.15 per cent pre-2000. Importantly, Hughes et al. (2011) concluded that technical change was the key contributor to long-run productivity growth. They also found that growth in technical change was offset by a small decline in technical efficiency, where declining technical efficiency implied that the gap between the most efficient farms and the less efficient farms had widened. However, when the spatial details of Hughes et al.'s findings are examined, it is clear that different results apply to farmers in Australia's south west.

Table 1 presents a sub-set of results from Table 6 in Hughes et al. (2011). What is interesting about the results is how different are the productivity change components in the western region (i.e. south-western Australia) compared to the southern region (i.e. southern and south-eastern Australia). In the western region the principal component of growth in climate-adjusted TFP for all farm types is scale mix efficiency which refers to changes in farm scale and input mix that influence productivity, typically in response to prevailing input and output prices.

Table 1. Average annual growth in productivity components for ABARES surveyed farms in the GRDC southern and western regions in 1999/2000 to 2007/8

Farming type and TFP components			GRDC Southern region	GRDC Western region	Australia
Cropping specialists and mixed enterprise farms	Technical change		0.45	0.37	0.40
	Technical efficiency change		-0.35	-0.34	-0.34
	Scale mix efficiency change		-0.26	1.30	0.17
	Climate-adjusted TFP change		-0.16	1.32	0.24
Cropping specialists only	Technical change		1.00	-0.42	0.54
	Technical efficiency change		-0.36	-0.09	-0.33
	Scale mix efficiency change		0.79	1.56	0.85
	Climate-adjusted TFP change		1.43	1.04	1.06

Source: Abstracted from Hughes et al. (2011)

Importantly, in the western region for cropping specialists, technical change exerted a strong negative influence over climate-adjusted TFP during the years 1999/2000 to 2007/8, whilst technical efficiency exerted a small negative influence.

The important role played by scale efficiency (*dROSE*) has previously been reported for studies of Australian broadacre agriculture (O'Donnell, 2010). He found that, during periods of significant declines in the terms of trade, scale (and mix) efficiency increased. In this current study of broadacre farming in south-western Australia, during a period of a slight reduction in the terms of trade, we also have found that scale efficiency and technical efficiency have played important roles in boosting change in total factor productivity (*dTFP*). More recently, Boulton et al. (2018, p.4) point out that: "Large farms may benefit more from adopting innovations than small farms because they are in a stronger position to fund investment (Sheng & Chancellor, 2018). Additionally, technology providers are more likely to produce solutions that meet the needs of large farms (Jackson & Martin 2014)."

Hughes et al. (2011) and the current study both find that scale efficiency and technical efficiency, rather than technical change, have played important roles in generating productivity gain, particularly for crop farms 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. 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 has been often a greater reliance on wheat production, and wheat growing has supported the growth and resilience of many farm businesses during the study period (Lawes and Kingwell, 2012).

The current reliance on wheat production may also be a useful on-going farm business strategy. Support for this assertion comes from wheat yield modelling under future climate scenarios by Asseng and Pannell (2012), Potgeiter et al. (2012) and Addai (2013). These authors point to little decline in wheat yields over the next couple of decades, due to beneficial CO₂ fertilisation effects.

Asseng and Pannell (2012) recognise farmers' current sound use of best practice methods, yet they argue for the need to develop technologies that will boost technical change (*dTECH*). It is true that future productivity enhancement cannot solely rely on improvements in technical efficiency (*dEFF*).

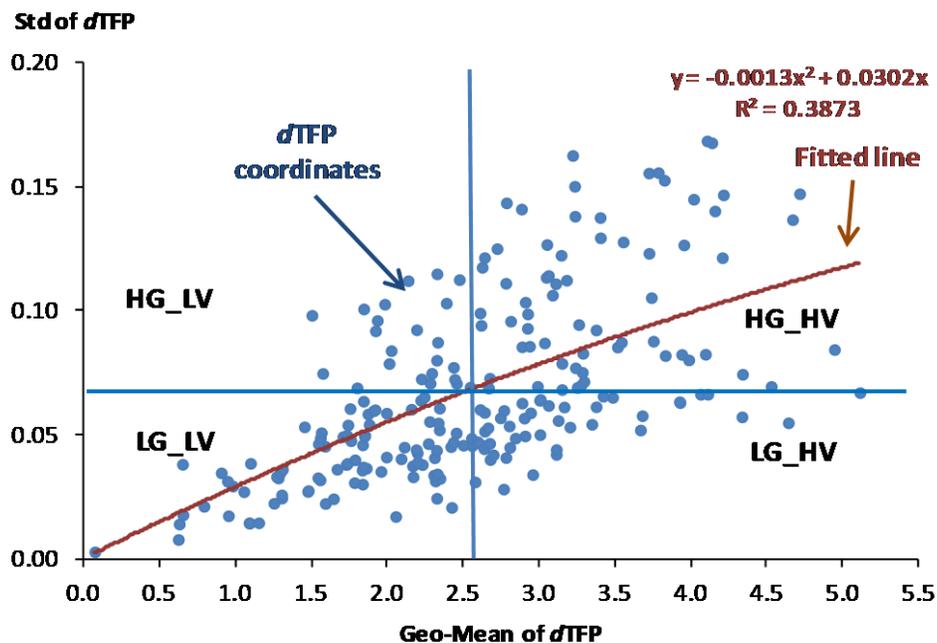
Rather, technical change is also essential so that, at some stage, farmers' production frontiers can move outwards. Hence, the call by Asseng and Pannell for further research and development that offers farmers beneficial technical change is a sound conclusion.

Other evidence that supports the greater dependence on cropping comes from Deards et al. (2012). Drawing on ABARES farm survey data, they found that, between 1977–78 and 2009–10, cropping specialists achieved average annual total factor productivity growth of 1.6 per cent, compared with the broadacre industry average of 1.2 per cent. The greater productivity growth of cropping specialists would have supported the growth in their farm profitability.

Productivity trajectories and farm characteristics

How profitability and productivity are affected by the variable nature of farm operating environments and characteristics is reflected in an examination of the relationship between the mean and standard deviation of farms' total factor productivity ($dTFP$) that utilises farms' annual data (Figure 7).

Figure 7. The mean and standard deviation of farms' total factor productivity ($dTFP$) growth



It is possible to overlay on Figure 7 a simple grouping of farms by the mean and standard deviation of their total factor productivity ($dTFP$) growth. The solid vertical and horizontal lines in Figure 7 split the farm sample into four categories: (i) high growth in $dTFP$ and high volatility in $dTFP$ (top right quadrant, HG_HV), (ii) high growth in $dTFP$ and low volatility in $dTFP$ (bottom right quadrant, HG_LV), (iii) low growth in $dTFP$ and high volatility in $dTFP$ (top left quadrant, LG_HV) and, (iv) low growth in $dTFP$ and low volatility in $dTFP$ (bottom left quadrant, LG_LV). The point of splitting is the median values of the mean and standard deviation of farms' total factor productivity ($dTFP$) growth.

The data in Figure 7 show the heteroskedastic response of increasing variance in $dTFP$ as the mean of $dTFP$ increases. In practice, this means that the group of farms that recorded a high mean in $dTFP$ over the study period also displayed a large range in the variance of their $dTFP$ over that same period.

Farm businesses in each quadrant can be compared to generate insights about what sorts of farm characteristics are associated with that quadrant of *dTFP* performance. Comparative data are listed in Tables 2 and 3.

Table 2. Productivity components of farms in the four quadrants of total factor productivity (*dTFP*) performance during 2002 to 2011 (mean values)

Variable	Unit	HG_HV	HG_LV	LG_HV	LG_LV
<i>dTFP</i>	index	3.41	2.98	2.12	1.70
<i>dPROF</i>	index	2.68	2.75	2.45	2.27
<i>dTT</i>	index	0.87	0.96	1.40	1.97
<i>dTECH</i>	index	1.02	1.02	1.02	1.02
<i>dEFF</i>	index	3.31	2.93	2.05	1.66
<i>dOTE</i>	index	3.16	2.91	2.75	2.43
<i>dOSE</i>	index	1.01	1.04	0.92	0.96
<i>dOME</i>	index	1.04	1.04	1.02	1.01
<i>dROSE</i>	index	1.00	0.99	0.76	0.73
<i>dOSME</i>	index	1.05	1.03	0.79	0.73
<i>dITE</i>	index	1.31	1.23	1.29	1.21
<i>dISE</i>	index	2.44	2.44	1.95	1.87
<i>dIME</i>	index	1.06	1.09	1.01	1.06
<i>dRISE</i>	index	2.36	2.20	1.59	1.31
<i>dISME</i>	index	2.52	2.39	1.63	1.40
<i>dRME</i>	index	1.02	0.99	0.84	0.76

Most farms fall either into the quadrant with high mean and high variance of *dTFP* (36 per cent of all farms) or the quadrant with low mean and low variance of *dTFP* (36 per cent of all farms). Drawing on the data in Tables 2 and 3 reveals that farms in the HG_HV quadrant, relative to those in the LG_LV quadrant are:

- larger in size; 4581 hectares versus 2199 hectares,
- recipients of less growing season rainfall; 227 mm versus 285 mm, and are more likely to be in a low rainfall region,
- more crop dominant, with 87 per cent of farm income coming from crop revenues versus 65 per cent,
- similar in farm equity, 80 per cent,
- more profitable, \$288K of farm profit versus \$63K,
- similar in their ratios of operating expenses to gross farm income, 0.73 versus 0.74,
- able to generate more crop yield per 100mm of growing season rainfall, 0.77 versus 0.70 tonnes per 100mm per hectare,
- more lucrative in terms of return on equity, 5 per cent versus 2 per cent,
- mostly crop specialists and mixed enterprise farms rather than livestock specialists,
- less exposed to debt as indicated by the debt to income ratio, 1.02 versus 1.39 and the debt burden, \$352 per hectare versus \$535 per hectare,
- able to generate more livestock income per mm of growing season rainfall, \$1.78 versus \$1.56 per mm per hectare,

Table 3. Characteristics of farms in the four quadrants of total factor productivity (dTFP) performance during 2002 to 2011 (mean values)

Variable	Unit	HG_HV	HG_LV	LG_HV	LG_LV
Gross farm income (GFI)	\$	1,784,678	1,440,726	857,410	813,782
Operating costs (OC)	\$	1,149,648	967,756	588,481	548,595
Operating surplus	\$	635,030	476,093	268,929	265,187
Profit	\$	288,298	147,428	77,658	62,977
Personal expenses	\$	122,907	115,299	79,353	80,980
Interest payments	\$	84,934	113,723	41,759	56,731
Machinery replacement	\$	138,891	99,642	70,159	64,293
Debt to Income	Ratio	1.02	1.08	1.15	1.39
Share of OC to GFI	%	72.85	71.21	80.52	73.76
Land own	Ha	4,444	3,557	3,220	2,261
Land used	Ha	4,581	3,427	3,451	2,199
Land value	\$	5,047,171	5,257,836	2,647,798	3,583,867
Equity	%	80	80	79	80
Cropped area	Ha	3,539	2,462	2,089	1,195
Pasture area	Ha	1,044	957	1,362	1,004
Crop income share	%	87	84	77	65
Crop Income	\$/Ha	428	491	336	466
Livestock income	\$/Ha	209	365	160	287
Farm asset	\$/Ha	1,550	2,169	1,205	2,448
Business asset	\$/Ha	1,734	2,418	1,385	2,650
Debts	\$/Ha	352	444	294	535
Equity	%	1,426	1,963	1,077	2,082
Return on capital (ROC)	%	0.12	0.09	0.10	0.07
Return on equity (ROE)	%	0.05	0.03	0.03	0.02
Growing season rainfall (gsr)	mm	227.2	251.2	227.0	284.8
Crop yield	tone/Ha/100mm	0.77	0.80	0.64	0.70
Livestock yield	\$/Ha/100mm	1.78	2.40	0.76	1.56
Livestock expenses	\$/Ha	57.08	67.27	48.89	90.25
Profit	\$/Ha/100mm	16.25	14.66	2.61	6.96

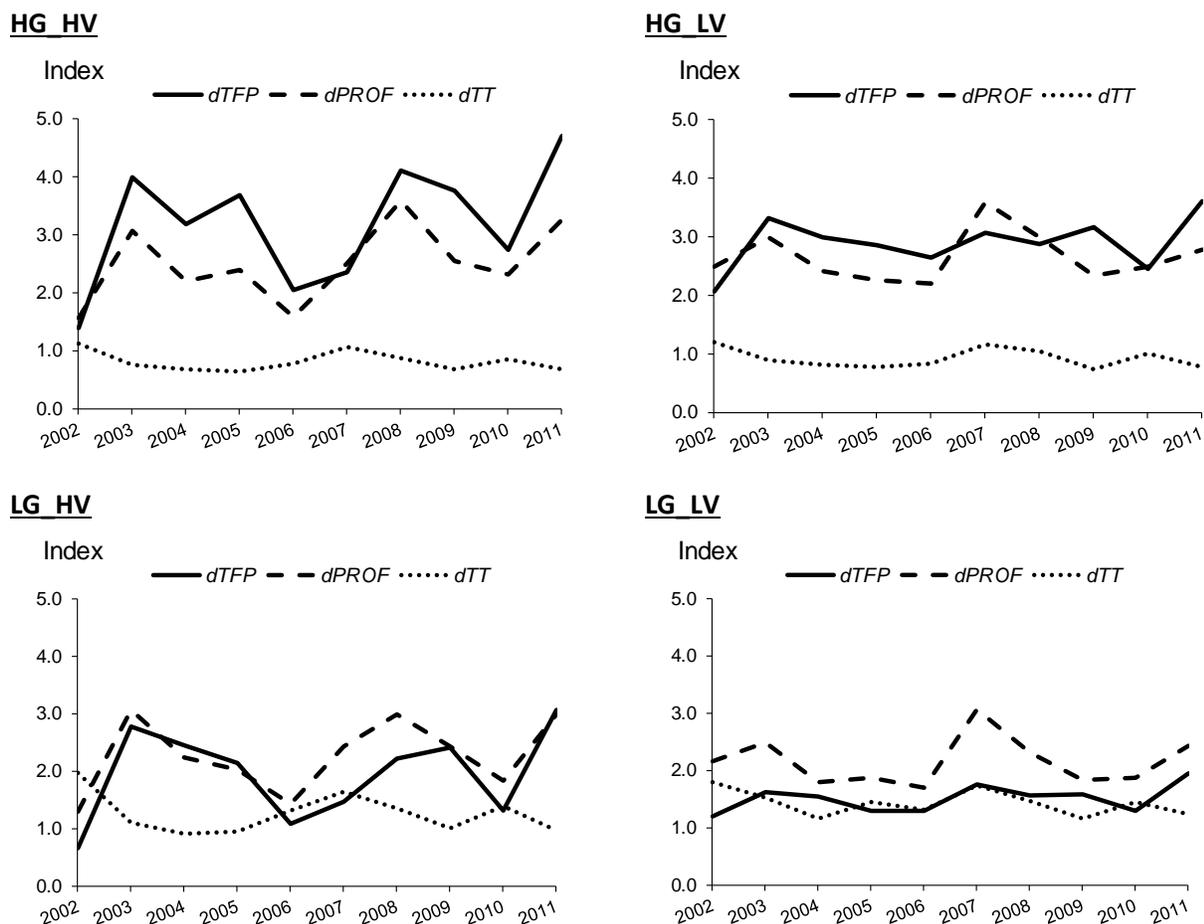
- more likely to be a growing farm, and
- less likely to be a less secure farm.

Farms in the LG_LV quadrant were principally livestock specialist farms and mixed enterprise farms mostly operating in higher and moderate southern rainfall zones (M4, M5 and H5 in Figure 1). The positive terms of trade effect (Table 2) for farms in the LG_LV group was principally due to increased

livestock and wool prices during the study period and was associated, as expected, with a decline in $dTFP$. By contrast, the slight decline in terms of trade for farms in the HG_HV quadrant, principally due to farm-gate crop prices trending slightly downwards in real terms, was linked to an increase in $dTFP$. In practice, this meant that the large crop dominant farms in the low and moderate rainfall northern regions (L1, M1 and M2 in Figure 1) greatly capitalised on the reasonable number of favourable weather years during the study period and curtailed their losses in the very poor years, often by restricting crop area and input use. The net result was that mean $dPROF$ was greater for farms in the HG_HV quadrant relative to those in the LG_LV quadrant, 2.68 versus 2.27, respectively (see Table 2).

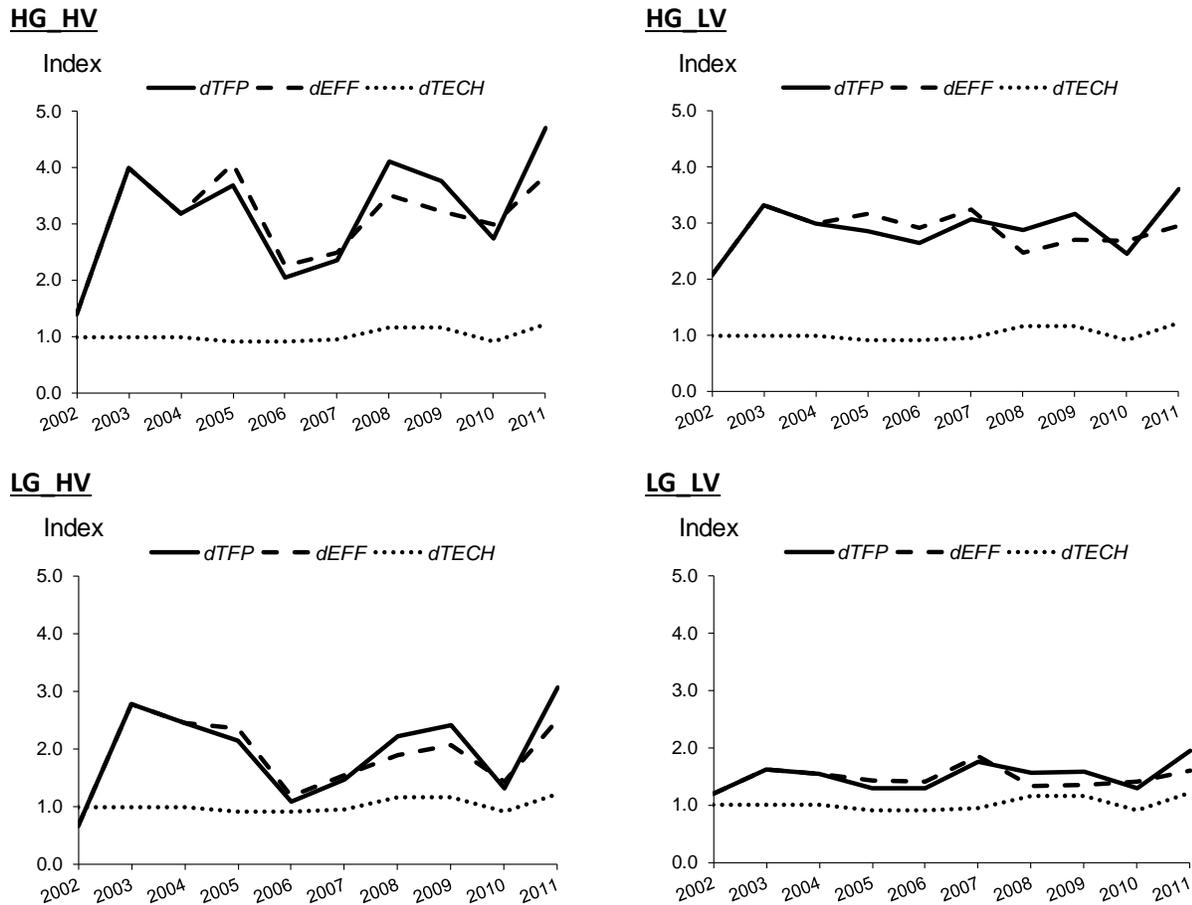
In relation to equation (1), the respective geometric means of $dPROF$, $dTFP$ and dTT for farms in the four quadrants are shown in Figure 8. On average, farms in the HG_HV quadrant face a similar pattern in dTT to farms in the HG_LV quadrant. However, their trajectories, especially regarding their volatility in $dTFP$ are very different and, hence, so are their trajectories in $dPROF$.

Figure 8. Trajectories for geometric means of $dPROF$, $dTFP$ and dTT for farms in each quadrant of productivity performance



Applying equation (2) to the four quadrants of productivity performance shows the different trajectories for $dTFP$, $dTECH$ and $dEFF$. Especially for groups displaying high growth in $dTFP$, $dEFF$ rather than $dTECH$ is the principal source of growth in $dTFP$ (see Figure 9).

Figure 9. Trajectories of mean $dTFP$, $dTECH$ and $dEFF$ for farms in each quadrant of productivity performance



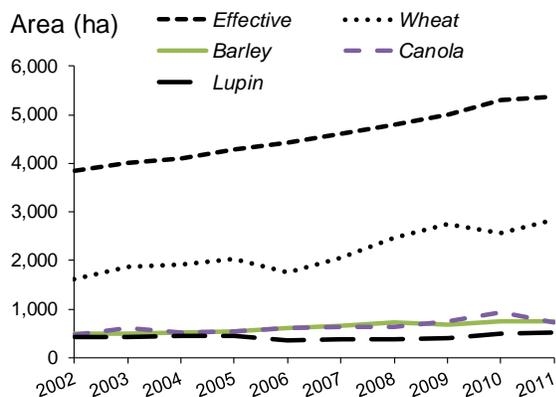
The practical implication of these findings is that farms that have experienced higher growth in their $dTFP$ have done so by ensuring they use commonly available technologies consistently in the best possible way. Moreover, the crop dominance of these farms, when combined with their experience of a reasonable frequency of favourable seasons, has allowed these farms, on average, to lift their total factor productivity.

Interestingly, yet of some concern, is the finding that $dTECH$ has played a relatively minor role in boosting farms' total factor productivity. The implication is that farmers have either not adopted new technologies or these technologies have not been available or have not delivered the anticipated outcomes. Either way, technical change has not been the pathway for lifting total factor productivity. Rather, mostly it is farmers' improved use of existing technologies that has lifted their productivity performance, with reliance on scale economies playing an additional role.

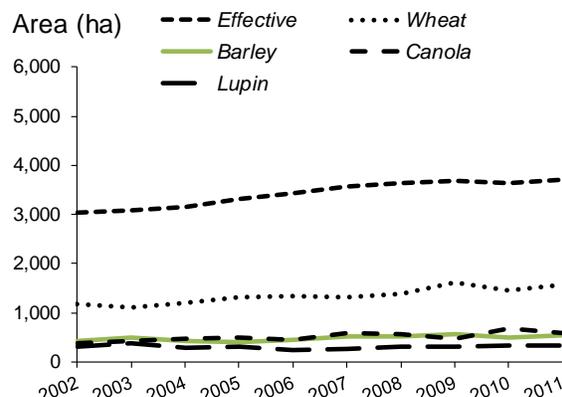
The route to lifting growth in $dTFP$ is often larger farm size, increased plantings of wheat and greater crop dominance, especially in terms of the proportion of farm income stemming from crop revenue (see Figures 10a and 10b).

Figure 10a. Trajectories of key farm characteristics in each quadrant of productivity performance (Panel A. Average farm size and crop planted areas)

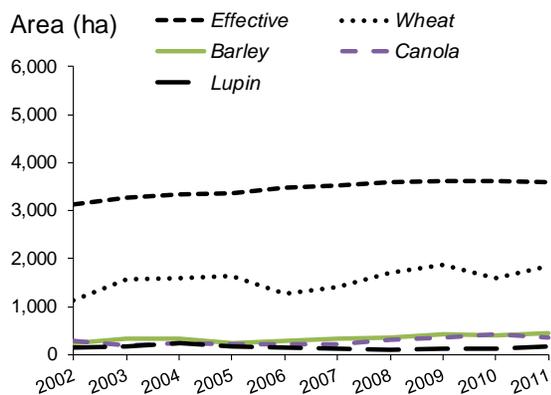
HG HV



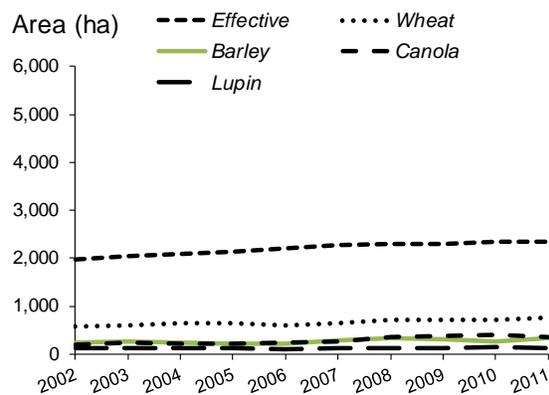
HG LV



LG HV



LG LV



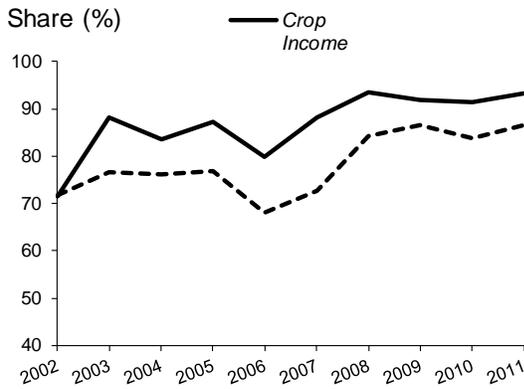
Farm businesses that have experienced highest growth in their total factor productivity have employed a range of business strategies and tactics. Relative to farms that, by contrast, have achieved low growth in productivity, the high growth farms have increased their farm size, become more crop dominant, have often operated farms in lower rainfall regions, have generated more profit and are less exposed to debt. They generate more crop yield per 100mm of growing season rainfall, yet also generate more livestock income per mm of growing season rainfall. Over the decadal study period, high growth farms often have been crop specialists or mixed enterprise farms rather than livestock specialists.

Conclusion

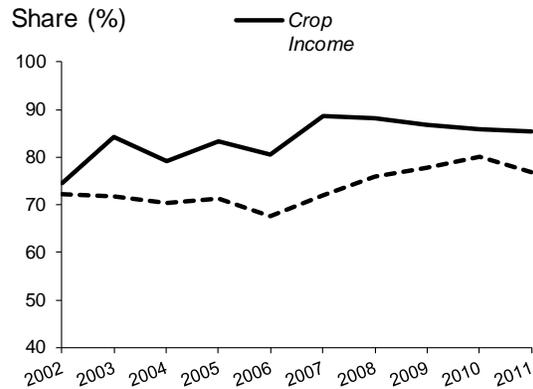
Australia’s broadacre agriculture sector relies on productivity gain to support and lift its profitability. This paper estimates the annual productivity of the same group of 223 farms over the period 2002 to 2011. Farms are classed according to the geometric mean of their total factor productivity and the variance of this productivity. The sample population of farms displays convexity in this relationship and high growth in productivity is associated with greater volatility in productivity.

Figure 10b. Trajectories of key farm characteristics in each quadrant of productivity performance (Panel B. Share of crops in farm income and farm area)

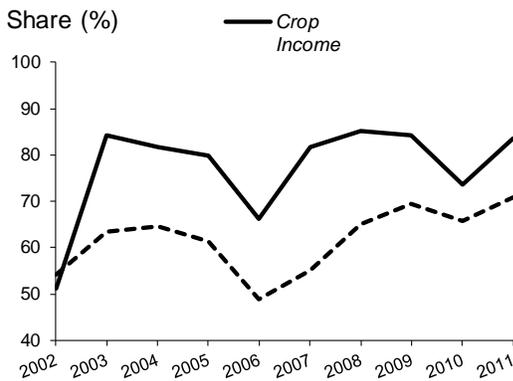
HG HV



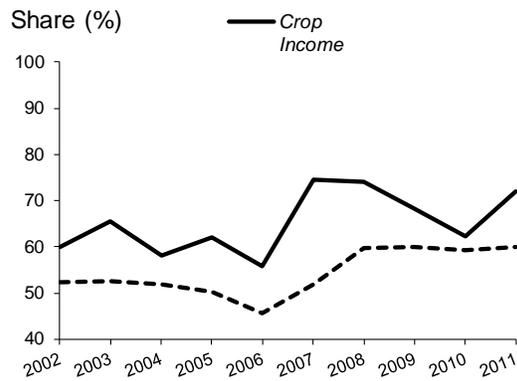
HG LV



LG HV



LG LV



Most farms experienced either high growth and high variability in productivity, or low growth and low variability in productivity. The decomposition of productivity change reveals that efficiency gain rather than technical change is the principal source of improvement in total factor productivity. The practical implication of this finding is that farms that have experienced higher growth in their total factor productivity have done so by ensuring they use commonly-available technologies consistently in the best possible way. Of some concern is the finding that technical change over the study period has played a minor role in boosting farms' total factor productivity.

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Appendix One

Table A.1. Indexes of changes in profitability and productivity components

Year	dPROF index	dTT index	dTFP index	dTech index	dEff index	dOTE index	dOSE index	dOME index	dROSE index	dOSME index
2002	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
2003	1.55	0.73	2.13	1.00	2.13	1.54	1.31	1.08	1.29	1.39
2004	1.14	0.61	1.87	1.00	1.87	1.27	1.24	1.07	1.38	1.47
2005	1.17	0.64	1.81	0.91	1.99	1.52	1.31	1.06	1.23	1.31
2006	0.92	0.70	1.31	0.91	1.44	1.32	1.09	0.99	0.99	1.04
2007	1.54	0.94	1.64	0.95	1.73	1.51	1.24	1.04	1.10	1.15
2008	1.60	0.79	2.02	1.17	1.73	1.27	1.30	1.08	1.26	1.36
2009	1.22	0.60	2.02	1.17	1.73	1.25	1.26	1.07	1.29	1.39
2010	1.15	0.78	1.48	0.92	1.62	1.41	1.04	1.02	1.14	1.15
2011	1.55	0.62	2.48	1.22	2.03	1.56	1.33	1.02	1.27	1.30
Geo- Mean	1.26	0.73	1.73	1.02	1.70	1.35	1.21	1.04	1.19	1.25