Nonparametric Estimates of Productivity and Efficiency Change in Australian Broadacre Agriculture

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Abstract

This paper uses distance functions estimation methods to compute and decompose Färe-Primont indexes of total factor productivity of Australian broadacre agriculture. Using state level data from 1990 to 2011, the empirical results show there are variations of total factor productivity (TFP) growth across states and fluctuations within each state and territory. However, TFP grew at an average rate of 0.59% per annum in the broadacre agriculture over the period 1990-2011. Despite this negligible productivity growth in the entire sample period broadacre agriculture experiences a declining growth in recent years. Further the results demonstrate that decline in technical possibilities (technological progress) as the main drivers of low productivity in broadacre agriculture in Australia. Thus, the declining technical progress warrants government policy making aimed at increasing investment in agricultural research and development (R&D) to improve production environment.

Kew Words: Total Factor Productivity; Färe-Primont Index; Technical Efficiency; Mix Efficiency; Scale Efficiency; Distance Function; Broadacre Agriculture; Australia

JEL Classifications: C20, F10

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1. Introduction

Over the last few decades, efficiency and productivity growth analysis in agriculture has attracted attention of the economic researchers as well as policy makers in both developed and developing countries (Battese and Coelli, 1995; Van Beveren, 2012; Bravo-Ureta et al., 2007; O'Donnell, 2012a; Samarajeewa et al., 2011). It is not easy for a country to move forward towards prosperity without attaining a considerable growth in productivity. The firm as well as the industry can maintain or increase their competitiveness and market share by enhancing productivity. However, in the global context the recent concern has been that productivity is falling, particularly in developed economies where maintaining growth in agricultural productivity is important for improving standards of living. In addition, this has implications for food security in developing countries where growing populations will continue to raise demand for food in the coming decades (Pardey et al., 2006). Thus, in face of the global warming and reduced food security, the declines in agricultural productivity growth have renewed interest in the productivity analysis.

Though it is important for effective policy measures, there is limited empirical evidence concerning the total factor productivity (TFP) change and its components in Australian broadacre agriculture. Previous empirical studies of Australian broadacre agriculture hardly use decomposition analysis to find the components of productivity and efficiency changes. They are mainly concerned with estimating the growth of total factor productivity and technical efficiency change. However, productivity researchers and policy makers have recognized the importance of measuring different types of efficiency change in both agriculture and manufacturing sector.

Using country-level data O'Donnell (2010) computes TFP indexes and the components of TFP change in Australian agriculture for the period from 1970 to 2001. One of the major limitations of this study is the use of the Hicks-Moorsteen TFP index which fails the transitivity test and is thus unsuitable for multi-lateral and multi-temporal comparisons (O'Donnell, 2012a). O'Donnell (2011) has also provided evidence that the

Fare-Primont index is preferred to the Hicks-Moorsteen index in estimating productivity changes and its components. Similarly, other previous studies in Australian agriculture mainly focus on country-level (Mullen and Cox, 1996) or regional and industry-specific (Fraser and Hone, 2001) productivity growth that do not reflect state level variation. However, studies in other country context indicate importance of state-level productivity analysis in agricultural sector which has policy implications for improving productivity (O'Donnell, 2012a; Rahman and Salim, 2013; Ball et al., 2004; and Laurenceson and O'Donnell, 2011).

This paper aims to fill this empirical research gap exploring productivity changes in Australian broadacre agriculture. Specifically, the main objective of this paper is to estimate total factor productivity changes in Australian broadacre agriculture and to decompose these changes into measures of technical change, technical efficiency change, and scale and mix efficiency change. This paper contributes to the existing literature in various aspects. First, it uses the Färe-Primont index, which satisfies all axioms of index number theory including the identity and transitivity axioms. Second, it uses a new linear programming methodology developed by O'Donnell for exhaustively decomposing TFP into measures of technical change, technical efficiency change, scale efficiency change and mix efficiency change. Third, by exploring the different components of productivity growth this paper fills an important information gap in Australian broadacre agriculture. This information is important for policy formulation. In other words, different policies have different effects on various components of productivity change and this decomposition analysis allows the differential impact of policies to be identified.

The rest of the paper proceeds as follows. The next section reviews theoretical issues and previous empirical studies. Section 3 outlines the empirical methodology to be used in this article, followed by a discussion on data sources in Section 4. Section 5 presents the empirical estimates and an analysis of results. Finally, Section 6 concludes the paper.

2. Review of Theoretical and Empirical Literature

Theoretical Issues: Total Factor Productivity Index

The change in the TFP index can be measured as changes in the ratio of an aggregate outputs index to an aggregate inputs index. To construct a ratio of an index of all outputs over all inputs, it is necessary to aggregate the inputs together and the outputs together. There are several formulas available for constructing such indexes in the productivity literature. The Tornqvist index (better known as Solow residual), the Fisher index, and the Malmquist index of Caves, Christensen and Diewert (1982) are some of the widely used indexes in empirical research in agriculture. Both the Tornqvist index and the Fisher index do follow the identity axiom, which says that if the two firms produce the same outputs using the same inputs the index value is one. Or, it says if $q_{hs} = q_{it}$ then $Q_{hs,it} = 1$. However, neither of these two indexes is transitive, which means that both a direct comparison and an indirect comparison of two firms will yield the same estimate of productivity change. Intransitivity makes indexes inappropriate to be used to make multi-lateral or multi-temporal comparisons (O'Donnell, 2012a).

Malmquist productivity indexes are one of the standard approaches in the productivity literature (Lovell, 2003), that can be decomposed exhaustively (Färe et al., 1994), especially in nonparametric specifications and for translog technologies (Bjurek, 1996). However, the DEA (Data envelopment analysis) estimates of Malmquist indexes are incomplete measures of productivity change as they fail to capture productivity changes associated with changes in scale (Grifell-Tatje and Lovell, 1995; O'Donnell, 2012a). In fact, Malmquist index is not a productivity index rather it is only a measure of technical change and technical efficiency change (Färe et al., 1994). Except in restrictive special cases (e.g., constant returns to scale, no technical change), DEA estimate of Malmquist index unreliably indicates unchanged productivity even if a firm can produce the same output using fewer inputs (O'Donnell, 2011).

Recently, two other indexes, namely the Hicks-Moorsteen TFP index proposed by Bjurek (1996) and the Färe-Primont index proposed by O'Donnell (2011) are used in constructing productivity indexes. They are more reliable and can be broken into recognizable components without requiring data on prices and any restrictive assumptions concerning statistical noise. However, between two indexes O'Donnell (2011) argues that the Färe-Primont index is more reliable than the Hicks-Moorsteen index, as the former can be used to make reliable multi-lateral and multi-temporal comparisons. The Hicks-Moorsteen index thus can generally only be used to make a single binary comparison as it fails the transitivity test.

Apart from choosing an index formula, decomposing TFP indexes into measures of technical change and other measures of efficiency change involves estimating the production frontier. A range of approaches has been proposed in the literature on how to estimate the production technology. The two competing approaches to obtain potential or frontier output are stochastic frontier analysis (SFA) and data envelopment analysis (DEA). The SFA approach is a stochastic parametric approach, which parameterises the production frontier under some distributional assumptions of random error terms. This approach uses a two-component error term - a stochastic random error component and a technical inefficiency component (Aigner et al., 1977; Aigner and Chu, 1968; Meeusen & Broeck, 1977). The main problem of this approach comes from its underlying assumption that the frontier production function is a neutral shift from the conventional production function. This assumption is restrictive, especially in the case of heterogeneity among farms in using their inputs in the production process. Besides, using SFA it is difficult to distinguish between the estimates of pure scale efficiency change and pure mix efficiency change components of TFP change. Moreover, the estimates of unknown parameters may be statistically unreliable if sample sizes are small and model specification is incorrect (O'Donnell, 2012b).

The alternative DEA approach is a technique of a non-parametric deterministic approach popularly employed to estimate the production frontier. This approach primarily involves mathematical programming and requires no assumption of the error term and the distributions of the parameters (e.g., means and variances) (Farrell, 1957). Moreover, it does not require any explicit assumptions regarding the functional form of the production frontier or any structure to compute relative efficiency scores (Banker, 1993). However, a limitation of assuming away the statistical noise is that it leads to an intrinsic bias with all deviations from the estimated frontier are attributed to inefficiency as it does not allow statistical noise (Coelli et al., 2005).

However, DEA is implicitly supported by the assumption that the frontier is locally linear, which means that the frontier of a firm takes the linear form in the neighbourhood of the technically efficient point (O'Donnell, 2011). For example, output and input distance functions are representations of the locally linear technology. In this paper, a non-parametric DEA is used to estimate a production frontier and then to compute and decompose the TFP index.

Empirical Studies: Productivity Growth in Agriculture

A substantial body of literature has emerged over the past few decades on efficiency and productivity measurement in Australian agriculture. At the economy-wide level, Males et al. (1990) measure productivity growth of broadacre industries and find that TFP growth averaged 2.2% per annum over the period 1978 to 1989. They also disaggregate the sample size into different enterprise-types and find that productivity rates vary across enterprise-types. Particularly, they report 5.5% productivity growth per annum for specialist crops industry. Knopke et al. (1995) extend the similar dataset to Males et al. to 1994 and find the productivity growth of the crop industry has slowed to 4.6% per annum, while productivity growth in broadacre agriculture remains at 2.7% per annum for the period 1978 to 1994. Dividing the farms into three groups, they also find that scale matters significantly in productivity growth.

Using a farm-level data set covering the period from 1953 to 1994 Mullen and Cox (1996) find an average rate of productivity growth of 2.5% per annum in Australian broadacre agriculture. They compare alternative measures of productivity growth including traditional index number approaches, a scale adjusted Christenson and Jorgenson index, nonparametric measures and an econometric estimate of a translog cost function. They find a small variation in average TFP growth from 2.4% to 2.6% over the different estimation approaches. These robust results from parametric and nonparametric methodologies suggest confidence for traditional index number approaches such as the Fisher index. However, they disaggregate the study periods into three sub-periods and find that productivity in Australian broadacre agriculture declines from 2.0% to 1.8% between the sub-periods 1953–1968 and 1969–1984.

Recently, using country-level agriculture data for 88 countries over the period 1970–2001, O’Donnell (2010) computes indexes of TFP change and decompose them into economically meaningful components. Particularly in Australia, O’Donnell shows that over the period agriculture experienced a 15% decline in productivity and he explains that increases in net returns to agriculture are associated with falls in productivity. However, this study uses the Hicks-Moorsteen TFP index which can only be used for binary comparisons. Moreover, it uses only two outputs and is for overall country-level agriculture data which fails to capture regional variations in agricultural resources and environment.

One major drawback of the previous studies of productivity change for Australian broadacre farms is that it is difficult to disentangle changes in technical efficiency and scale-mix efficiency from the contribution of technical change to productivity growth. Studies that use the conventional measures of productivity do not take the multiple sources of the productivity growth into account. For example, the previous studies of productivity change of Australian broadacre farms cannot properly assess whether the productivity change is sourced from improving the rate of technical progress or from improving levels of either technical or scale and mix efficiency. This lack of information can lead to poor public policy. Further, most of the previous studies use imputed prices for the broadacre outputs or inputs to construct the indexes, which may bias the estimates due to measurement error. Moreover, the previous studies, often, have an industry-specific or region-specific focus and are not sufficient to provide proper policy suggestions for improving productivity growth given the differences in industry and state characteristics.

4. Analytical Framework

Total Factor Productivity Indexes

This article uses the Färe-Primont index to compute and decompose total factor productivity (TFP) into a measure of technical change and several finer measures of efficiency change of Australian broadacre agriculture. Index number approaches to measuring total factor productivity as a ratio of aggregate outputs over aggregate inputs can be traced back to Jorgenson and Grilliches (1967), Nadiri (1970) and Good et al. (1996). However, one common missing point of those authors work is as to how the aggregates should be formed in case of multiple outputs and multiple inputs farms.

Recently, O'Donnell (2012a) defines TFP as the ratio of an aggregate output to an aggregate input where the aggregator functions are non-negative, non-decreasing and linearly homogeneous. However, these properties of the aggregator functions are crucial to conceptualize TFP index that satisfies basic axioms from index theory. Following O'Donnell (2012a) TFP can be defined as $TFP_{it} = Q_{it}/X_{it}$ where TFP_{it} indicates the *TFP* of firm *i* in period *t*, $Q_{it} = Q(q_{it})$ and $X_{it} = X(x_{it})$, where Q_{it} and X_{it} are aggregate output and aggregate input respectively. Using this TFP definition, the associated productivity index that compares the TFP of firm *i* in period *t* with the TFP of firm *h* in period *s* is (O'Donnell, 2011):

$$TFP_{hs,it} = \frac{TFP_{it}}{TFP_{hs}} = \frac{Q_{it}/X_{it}}{Q_{hs}/X_{hs}} = \frac{Q_{it}/Q_{hs}}{X_{it}/X_{hs}} = \frac{Q_{hs,it}}{X_{hs,it}} \qquad (1)$$

where $Q_{hs,it}$ *and* $X_{hs,it}$ are output quantity index and input quantity index, respectively. Thus, Equation 1 shows that changes in TFP or TFP growth can be obtained by dividing an index of output growth by an index of input growth. The index number formed in this way as a measure of relative productivity is said to be multiplicatively complete (O'Donnell, 2012b).

The Färe-Primont index is a member of a class of "multiplicatively complete" productivity indexes that uses the following non-negative, non-decreasing and linearly homogenous aggregator functions: $Q(q) = D_{\mathrm{o}}(\mathrm{x}_0, q, t_0)$ and $X(x) = D_I(x, q_o, t_0)$, where $D_{\mathrm{o}}(\mathrm{x}_0, q, t_0)$ and $D_{\mathrm{I}}(x, q_o, t_0)$ are the Shephard output and input distance functions respectively, representing the production technology available in period *t*. Then the Färe-Primont index that measures the TFP of firm *i* in period *t* relative to the TFP of firm *h* in period *s* is (O'Donnell, 2011):

$$TFP_{hs,it} = \frac{D_o(\mathrm{x}_0, \mathrm{q}_{\mathrm{it}}, t_0)}{D_o(\mathrm{x}_0, \mathrm{q}_{\mathrm{hs}}, t_0)} \frac{D_I(\mathrm{x}_{hs}, \mathrm{q}_{\mathrm{o}}, t_0)}{D_I(\mathrm{x}_{\mathrm{it}}, \mathrm{q}_{\mathrm{o}}, t_0)} \qquad (2)$$

Measures of Efficiency

Following O'Donnell (2012b), several finer measures of efficiency are obtained by decomposing the output oriented TFP changes.

Output-oriented technical efficiency, $OTE_{it} = \frac{Q_{it}}{\bar{Q}_{it}}$, (3.a)

Output-oriented scale efficiency, $OSE_{it} = \frac{\bar{Q}_{it}/X_{it}}{\tilde{Q}_{it}/\tilde{X}_{it}}$, (3.b)

Output-oriented mix efficiency, $OME_{it} = \frac{\bar{Q}_{it}}{\hat{Q}_{it}}$, (3.c)

Residual output-oriented scale efficiency, $ROSE_{it} = \frac{\hat{Q}_{it}/X_{it}}{Q^*_{it}/X^*_{it}}$ and (3.d)

Residual mix efficiency, $RME_{it} = \frac{\tilde{Q}_{it}/\tilde{X}_{it}}{Q^*_{it}/X^*_{it}}$. (3.e)

Where, $\bar{Q}_{it}$ is the maximum aggregate output that is technically feasible to produce a scalar multiple of q_{it} using x_{it}; $\hat{Q}_{it}$ is the maximum possible aggregate output using x_{it} to produce any output vector; $\tilde{Q}_{it}$ and $\tilde{X}_{it}$ denote the aggregate output and input quantities at the point where *TFP* is maximised subject to the constraint that the output and input vectors are scalar multiples of q_{it} and x_{it} and Q_{it}^{*} and X_{it}^{*} denote the aggregate output and input quantities at the point of maximum productivity.

TFP efficiency

As an overall measure of firm performance, O'Donnell (2011) measures TFP efficiency (TFPE) as the ratio of observed TFP to the maximum TFP given the available technology. Mathematically, TFP efficiency of firm *i* in period *t* is

$$TFPE_{it} = \frac{TFP_{it}}{TFP_t{}^*} = \frac{Q_{it}/X_{it}}{Q_{it}^*/X_{it}^*} \qquad (4)$$

where $\mathrm{TFP_t}^*$ indicates maximum TFP possible given the technology in period *t* and $\mathrm{Q_t^*}$ and $\mathrm{X_t^*}$ are the TFP-maximizing aggregate output and aggregate input, respectively. Following O'Donnell (2012a), the TFP decompositions are as follows:

$$TFP_{it} = TFP_t{}^* \times (OTE_{it} \times OME_{it} \times ROSE_{it}) = TFP_t{}^* \times (OTE_{it} \times OSE_{it} \times RME_{it}). \quad (5)$$

A similar decomposition holds for firm *h* in period *s*. Then, the relative TFP index comparing TFP of firm *i* in period *t* with the TFP of firm *h* in period *s* can be decomposed exhaustively in either of the two following ways:

$$TFP_{hs,it} = \frac{TFP_{it}}{TFP_{hs}} = \left(\frac{TFP_t{}^*}{TFP_s{}^*}\right)\left(\frac{OTE_{it}}{OTE_{hs}} \times \frac{OME_{it}}{OME_{hs}} \times \frac{ROSE_{it}}{ROSE_{hs}}\right) \qquad (6.a)$$

$$TFP_{hs,it} = \frac{TFP_{it}}{TFP_{hs}} = \left(\frac{TFP_t{}^*}{TFP_s{}^*}\right)\left(\frac{OTE_{it}}{OTE_{hs}} \times \frac{OSE_{it}}{OSE_{hs}} \times \frac{RME_{it}}{RME_{hs}}\right). \qquad (6.b)$$

The first term in parentheses on the right-hand side of each of the above equations is a measure of technical change, which compares the maximum TFP possible in period *t* with the maximum TFP possible in period *s*. The other terms on the right-hand sides of the equations are the different output-oriented measures of efficiency change, including technical efficiency change, mix efficiency change, and residual scale efficiency change. The other two alternative components are output oriented scale efficiency change and residual mix efficiency change.

Finally, Equations 6.a or 6.b can be written as

$$TFP_{hs,it} = \frac{TFP_{it}}{TFP_{hs}} = \left(\frac{TFP_t{}^*}{TFP_s{}^*}\right)\left(\frac{OTE_{it}}{OTE_{hs}}\right)\left(\frac{OSME_{it}}{OSME_{hs}}\right) \qquad (6.c)$$

where $OSME_{it} = OME_{it} \times ROSE_{it} = OSE_{it} \times RME_{it}$ is the measure of scale-mix efficiency defined by O'Donnell (2012a) which is a combined measure of scale and mix efficiency change. The output-oriented scale-mix efficiency, OSME measures the increase in TFP due to movements from the technically efficient point to the point of maximum productivity.

Estimation using the DEA approach

The Färe-Primont index is a distance-based index which can be estimated relatively straightforwardly by DEA methodology. The main assumption underpinning the use of DEA is that the distance function representing the production technology is locally linear. Then, the output distance function representing the production frontier available in period *t* takes the form (O'Donnell, 2011):

$$D_O(x_{it}, q_{it}, t) = (q_{it}^{'}\alpha)/(\gamma + x_{it}^{'}\beta) \qquad (7)$$

The standard output-oriented DEA problem involves finding the solutions for the unknown parameters in Equation 7 in order to minimize technical efficiency: $OTE_{it} = D_O(x_{it}, q_{it}, t)$. If α and β are non-negative and the intercept γ which indicates potential technology exhibits VRS, then the only constraint that needs to be satisfied is $D_O(x_{it}, q_{it}, t) \leq 1$. Setting an additional constraint $q_{it}^{'}\alpha = 1$ the DEA problem takes the following form of linear programming (LP):

$$D_O(x_{it}, q_{it}, t)^{-1} = OTE_{it}^{-1} = \min_{\alpha,\gamma,\beta}\{\gamma + x_{it}^{'}\beta : \gamma\tau + X'\beta \geq Q'\alpha; q_{it}^{'}\alpha = 1; \alpha \geq 0; \beta \geq 0\} \qquad (8)$$

where Q is a vector of observed outputs, X is a vector of observed inputs, τ is a unit vector (for details, see O'Donnell, 2011). To compute the Färe-Primont aggregates, the variant of LP that needs to be solved is:

$$D_O(x_0, q_0, t_0)^{-1} = \min_{\alpha,\gamma,\beta}\{\gamma + x_0^{'}\beta : \gamma\tau + X'\beta \geq Q'\alpha; q_0^{'}\alpha = 1; \alpha \geq 0; \beta \geq 0\} \qquad (9)$$

Estimates of aggregate outputs, Q_{it} and aggregate inputs, X_{it} for all *i* and *t* are then estimated as:

$$Q_{it} = (q_{it}^{'}\alpha_0)/(\gamma_0 + x_0^{'}\beta_0) \qquad (10)$$

$$X_{it} = (x_{it}^{'}\eta_0)/(q_0^{'}\phi_0 - \delta_0) \qquad (11)$$

where α_0 , β_0 , γ_0 solve Equation 9. The computer software DPIN[1] 3.0, uses linear programming technique to decompose productivity into various efficiency changes.

5. Data Sources

This paper makes use of a state-level panel dataset from the AgSurf covering the period 1990-2011. The data in AgSurf is sourced from the annual farm surveys of ABARES (Australian Bureau of Agricultural Resource Economics and Sciences). The dataset consists of observations on quantities of agricultural inputs, outputs and values in each state in each year. The limitation of the dataset is that it contains no price data for inputs and outputs. Moreover, in the case of some outputs, quantities data are not available. This study uses six major inputs: land, labour, capital, fertilizer, materials and services and rainfall, and four outputs: crops, livestock, wool and other output variables. The growing season (April to October) rainfall data is collected from Australian Bureau of Meteorology. However, this study includes rainfall variable as an important input of broadacre agriculture production assuming that seasonal conditions may have influence on broadacre agriculture in Australia. The details of the construction of variables are given in the Appendix.

6. Analysis of Empirical Results

Productivity Change, Technical Change and Efficiency Change

Table 1 presents the Färe-Primont indexes comparing TFP change, technical change and efficiency change between 1990 and 2011. The Färe-Primont indexes are estimated assuming that the production technology exhibits variable returns to scale (VRS). The production possibilities set are also allowed both technical progress and technical regress. All the estimates reported in this table are meaningfully comparable in performance spatially or inter-temporally as the indexes are transitive. The estimates of TFP in the first column show that WA (Western Australia) is the most productive state and QLD (Queensland) is the least productive state in 1990. The difference in productivity between the two states is 72% (ΔTFP= 0.69/0.40= 1.72) that is, WA is 72% more productive than QLD in 1990. The TFP estimates in the second column show that by 2011, both WA and

[1] DEPIN 3.0 is computer software introduced by the Centre for Efficiency and Productivity Analysis, University of Queensland, Australia.

QLD has remained as the most productive state and the least productive state, respectively. The productivity change between the highest and the least productive states has remained almost the same, 70% (ΔTFP= 0.97/0.57= 1.70). The third column reveals an increase in productivity of all states over the sample period. Among them, the SA (South Australia) experiences the largest increase in productivity, which is around 46% between the period 1990 and 2011. The last row of the table shows average estimates for Australia. It shows that, on average, Australian broadacre agriculture has experienced approximately a 33% productivity increase between the periods 1990 and 2011.

Table 1: TFP Change, Technical Change and Efficiency Change: 1990-2011

	TFP			TFP*			TFPE =(OTE x OSME)			OTE			OSME=(OME x ROSE) =(OSE x RME)		
States	1990	2011	Δ	1990	2011	Δ	1990	2011	Δ	1990	2011	Δ	1990	2011	Δ
NSW	0.63	0.73	1.14	0.69	0.97	1.41	0.92	0.75	0.81	1.00	1.00	1.00	0.92	0.75	0.81
VIC	0.53	0.72	1.38	0.69	0.97	1.41	0.76	0.75	0.98	1.00	1.00	1.00	0.76	0.75	0.98
QLD	0.40	0.57	1.43	0.69	0.97	1.41	0.58	0.59	1.02	1.00	1.00	1.00	0.58	0.59	1.02
SA	0.59	0.86	1.46	0.69	0.97	1.41	0.85	0.89	1.04	1.00	1.00	1.00	0.85	0.89	1.04
WA	0.69	0.97	1.41	0.69	0.97	1.41	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
TAS	0.50	0.61	1.20	0.69	0.97	1.41	0.73	0.62	0.86	1.00	1.00	1.00	0.73	0.62	0.86
AUS	0.56	0.74	1.33	0.69	0.97	1.41	0.81	0.77	0.95	1.00	1.00	1.00	0.81	0.77	0.95

Note: Other outputs-oriented measures OSE, OME, ROSE and RME are not reported here to conserve space. Details are reported in the Appendix. However, the estimates of OSE and OME are almost identical to the estimates of OTE (=1).

Table 1 also reports Färe-Primont estimates of technical change and efficiency components of TFP over the period 1990 to 2011. These estimates are obtained under the assumption that in any given period all states experience a same set of production possibilities. This means all states experience the same estimated technical change in each period, which can be observed in the first and second column of TFP* estimates in Table 1. The third column of TFP* estimates reveals that over the period between 1990 and 2011, on average, each state in Australia experiences around 41% technical progress (ΔTFP*= 0.97/0.69 = 1.41). In other words, each state faces an average rate of technical progress of 0.70% per annum ($\Delta \ln dTech$ = ln(1.41)/(2011-1990) = 0.00705 or 0.70%).

Further, Table 1 also presents components of TFP change over the periods 1990 to 2011. The change in productivity is a combined effect of technical change and efficiency change (ΔTFP = ΔTFP* x ΔTFPE). The third column of TFPE estimates reveal that overall efficiency has improved over the period in SA, QLD and WA. But it falls for NSW (New South Wales), TAS (Tasmania) and a bit in VIC (Victoria). Estimates shown in Table 1 suggest that, in spite of fall in overall efficiency in few states, all states experience productivity improvement due to the improvement in technology. However, in QLD, SA, and WA both technical progress and efficiency improvements are acting together and resulting in a larger productivity increase.

The remaining entries in Table 1 indicate that overall efficiency estimates (ΔTFPE =ΔOTE x ΔOSME) are fully due to an improvement in the scale-mix efficiency component. Because in relation to the other components, results show that all states are highly technically efficient (OTE) throughout the sample period. In general, these results indicate that the productivity change of the states over the sample period is mainly due to the technical change. This implies that there is scope for improving productivity of Australian broadacre agriculture by maintaining technical progress and improving overall efficiency.

Table 2: Average Annual Rates of Growth in TFP and Efficiency (%)

	1990-2000			1990-2007			1990-2011			2000-2007			2007-2011		
States	TFP	TFP*	TFPE	TFP	TFP*	TFPE	TFP	TFP*	TFPE	TFP	TFP*	TFPE	TFP	TFP*	TFPE
NSW	0.16	1.64	-1.48	0.42	1.24	-0.83	0.28	0.70	-0.43	0.78	0.67	0.11	-0.31	-1.58	1.27
VIC	1.06	1.64	-0.58	0.87	1.24	-0.37	0.66	0.70	-0.04	0.60	0.67	-0.07	-0.23	-1.58	1.35
QLD	0.82	1.64	-0.82	0.80	1.24	-0.45	0.74	0.70	0.04	0.76	0.67	0.09	0.51	-1.58	2.09
SA	1.60	1.64	-0.05	0.72	1.24	-0.52	0.79	0.70	0.08	-0.52	0.67	-1.19	1.06	-1.58	2.64
WA	1.64	1.64	0.00	1.24	1.24	0.00	0.70	0.70	0.00	0.67	0.67	0.00	-1.58	-1.58	0.00
TAS	0.98	1.64	-0.66	1.41	1.24	0.17	0.38	0.70	-0.32	2.02	0.67	1.34	-3.98	-1.58	-2.40
AUS	1.04	1.64	-0.60	0.91	1.24	-0.33	0.59	0.70	-0.11	0.72	0.67	0.05	-0.76	-1.58	0.82

Note: TFPE growth and OSME growth are similar in this particular case because change in OTE throughout the periods is unchanged. Annual TFP indexes are reported in Table A.1 in the appendix for details results of TFP changes across states.

Table 2 reports estimated annual growth in TFP, maximum TFP and overall efficiency of broadacre agriculture in Australian states for three cumulative periods of 1990-2000, 1990-2007, and 1990–2011 and also for two recent sub-periods of 2000–2007 and 2007–2011. The choices of these sub-periods are made based on other studies by ABARES in Australia and to facilitate comparison with them (e.g., Sheng et al., 2011). The entries in the table can be interpreted as the average rate of growth for the indicated periods. For example, in the 1990s WA experiences the largest average rate of

TFP growth which is estimated to be 1.64% (ΔlnTFP = ln(TFP_{2000}/TFP_{1990})/(2000-1990) = ln(1.006/0.689)/10 = 0.0164). During this sub-period broadacre agriculture experiences a 1.64% annual average rate of technological progress.

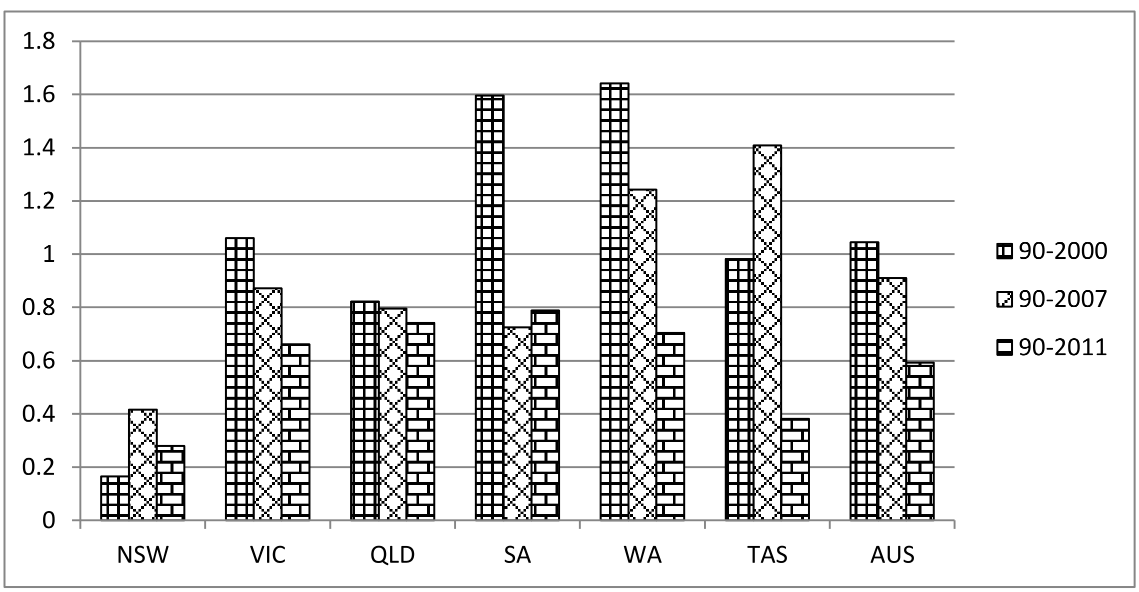
The last row of Table 2 presents estimates of the average annual rate of growth of broadacre agriculture in Australia, which shows that on average broadacre agriculture in Australia experiences an annual productivity growth rate of 0.59% during the study period of 1990 to 2011. In spite of a 0.11% fall in overall efficiency growth, the main driver on back of this productivity growth is a 0.70% technical progress over the entire period of study. However, at the cumulated or disaggregated levels, the average rate of TFP growth declines as more and more recent periods are added with the sample or as sub-periods move forward. For example, average TFP growth is estimated to be 1.04% in 1990-2000, 0.91% in 1990-2007 and 0.59% in the full sample period 1990-2011. Further, the annual productivity growth has slowed from 1.04% in 1990-2000 to 0.72% in 2000-2007. In the more recent period 2007 to 2011, the productivity growth has been negative, dropping to -0.76%. These results, therefore, suggest that though broadacre agriculture maintains a slow average productivity growth during the past two decades, it has continued to decline in recent periods.

The slowdown of total factor productivity growth in broadacre agriculture is largely resulted from a slowing technical change during the past two decades. Table 2 shows that technical change in broadacre agriculture has slowed from 1.64% in 1990-2000 to 0.67% in 2000-2007, showing a slowing technical progress. However, in 2007-2011 it has dropped as slow as -1.58%, leading to a technical regress. However, this study allows both technical progress and technical regress viewing technical change as the change in the production possibilities set caused by any changes in external environment including climatic variations (O'Donnell, 2010). Hence, this recent negative technical change (technical regress) is believed to be due to the recent major drought over most of Australia in recent period, leading to a decline in productivity growth.

These findings are consistent with a few recent studies indicating slowing broadacre agricultural productivity growth in recent years. The ABARES research report by Sheng et al. (2011), reports that productivity declines from 2.2% to 0.4% between the two sub-periods 1953–94 and 1994–2007. Similarly, assembling a productivity dataset for 1953 to 2007 using ABARE farm survey data, Mullen (2010) finds a strong variability in MFP (multi factor productivity) growth in Australian broadacre agriculture including a negative productivity growth rate, – 1.4% in broadacre agriculture for the period from 1998 to 2007.

An alternative perspective on performance of broadacre farms can be explored by examining productivity trends across periods and states. For example, the state level estimated annual rate of productivity growth over the disaggregated, but cumulated, periods of 1990 to 2000, 1990 to 2007 and 1990 to 2011 are presented in Figure 1. The slowdown of average productivity growth has been obvious in broadacre agriculture in Australia. Long-term productivity growth in most of the states (VIC, QLD, SA and WA) is significantly higher in the earlier period between 1990 and 2000 than the recent cumulated period between 1990 and 2011. In the figure, the associated average annual rate of productivity growth is estimated to be 1.04% in 1990 to 2000, 0.91% in 1990 to 2007 and 0.59% in 1990 to 2011. These estimated rates of productivity growth over the cumulated sub-periods, therefore, again indicate that though broadacre agriculture in Australia maintains a slow productivity growth, it is facing a productivity decline in recent periods.

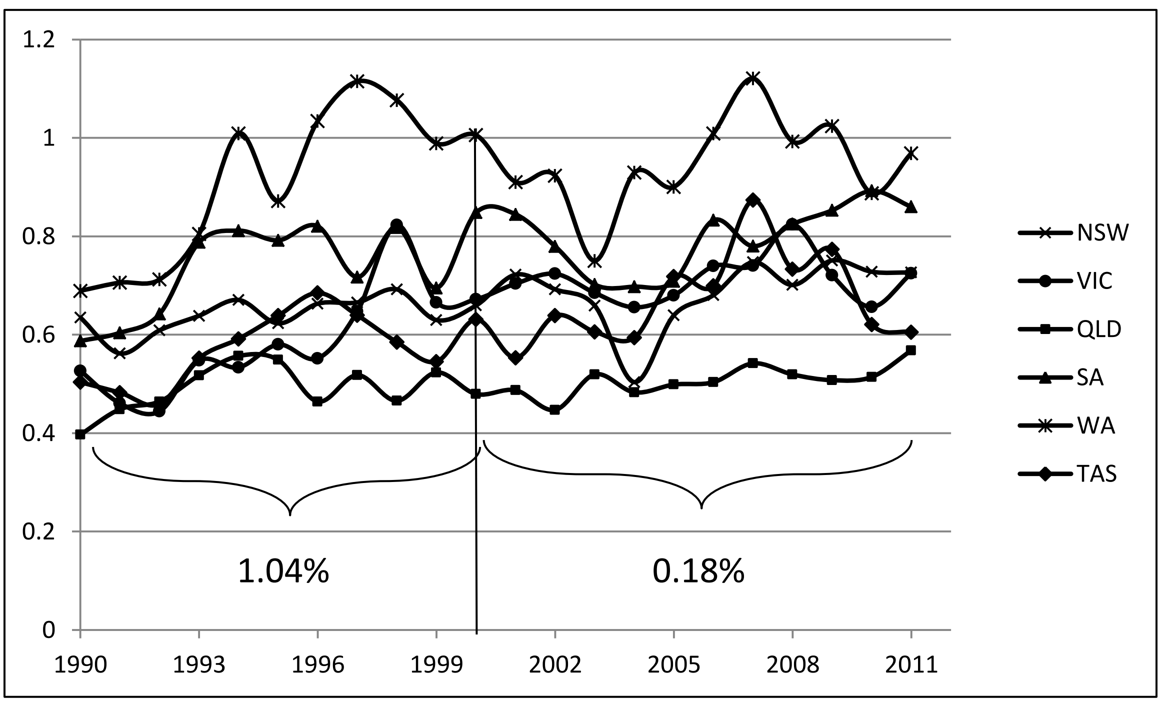
Figure 1. Changes in Broadacre Productivity Growth Trends



Level of Productivity and Efficiency

Using the Färe-Primont index formula, this paper estimates the level of productivity and efficiency within the aggregate quantity framework of O'Donnell (2012b). Figure 2 presents Färe-Primont estimates of TFP for broadacre agriculture in the Australian states. This figure reveals a few important insights into the Australian broadacre agriculture throughout the sample period. First insight is that, the productivity and efficiency levels in broadacre agriculture have fluctuated considerably across the states and over the sample periods. It shows an overall increasing pattern of productivity from 1990 to 1995/1996. Then productivity starts to decline and continues until 2004/2005. Since 2005, productivity increases for a couple of years then starts to fall again. More generally, TFP trends up by an average annual rate of 1.04% in the 1990s, then this productivity trend goes down to an average 0.18% annually in period 2000 to 2011. Second, since 2007, the overall productivity in the broadacre industry has been falling in recent times. However, very recently except for SA and NSW all other states have experienced increasing productivity levels. Third, among the states, WA maintains a higher productivity levels during the sample period.

Figure 2. Productivity levels in Australian States: 1990–2011



Moreover, the interstate differences in TFP over the periods indicate a substantial regional disparity exist in the productivity levels among the Australian states. Figure 2 shows that over the study period, WA leads other states as it maintains the maximum TFP among the states (TFP=TFP*). The same technological possibilities have been assumed for each state at each period. This means that given the same technology, other states are not as productive as WA as there are observed productivity gaps between them and WA. These gaps are then due to the variations into overall efficiency across states. This indicates the possibility of enhancing productivity and reducing interstate productivity gaps through improving overall efficiency in broadacre agriculture in Australia.

7. Conclusions and Policy Implications

This article estimates TFP changes and decomposes these changes into technical change, technical efficiency change, and scale and mix efficiency change in Australian broadacre agriculture by using Färe-Primont TFP indexes. The empirical results show that TFP increases by an average annual rate of growth of 0.59% in broadacre agriculture over the period 1990–2011. This slow productivity growth is mainly due to the effect of a 0.70% annual rate of increase in production possibilities (technical progress) and a 0.11% annual decrease in overall efficiency during this period. The results also show that most states are highly technically efficient (OTE) during the sample period indicating that output-oriented scale and mix efficiency are the main drivers of overall efficiency change in broadacre agriculture.

Broadacre agriculture has experienced a recent fall in productivity growth, leading to only a small productivity increase over the entire study period. In the 1990s, broadacre agriculture experienced an average annual rate of productivity growth of 1.04%, which decreased to 0.72% in 2000–2007 and -0.76% in 2007–2011. Also, the estimates of TFP* changes for different sub-periods show that the production possibilities changes or technical changes experienced by broadacre agriculture are highly unstable. In the earlier periods, broadacre agriculture experienced higher technical progress, which has slowed in recent periods and even turns negative i.e. technical regress in 2007-2011. These findings are consistent with earlier empirical studies that productivity in Australian broadacre agriculture has been falling in recent periods (Sheng et al., 2011; Mullen, 2010). This slowing productivity in broadacre agriculture could be contributed by the reducing rate of technical change in recent periods. However, studies indicate that a result of low research and expenditure could be the main determents of technical change that drives productivity in Australian agriculture (Salim and Islam, 2010: Mullen and Cox, 1995). In addition, the recent negative productivity growth is found to be mainly driven by technical regress, which may be associated with environmental factor such as recent major drought over most of Australia.

By exploring the different components of productivity growth this study provides important information to policy makers on what policy measures need to be adopted to escape from the recent productivity slowdown. The declining technical progress warrants government policymaking aimed at increasing in agricultural research and development (R&D) to improve production environment. Moreover, State level variations in scale and mix efficiency suggest that there exists a scope for improving productivity by taking a differential approach to the efficient use of agricultural resources and to increasing scale and mix efficiency in production in the Australian states.

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Appendix

Variable Construction

In this study, the following six major input and four output variables are constructed from detailed inputs and outputs data by using a weighted aggregative method:

Crop output (q1): It is a weighted aggregate quantity of all crops, where weights are given based on revenue shares of individual crops to total receipts of crops. The ABARES farm surveys contain data on the value and quantity for different crops. The varieties of crops included in the Crop output are Wheat, Barley, Oats, Sorghum, Rice, Oilseeds and Grain legumes (includes lupins, field peas and others).

Livestock (q2): Livestock is generated as a weighted aggregate of the number of Beef Cattle and Sheep (including lambs) during the survey period using revenue share as a weight.

Wools (q3): Total Wool produced during the survey period (kg).

Other Output (q4): Farm's total receipts from off-farm contracts, off-farm share farming and other farm income ($).

Land (x1): Land includes all land areas operated on 30 June (ha) by the farm business whether owned or rented by the business but share farmed land on another farm is excluded.

Labour used (x2): Labour used is the total number of weeks worked by all farm workers including hired labour.

Capital (x3): This is the average of total closing value of capital on 30 June and opening value of capital on 1 July. Capital includes the value of all assets used on the farm including leased equipment but excluding machinery and equipment either hired or used by contractors. ABARE uses market value of land and fixed improvements and livestock/crop inventories and replacement value less depreciation for plant and machinery.

Fertilizer (x4): The implicit quantity of fertilizer is calculated by dividing expenditure on fertilisers and soil conditioners during the survey year by the price index of fertiliser paid by farmers in Australia.

Materials and Services (x5): Most of the materials and services data collected by

ABARE are in value terms. Therefore, this variable is constructed by summing a wide range of input costs including materials, such as fodder, seed, fuel, crop chemicals; and services, such as contract services, rates and taxes and administrative services.

Rainfall (x6): Growing season (April to October) total rainfall across the states is collected from Australian Bureau of Meteorology (BOM).

Table A.1: Indexes of changes in total factor productivity in broadacre agriculture (base: NSW 1990=1)

Year	NSW	VIC	QLD	SA	WA	TAS
1990	1	0.829	0.625	0.925	1.086	0.793
1991	0.885	0.726	0.706	0.951	1.112	0.760
1992	0.959	0.699	0.731	1.011	1.122	0.723
1993	1.006	0.863	0.815	1.241	1.267	0.870
1994	1.056	0.840	0.877	1.278	1.589	0.932
1995	0.981	0.914	0.864	1.247	1.373	1.006
1996	1.045	0.869	0.731	1.292	1.629	1.079
1997	1.048	1.019	0.816	1.129	1.756	1.007
1998	1.090	1.296	0.733	1.288	1.696	0.921
1999	0.992	1.048	0.824	1.094	1.558	0.859
2000	1.039	1.059	0.755	1.336	1.584	0.994
2001	1.137	1.108	0.767	1.330	1.434	0.871
2002	1.090	1.140	0.704	1.228	1.454	1.006
2003	1.038	1.079	0.818	1.106	1.182	0.954
2004	0.793	1.033	0.761	1.099	1.464	0.935
2005	1.007	1.071	0.785	1.116	1.418	1.131
2006	1.072	1.164	0.793	1.312	1.589	1.102
2007	1.177	1.166	0.853	1.228	1.765	1.375
2008	1.104	1.298	0.818	1.299	1.563	1.155
2009	1.183	1.135	0.800	1.343	1.613	1.219
2010	1.146	1.034	0.810	1.405	1.398	0.978
2011	1.144	1.141	0.895	1.354	1.526	0.953