# An Investigation of the Technical and Allocative Efficiency of Broadacre Farmers[a]

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## Abstract

The technical and allocative efficiency of broadacre farmers in a southern region of Western Australia is investigated over a three-year period. Applying data envelopment analysis (DEA) and stochastic frontier analysis (SFA) reveals there is some inefficiency in each year, which decreases over time. The distributions of technical efficiency in each year are positively skewed toward higher efficiency levels, indicating a majority of farms produce close to their maximum technical efficiency. DEA and SFA produce similar efficiency rankings of farms yet DEA rankings are more stable.

The relationships between farm-specific variables and the DEA and SFA efficiency scores are investigated. There is evidence that farmers benefit from using at least a small amount of tillage, rather than using 'no-till' practices. Education levels and farmer age are found to positively influence technical efficiency.

Using a DEA profit efficiency model, the duality between the directional distance function and the profit function allows the decomposition of economic efficiency into its technical and allocative components. Greater gains in profitability are possible by improving allocative rather than technical efficiency. Technically efficient farms are not necessarily allocatively efficient. Also, Tobit regression results indicate that the variables associated with variation in technical efficiency are different to those explaining the variation in allocative efficiency.



*Key words: farm efficiency, data envelopment analysis, stochastic frontier analysis*

## Introduction

Farmers in Western Australia (WA) produce around a third of the Australian grain crop. They have a relatively small domestic market, and therefore rely heavily on export markets (ABARE/GRDC, 1999). Consequently, the economic sustainability of the WA broadacre industry is highly dependent on maintaining and improving its international competitiveness and profitability. These are contingent upon the prices paid for factors of production, prices received for commodities produced and the productivity of farming operations.

The prices farmers receive for their commodities and pay for inputs are subject to variation, mostly beyond the control of farm managers. As price-takers the most that individual farm managers can do to increase their competitiveness, with regard to these prices, is to select the most profitable combinations of inputs and outputs available to them. Farmers can also improve their competitiveness in the long-term by increasing their level of productivity.

Improvements in productivity may arise through technological advances, improvements in production efficiency and through exploiting scale economies. Technological improvements such as the development of new herbicides, new crop varieties and advances in tractor and machinery design, can improve the productivity of farms that adopt these new technologies. On the other hand, improvements in production efficiency arise through better use of existing technologies. Improving efficiency may be a more effective short-term solution to raising productivity.

Broadacre farmers in Western Australia are known to have experienced higher levels of productivity[1] growth compared with producers from many other regions in the country, with average per farm productivity growth of 3.5 per cent per annum over 21 years up until 1998-1999 (Ha and Chapman, 2000). However, there are currently no studies that investigate efficiency in WA broadacre agriculture.

To redress this neglect, this paper investigates the efficiency of a sample of WA broadacre farms. This paper comprises 3 sections. The first section outlines some key concepts and describes two methods of efficiency measurement. The second section presents an analysis of farm-level efficiency of broadacre farms in a southern agricultural region of Western Australia. A final section offers a set of conclusions and caveats on findings.

## Section 1: Efficiency Concepts and Efficiency Measurement

In the literature on efficiency and performance measurement (e.g. Coelli *et al* 1998) two related efficiency concepts are often discussed. The first is technical efficiency. In a farm-setting this is the ability to produce maximal output from a given set of inputs, or where output levels are fixed (e.g. by contract), to produce the output from a minimal set of inputs. The second concept is known as price efficiency (Farrell 1957) or allocative efficiency (Färe *et al* 1985). In a farm-setting this refers to the optimal selection of inputs, given their prices. In other words, a combination of inputs is chosen to produce a set quantity of output at minimum cost. However, allocative efficiency can also refer to the optimal combination of outputs. This is particularly important in broadacre farming that is characterised by multiple inputs (e.g. labour, machinery, fertilisers, fuel) and multiple outputs (e.g. wool, grain, sheep).

[1] Productivity here refers to total factor productivity (TFP), which is inclusive of all inputs and outputs and is constructed using a Tornqvist Index for aggregation.

There are two commonly used methods of measuring technical and allocative efficiency. The following sub-sections describe briefly each method.

### *Data Envelopment Analysis*

The origins of data envelopment analysis (DEA) lie with Farell (1957), yet it was Charnes *et al* (1978) who first coined the term 'data envelopment analysis'. They suggested solving a set of linear programs to identify the efficient production frontier and thereby estimate Farrell's radial measures of efficiency. Their approach overcame many of the computational difficulties outlined by Farrell (1957), especially for cases involving multiple inputs and outputs.

With DEA technical efficiency could be measured using either output-oriented or input-oriented production function specifications. If constant returns to scale were assumed then the output or input orientations would generate equivalent measures of technical efficiency. DEA models could be modified to account for increasing or decreasing returns to scale (Banker et al 1984). Also, when price and quantity data were available then DEA could also measure allocative efficiency.

Färe et al. (1999) developed a set of linear programs to estimate a production function and used directional distance functions (DDF) to estimate measures of technical inefficiency. They also solved a second set of linear programs to estimate a profit function and its corresponding measures of profit inefficiency. Measures of allocative efficiency could then be obtained residually. They showed that the traditional input and output oriented DEA models were special cases of the directional distance function (DDF). The DDF provided a tighter 'fit' around the data and thus identified lower levels of inefficiency than the traditional DEA models.

### *Stochastic Frontier Analysis*

Not only did Farrell (1957) suggest using non-parametric approaches to efficiency measurement but he also suggested using a parametric function, such as the Cobb-Douglas function, to represent the efficient frontier. While a number of authors chose to estimate production frontiers and Farrell measures of technical and allocative efficiency using non-parametric approaches, another group employed parametric techniques. Aigner and Chu (1968) used a Cobb-Douglas production function to estimate technical efficiency. Later, to cope with statistical noise influencing frontier estimates Aigner *et al* (1977) and Meeusen and van den Broeck (1977) independently proposed the now popular stochastic frontier analysis (SFA) technique. They added a symmetric error term to their frontier models.

Following Afriat (1972) the parameters of their models were estimated using maximum likelihood (ML) methods. Aigner *et al* (1977) assumed that the symmetrical error term, $v_i$, had a normal distribution and the one-sided error term, $u_i$, had either a half normal or exponential distribution[2].

Stochastic frontier production functions can also be estimated using a method known as corrected ordinary least squares, but as Coelli (1995) points out, the ML estimator is asymptotically more efficient and should, therefore, be used in preference to the corrected ordinary least squares estimator.

[2] A more detailed outline of the stochastic frontier and its measure of efficiency can be found in chapter 4 of Henderson (2002).

The Cobb-Douglas has been the most popular functional form in SFA applications, largely because it is simple to apply[3]. However, its simplicity comes at the cost of some very restrictive assumptions, including the assumption that all firms operate at the same scale and that the marginal rate of input substitution (i.e. elasticities of substitution) is unity (Coelli 1995). Alternative forms such as the translog production function (Greene 1980) and the Zellner-Revankar generalised production function (Kumbhakar *et al* 1991) have also been suggested and applied. The first of these has a more flexible functional form than the Cobb-Douglas, imposing no restrictions on returns to scale and input substitution, but it has the unfortunate property of being susceptible to multicollinearity. Also, because many more parameters are required than in an equivalent Cobb-Douglas model, larger data sets are required to avoid problems associated with degrees of freedom.

Other developments include generalisations about the distributional assumptions of the one-sided error term ($u_i$). Stevenson (1980) proposed a truncated-normal distribution for $u_i$, assumed to be normally distributed with a non-zero (constant) mean truncated at zero from above. This more general distribution accounted for situations in which the majority of firms were not in the neighbourhood of full technical efficiency. Another generalisation follows the approach outlined by Reifshneider and Stevenson (1991) and Kumbhakar *et al* (1991), in which $u_i$ is estimated as an explicit function of firm-specific factors. Previously, firm specific factors were regressed in a second stage on technical efficiency scores estimated by the stochastic frontier in the first stage. The problem with this approach is that the $u_i$s are assumed to be independently and identically distributed in the first stage, but they are assumed to be a function of a number of firm-specific variables, rather than being independently and identically distributed in the second stage (Coelli, 1995).

Besides measures of technical efficiency, measures of cost efficiency can also be obtained using SFA if a cost function is derived. Drawing on the duality between the cost function and the production function, cost inefficiency estimates can be decomposed into their technical and allocative components. For more on this see Coelli *et al* (1998).

***Strengths and Weaknesses of DEA and SFA***

The arguments for and against the application of either approach revolve around their respective strengths and weaknesses. SFA, as a parametric approach, requires the specification of a functional form for the production frontier, which implies that the actual shape of the frontier is known. Also, parametric measures of efficiency make assumptions about the distribution of efficiency. This is the main shortcoming of the SFA method to estimate efficiency. However, these assumptions permit statistical hypothesis testing of the most likely shape of the frontier and of the distribution of inefficiency. Hypothesis tests for the significance of inefficiency in the model are also possible.

The DEA approach, on the other hand, is non-parametric and employs linear programming techniques to construct a frontier. The DEA frontier is made up of actual observations and because it does not rely on the specification of a functional form for the frontier, it is free from assumptions about its shape. DEA also makes no assumptions about the distribution of efficiency. In instances where multiple outputs need to be specified, DEA would be the preferred method, because it can accommodate them more easily. Despite these advantages of the DEA approach, its deterministic nature raises questions about its usefulness in situations where statistical noise is likely to affect results.

[3] A logarithmic transformation produces a model that is linear in the logarithms of the inputs (Coelli 1995)

The stochastic frontier approach, as its name suggests, can cope with statistical noise, which may be present in the data as a result of measurement errors, missing variables, and variation in weather conditions. DEA on the other hand is deterministic, attributing all variation from the frontier to inefficiency, which is a questionable assumption if there is significant statistical noise in the data (Coelli 1995)[4]. Coelli *et al* (1998) argue that in agricultural industries with controlled production environments (e.g. intensive industries such as piggeries) and where the quality of inputs and outputs does not vary from firm to firm, DEA may be the preferred method. While record-keeping might be accurate, and while many outputs and factors of production are often homogenous in broadacre agriculture, the uncontrollable impact of weather and resource quality on production is likely to contribute to the statistical noise in the data. However, where weather effects and their impact on production can be measured, their impact on shaping the frontier and efficiency scores may be accounted for.

Another criticism often levelled at the DEA approach is that, unlike SFA, there is a lack of formal tests available to assess the validity of the functional form created by optimisation of the DEA problem. However, a number of such formal tests for non-parametric techniques such as DEA have and are still being developed. Some of these tests are outlined in Banker (1989) and Banker (1996).

The DEA approach is superior to SFA with regard to the amount of useful information it provides. For example, the DEA approach identifies, for every inefficient firm, technically efficient firms which have a similar production mix (i.e. their efficient peers) which could be useful for farm management because it provides a practical example for inefficient farms of how much more productive they might be.

Finally, a problem with all approaches to measuring frontier efficiency, noted by Farrell (1957), is that the technical efficiency of a firm must always, to some extent, reflect the quality of its inputs. Many practitioners make attempts to homogenise input and output qualities with varying approaches and success. In the dairy literature milk is often expressed in fat and protein equivalents in an attempt to homogenise output. Coelli *et al* (1998) list a number of weaknesses that apply to both DEA and SFA, including the fact that these techniques cannot easily account for risk in decision-making. Further, they comment that it is not possible to compare mean efficiency scores from a study that draws on one sample with a study that uses another sample, although comparing the spread or distribution of efficiency between samples is both useful and permissible.

### *DEA and SFA Studies of Broadacre Agriculture in Australia*

Henderson (2002) presents a detailed review of DEA and SFA studies of various agricultural industries. He identifies a small set of studies dealing with broadacre agriculture in Australia. Chapman *et al* (1999) examine wool producers and use expenditure data rather than quantities, and consequently refer to their results as productivity indexes rather than technical efficiency scores[5]. They use spatial information to make comparisons of the productivity measures with a map of seasonal rainfall. They found that areas with lower productivity scores tended to have poorer seasonal conditions. To gauge the impact of resource quality on

[4] Some work has been done by (Banker 1989) in developing a stochastic DEA frontier.

[5] Thomas and Tauer (1994) demonstrate graphically, mathematically and empirically that linear aggregation by value downwardly biases technical efficiency scores, because the technical efficiency measure post-aggregation is a compound of technical and allocative efficiencies.

productivity, the correlation between land values and productivity was examined and the two were found to be positively correlated.

Fraser and Hone (2001) like Chapman *et al* (1999) focused on wool production. The authors solved two different DEA models using a panel of Victorian wool producers from 1990-91 to 1997-98. The first model was an output-orientated DEA model used to calculate measures of technical efficiency in each year. The second involved using DEA to calculate Malmquist estimates of total factor productivity. In the first part of the analysis the stability of technical efficiency measures was investigated by observing the movement of efficient farms from one season to the next. The results indicated that there was little stability, as only one farm was found to be fully efficient over the entire study period. Spearman coefficients of rank correlation were the measures of the stability of efficiency ranks between seasons. Significant correlation between ranks was generally found. Despite this the authors still argued that variation in technical efficiency scores was high enough to suggest that farm-specific factors other than managerial ability may have been captured and consequently, that the measures should be treated with caution. The relationship between farms' enterprise mixtures and technical efficiency was also investigated; farms with a mixture of enterprises were found to be slightly more efficient than those that focused primarily on wool production.

The Malmquist total factor productivity measures revealed that the productivity of Victorian wool producers declined by an average of 2.5 per cent over the study period, and that this was caused by contraction of the production frontier rather than a decline in the technical efficiency of producers. Finally, the authors warned that single period estimates of technical efficiency should be viewed cautiously, because management decisions may be consistent with accounting for production risks, such as disease out-breaks, but may result in lower short-run levels of technical efficiency.

Fraser and Cordina (1999) used cross sectional data on Victorian dairy farms over two consecutive lactation seasons to calculate both variable returns to scale and constant returns to scale frontiers. The motivation for their paper was to assess whether gains in efficiency could be made to offset future water supply restrictions. The correlation between farm size and technical efficiency was examined too, and was found to be insignificant. Fraser and Cordina (1999) were also interested in the temporal stability of the frontier, suggesting that significant instability would cast doubt on the reliability of the DEA applications to agriculture. Three different hypothesis tests were used to compare the technical efficiency scores from both seasons. These tests were, the Wilcoxon signed-rank test for matched pairs (non-parametric), and two parametric t-tests, one assuming unequal variance and one assuming equal variance. The authors found that the technical efficiency scores between the seasons were not significantly different. An interesting 'rule of thumb' they suggested was that there should always at least three times as many data observations as variables. They considered that, if the ratio of variables to observations is greater than 1:3, then the problem of self-referencing would upwardly bias technical efficiency scores and reduce the discriminating power of the analysis. This is in contrast to Fernandez-Cornejo (1994), who insisted that the ratio of variables to observations be no higher than 1:5.

Battese and Corra (1977) was one of the first applications of SFA to farm-level data. Iit was also the first study of its kind to be applied to Australian farm-level data. The data came from a sample of sheep producers in the pastoral zone of eastern Australia. The maximum likelihood values of the variable coefficients were presented and the significance of both the one-sided and symmetric error terms were found to be significant, i.e. both the technical inefficiency effects and the stochastic effects were significant. The only other SFA application to Australian farm-level data is by Battese and Coelli (1988) who used a three-year panel of dairy farms spanning production regions in Victoria and New South Wales. In this study a generalisation of the technique suggested by Jondrow et al. (1982) for determining firm-level technical efficiency was proposed, which permitted estimation using panel data and assumed a more general distribution for the one-sided error term suggested by Stevenson (1980). Technical efficiency was found to be significant and significantly different between each State.

## Section 2: An analysis of broadacre farm efficiency in a region of Western Australia

The technical and allocative efficiency of a sample of farms drawn from the southeast and south coast agricultural regions of Western Australia (see figure 1) was measured using DEA and SFA. The nature of the DEA and SFA models is described in the following sub-sections. The sample comprised 93 farms with detailed price and quantity data for each year 1997 to 1999. The data were supplied by farm management consultants operating in the region.

***DEA Model***

The DEA model is based on the simultaneous expansion of outputs and contraction of inputs and is used to derive a measure of technical inefficiency for each farm in the sample. Mathematically, the model is described by equation (1).

$$TIE = \vec{D}_T(x, y; g_x, g_y) = \max \beta \qquad (1)$$

subject to:

$$\sum_{n=1}^{N} \lambda_n y_{in} \geq y_{in'} + \beta y_{in'} \qquad i = 1,\ldots, I$$

$$\sum_{n=1}^{N} \lambda_n x_{kn} \geq x_{kn'} - \beta x_{kn'} \qquad k = 1,\ldots, K$$

$$\sum_{n=1}^{N} \lambda_n = 1$$

$$\lambda_n \geq 0, \qquad n = 1,\ldots, N .$$

For farm n', the K inputs and I outputs are represented by the vectors $x_{kn'}$ for k =1,…, K inputs and $y_{in'}$ for the outputs i = 1,…, I, respectively. The frontier envelops the data points such that all observed points lie below or to the right of the frontier.

The λs are weights used to construct the efficient frontier. They also determine the point on the frontier where inefficient farms would be producing if they were efficient. Thus, the hypothetical point of maximum efficiency for an inefficient farm is determined by the weighted average of the bundle of inputs and outputs for efficient farms on the frontier.

Looking at the constraints in equation (1):

The first one states that farm n’s i-th output will be scaled up by β to an output level no greater than that created by the weighted linear combination of farm n’s efficient peers. The

second constraint states that farm n's k-th input is also scaled down y $\beta$ (note the negative sign on $\beta x_{kn'}$) to an input level no smaller than that created by the weighted linear combination of farm n's efficient peers. Maximising $\beta$ subject to both of these constraints brings farm n to a hypothetical point on the surface of the production frontier. The $\Sigma \lambda = 1$ constraint relaxes the assumption that all farms are producing at an optimal scale, i.e. constant returns to scale (CRS) is not imposed. The $\lambda_n \geq 0$ constraint is a non-negativity constraint, and ensures that none of the hypothetical points making up the frontier are in negative quadrants, i.e. both the farm's inputs and outputs need to be positive.
$\beta$ will satisfy $0 \leq \beta < \infty$ as a measure of technical inefficiency, with zero representing a fully efficient farm. To obtain a $\beta$ value for each farm, equation 1, a linear programming problem, must be solved N times for each sample farm.

### *SFA Model*

The SFA model is represented mathematically as equation (2).

$$\ln(y_i) = f\,(x_{i;}\, \beta) + v_i - u_i, \qquad i = 1,2, \ldots , N \qquad (2)$$

where:

$\ln(y_i)$ is the log of the observed level of production of the i-th firm;
$x_i$ is a (1 x k) vector of functions of input quantities used by the i-th firm;
$\beta$ is a (k x 1) vector of unknown parameters to be estimated;
$v_i$s are random variables accounting for measurement error and other random factors such as the effects of weather on the value of $y_i$, as well as the combined effects of unspecified input variables in the production function. They are assumed to be independent and identically distributed normal random variables having zero mean and constant variance N $(0, \sigma_V^2)$ and are independent of,
$u_i$s which are non-negative random variables that account for the technical inefficiency in production, and are often assumed to be independent and identically distributed with truncations at zero of the $N(\mu, \sigma_u^2)$ distribution.

The computer program, Frontier Version 4.1c[6], generates the ML estimates for the model parameters. The conditional expectation of $u_i$, given the value of $v_i - u_i$, is used to predict the farm level technical efficiency scores. For more detail see Coelli *et al* (1998).

### **Data**

Data from over 100 farmers for up to 5 consecutive years initially were gathered. Farms in this region are mixed, with most farm income coming from cropping enterprises. The data were detailed records of physical and financial items. Using ancillary data, indexing techniques and after clarifying data for some individual farms, each farm's data in each year were re-expressed as a series of input and output indexes. Missing data precluded the use of all of the observations in each year, leaving a reduced yet complete sample of 93 farms over 3 consecutive years.

[6] Developed by Tim Coelli, Centre for Efficiency and Productivity Analysis, UNE.

The DEA model comprised the following variables:

| *Outputs* | *Inputs* |
|---|---|
| Crops ($O_1$) | Capital ($I_1$) |
| Livestock ($O_2$) | Labour ($I_2$) |
| | Materials ($I_3$) |
| | Services ($I_4$) |

Summary statistics for these variables are listed in table 1. Over the period the average value of cropping enterprises rose, while the average value of livestock enterprises declined. The reduction in the value of the livestock enterprises was due mainly to a switch of land resources into more cropping and a reduction in the size of the sheep flock. ABARE (1999) reported these same enterprise trends for the central and southern broadacre farming regions of Western Australia. There was a large variation in the size of farms in the sample, leading to relatively large coefficients of variation in most input and output categories.

The SFA frontier was specified using the same variables, except that due to the frontier-fitting software (FRONTIER 4.1 (Coelli 1996)) not being able to cope with multiple outputs, crops and livestock items were aggregated to create a single output category.

**Table 1**: Summary statistics for the value of inputs and outputs in each year.

| Year/ Variable | Mean | Min Value | Max Value | Coefficient of variation (%)[7] |
|---|---|---|---|---|
| **1997** | | | | |
| Crop ($) | 301,858 | 9,463 | 963,654 | 67.2 |
| Livestock ($) | 125,437 | 22,274 | 527,659 | 57.1 |
| Capital ($) | 207,775 | 61,904 | 600,837 | 47.9 |
| Labour ($) | 56,332 | 20,012 | 137,014 | 43.8 |
| Materials ($) | 156,191 | 14,843 | 989,840 | 80.5 |
| Services ($) | 105,339 | 28,606 | 309,809 | 55.5 |
| **1998** | | | | |
| Crop ($) | 308,850 | 1,667 | 882,447 | 63.7 |
| Livestock ($) | 109,733 | 22,490 | 468,659 | 58.1 |
| Capital ($) | 217,903 | 65,012 | 673,565 | 43.8 |
| Labour ($) | 57,988 | 22,008 | 168,715 | 44.7 |
| Materials ($) | 145,701 | 21,852 | 380,756 | 56.3 |
| Services ($) | 99,375 | 26,579 | 262,695 | 45.5 |
| **1999** | | | | |
| Crop ($) | 347,368 | 4,026 | 992,234 | 64.2 |
| Livestock ($) | 104,090 | 19,287 | 329,826 | 56.8 |
| Capital ($) | 184,943 | 61,139 | 515,885 | 47.6 |
| Labour ($) | 59,454 | 20,942 | 141,623 | 41.6 |
| Materials ($) | 152,909 | 25,584 | 451,239 | 63.7 |
| Services ($) | 107,077 | 35,897 | 285,308 | 46.6 |

To derive the input and output categories required aggregation. For example, crop output was based on the aggregation of data involving several crop types including wheat, barley, oats,

[7] Coefficient of variation = (standard deviation / mean) * 100

lupins, canola and pulses. Aggregation involved the Fisher Index, adjusted by the EKS method (Elteto and Koves 1964, Szulc 1964), to derive multilateral transitive Fisher indices. See appendix one and Henderson (2002) for more detail on the aggregation process and data sources.

Besides the production and price data, information was also collected on farm-specific variables that might assist in explaining the variations in farm-level efficiency. These explanatory variables were:

Age ($Z_1$)
Age$^2$ ($Z_2$)
Rainfall ($Z_3$)
Minimum Tillage ($Z_4$)
Direct Drilling ($Z_5$)
Education ($Z_6$) and
Land ($Z_7$)

Their sample characteristics are given in table 2.

**Table 2:** Summary of farm-specific characteristics.

| Farm-specific characteristic | Unit | 1997 | 1998 | 1999 |
|---|---|---|---|---|
| Average age | Years | - | - | 48 |
| Average annual rainfall | mm | 436 | 488 | 440 |
| Average crop yield | kg/ha | 1890 | 1900 | 2207 |
| No. using minimum tillage | no. | 58 | 58 | 58 |
| No. using direct drilling | no. | 26 | 26 | 26 |
| No. using multiple tillage | no. | 9 | 9 | 9 |
| No. with ≤ year 10 education | no. | 52 | 52 | 52 |
| No. with > year 10 education | no | 41 | 41 | 41 |
| Average farm size | ha | 2175 | 2133 | 2174 |

Age ($Z_1$) is measured as the age of the farm operator in years and can also be viewed as a proxy for farming experience. The relationship of this variable to efficiency, for reasons given in chapter 3, could be negative or positive.

Age$^2$ ($Z_2$) is simply the square of $Z_1$. The inclusion of this variable allows the simple testing of the 'life-cycle' hypothesis. According to this hypothesis, the efficiency of the farmer increases at first with age and then decreases once the farmer is beyond middle age. If $Z_2$ is found to be significant then the relationship between farmer age and efficiency can be considered quadratic, increasing at first with age and then decreasing with age. The quadratic relationship specified by this variable makes a few restrictive assumptions including that the rate of increase and decrease of efficiency with farmer age is symmetrical. However, this assumption may not be unrealistic as Tauer (1984) and Tauer (1995) report such symmetry in their findings.

Rainfall ($Z_3$) represents the rainfall in millimetres in the calendar year, and is expected to have a positive effect on technical efficiency. This is because rainfall is directly and positively related to yield; in fact it is the largest natural driver of yields in broadacre dryland farming Western Australia (DAWA 1991, AWA 2000). Rainfall throughout the WA wheatbelt is a highly variable and scarce resource, so it is often the main factor influencing farm performance. Despite rainfall being a very important input in rainfed production processes, it does not typically enter the production function because it is a factor not under the control of the farm manager.

Given that rainfall is inextricably linked to yield, it is important to not only measure the impact of this variable on efficiency, but also to account for its impact on efficiency. Coelli *et al* (1998) suggest some approaches for accounting for environmental variables such as rainfall.

The methods of crop establishment used by farm operators are grouped into three broad categories; minimum tillage, direct drilling, and multiple tillage techniques. Two binary dummy variables account for the effect that each of these techniques has on efficiency. The first of these, minimum tillage ($Z_4$), assigns a value of 1 to farms whose crops are established with minimum tillage and a value of zero for all others. The second of the crop establishment dummy variables, direct drilling ($Z_5$), assigns a value of 1 to farms applying direct drilling to establish crops and a value of zero for all others.

Conventional or multiple tillage involves ploughing[8] or turning over the soil several times, and is the traditional method of seedbed preparation for WA broadacre farmers. Some of the benefits of this practice include killing weeds, aerating and loosening the soil to aid root growth, mineralizing soil nitrogen and other nutrients to increase their availability to newly established crops, and for controlling root diseases. Rhizoctonia, a root pathogen that is a particular problem on the Esperance sandplain, is one of many diseases reduced by cultivation.

Until the 1970s conventional cultivation was seen as essential for successful cropping. Despite its benefits, evidence emerged suggesting that these cultivation practices had some undesirable side effects, which could, in the long-term, reduce soil productivity and therefore technical efficiency. These include an increased risk of wind erosion, loss of organic matter, delayed time of seeding, increased weed germination and poorer pasture re-establishment after crop production. Acknowledgement of these negative attributes and the development of better and more affordable herbicides from the 1970s onwards led to the development of alternative crop establishment practices reliant on reduced tillage. Many different crop establishment techniques now come under the umbrella of reduced or minimum tillage. In this study minimum tillage refers to tillage of the entire topsoil using only one or two cultivations prior to sowing, while direct drilling typically involves sowing in a single pass in previously uncultivated soil (ABARE 2000).  This technique can improve soil properties and preserve its long-term productivity, by retaining soil organic matter and reducing soil erosion. This can help to increase microbiological activity in the soil and increase fertility through the modification of the soils' physical, chemical and biological components. Bligh and Findlater (1996) outline other benefits associated with no-till farming.

While all of the soils in the study region can support no-till operations, sandy soils are the most typical in the WA wheatbelt and yet these soils are the least responsive to the benefits of no-till practices. This is largely due to the fact that these soils have little structure and often

[8] Disc ploughs, tined scarifiers and chisel ploughs are the primary cultivation equipment.

form surface 'hard pans', after rainfall and farm traffic, that restrict the early development of crop roots and hence crop yields[9]. Tillage removes these surface 'hard pans'.

The choice of ‘no-till’ versus ’min-till’ involves considering a range trade-offs. Farms on the south coast of WA, which make up a significant proportion of sample farms (see figure 1), typically have fine sands that are particularly susceptible to erosion and don’t form surface crusts. In these instances, 'no-till' methods of crop establishment may improve the productive capacity of the soil and subsequently, the productive performance of the farm.

Education ($Z_6$) of the farm operator is measured by a simple binary dummy variable; farmers educated at the level of year 12 and above are assigned a value of one and farmers educated below this level are assigned a value of 0. This variable captures the main source of variation in education between farmers. Education is expected to be positively related to efficiency, because it should increase farmers' capacity to process the information necessary to apply ‘best practices’.

Land ($Z_8$) represents the number of hectares operated on the farm. Farm size is expected to be positively related to efficiency.

### Technical Inefficiency Findings

The DEA and SFA approaches both record mean technical inefficiency as highest in 1997 and lowest in 1999 (see table 3). The overall level of technical inefficiency is greater in the SFA than DEA in all three years. This result does not comply with *a priori* expectations about the degree of inefficiency measured by each technique. Given that DEA is deterministic it should attribute all variation from the frontier to inefficiency. SFA on the other hand is stochastic attributing some of the variation to random error in the data and consequently is expected to estimate higher levels of efficiency.

**Table 3:** Summary of mean technical inefficiency scores.

| Years | DEA | SFA [10] |
|---|---|---|
| 1997 | 0.079 | 0.264 |
| 1998 | 0.073 | 0.134 |
| 1999 | 0.066 | 0.093 |

However, the same result from DEA and SFA comparison was found by Ferrier and Lovell (1990), Kalaitzandonakes *et al* (1992), Kalaitzandonakes and Dunn (1995) and Hjalmarsson *et al* (1996). In cases, such as this study, the DEA variable returns to scale frontier appears to provide a tighter fit to the data than the SFA frontier.

[9] “the advantage of cultivation over direct-drilling with a combine has averaged 0.27 t/ha over ten years and the application of nitrogenous fertilizer has failed to remove the yield advantage of the cultivated seed bed. The very poor yield from the ‘zero-disturbance’, triple disc drilled treatment emphasises the requirement for cultivation for best yield on sandplain soils” (Bligh and Findlater 1996).

[10] The SFA software, FRONTIER 4.1, actually generates technical efficiency estimates bound between 1 and 0. By subtracting 1 from these scores, technical inefficiency scores were calculated, where 0 now represents a fully efficient firm. Because the DEA scores are not bound by one, they may predict higher levels of inefficiency than the SFA model.

Table 4 outlines the distributions of the various technical inefficiency series. The SFA technical efficiency distributions, like the DEA technical inefficiency distributions, are highly skewed with a greater proportion of farms in the samples being close to the frontier. An obvious difference is that, according to the SFA approach, none of the sample farms were fully efficient, whereas 33 per cent were fully efficient when DEA was used. This is solely due to the differences in the way the respective frontiers are constructed. In DEA actual observations are used to construct the frontier, therefore a number of farms will inevitably be estimated as being fully efficient. Temporally, the distributions follow a similar pattern; both DEA and SFA distributions become more skewed as efficiency increases across time. This decline in technical inefficiency implies that farms are moving closer to the frontier over time. One implication is that over the sample period farms are gradually adopting more productive techniques and improving their technical management of enterprises.

**Table 4**: Technical inefficiency distributions[a].

| Inefficiency Range | 1997 | 1998 | 1999 | 1997 | 1998 | 1999 |
|---|---|---|---|---|---|---|
| | | **SFA** | | | **DEA** | |
| 0.0 | 0 | 0 | 0 | 33 | 37 | 36 |
| 0.0 – 0.1 | 23 | 48 | 73 | 23 | 26 | 34 |
| 0.1 – 0.2 | 12 | 26 | 11 | 29 | 21 | 14 |
| 0.2 – 0.3 | 16 | 13 | 4 | 6 | 8 | 6 |
| 0.3 – 0.4 | 18 | 4 | 2 | 2 | 1 | 3 |
| 0.4 – 0.5 | 17 | 2 | 3 | | | |
| 0.5 – 0.6 | 6 | | | | | |
| 0.6 – 0.7 | | | | | | |

[a] Figures in each cell refer to the number of farms recording a technical inefficiency in that range.

## Sources of Technical Inefficiency

Using DEA it is possible to examine possible sources of technical inefficiency; that is, which inputs are being overused and what outputs under-produced. Table 5 demonstrates where gains in efficiency could have been made for the average farm in 1997, 1998 and 1999, according to the DEA analysis.

On average farmers are inefficient in the use of all inputs and outputs in all years. In 1997 output levels could be increased by an average of 6.4 per cent and input levels could be reduced by an average of 16.4 per cent through gains in technical efficiency. In 1998 similar increases in output levels are suggested as achievable, while the level of input contraction is slightly less at 15.1 per cent. In 1999 the gains and reductions in outputs and inputs are slightly more modest at 6.0 per cent and 10.7 per cent respectively. The input used most inefficiently in each year is capital, while the gains in efficiency that can be made by expanding outputs are split evenly between the crop and livestock enterprises.

**Table 5:** Identifying potential gains in efficiency.

| | Crop | Livestock | Capital | Labour | Materials | Services |
|---|---|---|---|---|---|---|
| **1997** | | | | | | |
| Original levels | 2.250 | 0.799 | 0.961 | 0.773 | 1.035 | 1.425 |
| Optimal levels | 2.400 | 0.857 | 0.760 | 0.660 | 0.939 | 1.148 |
| Potential gains (%) | 6.2 | 6.7 | -20.8 | -14.6 | -9.2 | -19.4 |
| **1998** | | | | | | |
| Original levels | 1.890 | 0.563 | 0.875 | 0.643 | 1.097 | 1.415 |
| Optimal levels | 2.023 | 0.602 | 0.658 | 0.570 | 0.957 | 1.237 |
| Potential gains (%) | 6.5 | 6.4 | 24.8 | -11.2 | -12.7 | -12.6 |
| **1999** | | | | | | |
| Original levels | 2.547 | 0.438 | 0.700 | 0.720 | 1.267 | 0.862 |
| Optimal levels | 2.697 | 0.478 | 0.628 | 0.656 | 1.141 | 0.741 |
| Potential gains (%) | 6.5 | 6.4 | -16.6 | -10.9 | -12.8 | -12.5 |
| Summary: | | Total gains in outputs | | Total reductions in inputs | | |
| 1997 | | 6.4% | | 16.4% | | |
| 1998 | | 6.5% | | 15.1% | | |
| 1999 | | 6.0% | | 10.7% | | |

Possible sources of technical inefficiency can also be examined using SFA and its findings are that output could have been expanded by 26.4, 13.4 and 9.3 per cent in 1997, 1998 and 1999 respectively. Because SFA produces output-oriented measures of efficiency, these potential gains in output are calculated while holding input levels fixed. Therefore, it is not surprising that SFA produces more generous estimates of potential output than the directional distance function DEA model. SFA also produces more optimistic estimates of potential gains in output because it identified higher mean levels of inefficiency (Table 3).

## Comparing DEA and SFA Technical Efficiency Rankings

### *Are DEA and SFA technical efficiency rankings consistent?*

Spearman coefficients of rank correlation were calculated to test whether or not the two approaches produced similar efficiency rankings in each year. The magnitude of efficiency identified by each approach is not as important as their relative efficiency rankings because the magnitude of inefficiency identified is fairly arbitrary, depending largely on the direction used and assumptions about the shape and nature of the frontier (Chambers 2000). If rankings are similar, then the identification of top and bottom performers is thus not sensitive to the choice of methodology.

The following hypothesis is tested:
$H_0$: $r_s = 0$, i.e. there is no significant correlation between DEA and SFA efficiency rankings.
$H_1$: $r_s \neq 0$, i.e. there is significant positive correlation between DEA and SFA efficiency rankings.

Results in table 6 show significant and positive rank agreement between the technical efficiency series generated by the two methods in all three years. This suggests that farm efficiency rankings are robust to the choice of methodology. This finding gives confidence in the reliability of each technique to approximate the 'true' efficiency rankings of sample farms.

**Table 6:** Rank agreement between SFA and DEA efficiency series.

| Years | $r_s$ | t - test statistic | Decision |
|---|---|---|---|
| 1997 | 0.328 | 2.308[a] | Reject $H_0$ |
| 1998 | 0.423 | 4.453[a] | Reject $H_0$ |
| 1999 | 0.461 | 4.959[a] | Reject $H_0$ |

[a] denotes t-statistics significant at the 1 per cent level of significance.

***Do 'technically efficient' farms remain efficient?***

Spearman coefficients of rank correlation also reveal the stability of the ranks over time. Technical efficiency ranks across consecutive seasons 1997-1998 and 1998-1999 for both DEA and SFA were assessed. An assessment of the stability of ranks from the 1997 to the 1999 season was also made. The following hypothesis is tested:
following:
$H_0$: $r_s = 0$, i.e. there is no significant correlation between the two series of ranks.
$H_1$: $r_s \neq 0$, i.e. there is significant correlation between the two series of ranks.

Results are shown in table 7.

**Table 7:** Rank agreement between efficiency series over the consecutive years, 1997 - 98, and 1998 – 99 and 1997 – 99.

| Period | $r_s$ | t - test statistic | Decision |
|---|---|---|---|
| *1997 – 98* | | | |
| SFA | 0.161 | 1.610 | Accept $H_0$ |
| DEA | 0.375 | 3.865[a] | Reject $H_0$ |
| *1998 – 99* | | | |
| SFA | 0.280 | 2.787[b] | Reject $H_0$ |
| DEA | 0.424 | 4.464[a] | Reject $H_0$ |
| *1997 – 99* | | | |
| SFA | -0.076 | -0.724 | Accept $H_0$ |
| DEA | 0.278 | 2.765[b] | Reject $H_0$ |

[a] denotes t-statistics significant at the 1 per cent level of significance.
[b] denotes t-statistics significant at the 5 per cent level of significance.

The null hypothesis of no significant correlation was rejected for the pairs of DEA rankings across consecutive years 1997-1998 and 1998-1999. The DEA rankings between the years 1997-1999 are also significantly correlated. The SFA rankings, on the other hand, were not consistently significant across the periods. The only pair of SFA rankings that were significantly correlated at the 5 per cent level of significance were from the years 1998-1999.

Henderson (2002) also conducted a conditional probability analysis to examine the stability of technical efficiency rankings through time. The findings supported results in table 7 with the conclusion that DEA efficiency rankings are more stable over time than equivalent SFA rankings.

The movement of farms in and out of the DEA 'efficient set' (i.e. those efficient farms that are part of the frontier) is listed in table 8. This provides evidence specifically about the persistence of technical efficiency and also about the stability of the DEA envelope.

**Table 8:** The movement of farms in and out of the 'efficient set'.

| Year | No. of efficient farms | No. remaining efficient after one season | No. remaining efficient after two seasons |
|---|---|---|---|
| 1997 | 33 | 19 | 10 |
| 1998 | 37 | 21 | na |
| 1999 | 36 | na | na |

na not applicable

A majority of farms remain in the 'efficient set' from one year to the next: 18 out of 31 farms (58 per cent) remained efficient from 1997 to 1998 and 22 out 36 (61 per cent) remained efficient from 1998 to 1999. The movement of farms out of the 'efficient set' over the three years was much higher with only 10 out 33 farms (30 per cent) remaining efficient from 1997 to 1999.

### *What influences technical efficiency?*

*DEA*

The impact of farm-specific variables, described previously, on measures of technical inefficiency was investigated using regression analysis. A Tobit regression model was used to model DEA technical inefficiency scores, with farm-specific variables included directly in the production function to model technical inefficiency in a single stage parametric approach. The Tobit regression results are shown in table 9.

Three of the explanatory variables tested explain a significant amount of the variation in technical inefficiency for 1997. These include rainfall and both of the crop establishment dummy variables. However, the first crop establishment dummy variable ($Z_4$) is only significant at the 10 per cent level. The second crop establishment dummy variable ($Z_5$) has a higher level of significance at 5 per cent. $Z_5$ has a positive sign, and a higher coefficient value and level of significance than $Z_4$. This indicates that farmers using no-till methods or direct drilling when establishing their crops are more technically inefficient than those farmers employing either minimum or multiple tillage practices. Given that most of the sample farms use minimum tillage practices (62 percent), this positive sign signifies that farms practising no-till farming (28 percent of sample farms) are not as efficient as those using minimum tillage. This could be caused by a positive yield response to any or all of the beneficial effects of tillage, which include weed control, aerating and loosening soils to aid root growth, mineralizing soil nitrogen and other nutrients to increase their availability to newly established crops, and for controlling root diseases such as rhizoctonia. This result indicates that, in the study region, the benefits listed above outweigh those, such as the minimisation of soil erosion and lower labour and machinery requirements, that are associated with no-till farming.

Finally, the significant and positive relationship between rainfall and efficiency supports *a priori* expectations. This is due to the direct and positive impact of rainfall on crop and pasture yields.

**Table 9**: Tobit regression DEA results.

| IE/Variable | Parameters | Coefficient | Standard error | t-ratio |
|---|---|---|---|---|
| **1997** | | | | |
| Intercept | $\delta_0$ | 3.714 | 3.579 | 1.037 |
| Age ($Z_1$) | $\delta_1$ | -0.117 | 0.151 | -0.770 |
| Age$^2$ ($Z_2$) | $\delta_2$ | 1.33E-03 | 1.56E-03 | 0.854 |
| Rainfall ($Z_3$) | $\delta_3$ | -2.53E-03 | 1.19E-03 | -2.128$^b$ |
| Min till D ($Z_4$) | $\delta_4$ | 0.717 | 0.375 | 1.909$^c$ |
| Direct drill D ($Z_5$) | $\delta_5$ | 1.099 | 0.424 | 2.587$^b$ |
| Education ($Z_6$) | $\delta_6$ | -0.209 | 0.249 | -0.837 |
| Land ($Z_8$) | $\delta_8$ | -1.72E-04 | 1.10E-04 | -1.562 |
| Log likelihood | | 19.278 | | |
| **1998** | | | | |
| Intercept | $\delta_0$ | 5.998 | 3.641 | 1.648 |
| Age ($Z_1$) | $\delta_1$ | -0.203 | 0.156 | -1.299 |
| Age$^2$ ($Z_2$) | $\delta_2$ | 1.83E-03 | 1.60E-03 | 1.145 |
| Rainfall ($Z_3$) | $\delta_3$ | -2.05E-03 | 1.11E-03 | -1.848$^c$ |
| Min till D ($Z_4$) | $\delta_4$ | 0.603 | 0.378 | 1.596 |
| Direct drill D ($Z_5$) | $\delta_5$ | 0.966 | 0.413 | 2.340$^b$ |
| Education ($Z_6$) | $\delta_6$ | -0.251 | 0.250 | -1.003 |
| Land ($Z_8$) | $\delta_8$ | 1.18E-04 | 1.33E-04 | 0.891 |
| Log likelihood | | 14.735 | | |
| **1999** | | | | |
| Intercept | $\delta_0$ | 6.062 | 3.654 | 1.659 |
| Age ($Z_1$) | $\delta_1$ | -0.220 | 0.152 | -1.452 |
| Age$^2$ ($Z_2$) | $\delta_2$ | 2.32E-03 | 1.56E-03 | 1.484 |
| Rainfall ($Z_3$) | $\delta_3$ | -2.98E-03 | 1.31E-03 | -2.269$^b$ |
| Min till D ($Z_4$) | $\delta_4$ | 0.325 | 0.379 | 0.857 |
| Direct drill D ($Z_5$) | $\delta_5$ | 0.463 | 0.400 | 1.154 |
| Education ($Z_6$) | $\delta_6$ | 7.41E-02 | 0.2471 | 0.300 |
| Land ($Z_8$) | $\delta_8$ | 1.13E-04 | 1.19E-04 | 0.953 |
| Log likelihood | | 13.576 | | |

$^b$ and $^c$ denote t-statistics significant at the 5 per cent and 10 per cent levels of significance.

The 1998 Tobit regression results paint a very similar picture. Rainfall and direct drill coefficients, $\delta_3$ and $\delta_5$, are of a similar magnitude and level of significance as in 1997. The minimum tillage variable, however, is not found to be significant, even at the 10 per cent level. Farms practising no-till are found to be more technically inefficient than those using either minimum tillage or multiple tillage practices. Again this indicates the positive benefits from the small amount of tillage involved with minimum tillage, outweigh those associated with no-till farming. However, this time the positive effect of rainfall on efficiency is only significant at the 10 per cent level of significance.

In 1999 rainfall explains most of the variation in technical inefficiency and its effect on efficiency is positive and significant at the 5 per cent level of significance. In this year neither of the crop establishment dummy variables explain a significant amount of the variation in efficiency.

*SFA*

The results from the SFA technical efficiency effects model tell a different story to that of the Tobit analysis on the DEA scores. In 1997 land ($Z_7$) was the only explanatory variable with a significant effect on efficiency (see table 10). The relationship between land and efficiency in this case was positive and highly significant at the 1 per cent level. This supports *a priori* expectations that larger farms would perform better.

In 1998 the land variable is no longer significantly or positively related to efficiency. Age ($Z_1$) and age$^2$ ($Z_2$) are now significantly and positively related to efficiency at the 10 per cent level of significance. The first of these results indicates that older farmers, on average, perform better than young farmers as technical managers, possibly because due to their experience. The second finding provides some support for the ‘life cycle’ hypothesis outlined previously. However, neither of these variables was highly significant.

According to the 1998 results, education ($Z_6$) also has a positive and significant effect on farm level efficiency, although only at the 10 per cent level of significance. This also supports *a priori* expectations and indicates that farmers with year 12 level education and above perform better than those with less education.

The 1999 results are different again. Rainfall ($Z_3$) is now positively and significantly related to efficiency at the 1 per cent level of significance. None of the age variables nor land is significantly related to efficiency. Education, however, is again found to have a positive effect on efficiency at the 10 per cent level.

There is a mixture of results across the years and the methodologies. The main differences between the analyses that relate farm-specific variables to the DEA and SFA scores are as follows: land ($Z_8$), education ($Z_6$) and age ($Z_1$), did not significantly explain any of the variation in the DEA scores. Rainfall ($Z_3$) explained the variation in DEA scores more consistently than it did for SFA scores, and the crop establishment variables did not explain any of the variation in the SFA scores.

The only finding consistent between both analyses was that rainfall ($Z_3$) had a positive and highly significant effect on technical efficiency in 1999. Drawing on results across all three years, and both methodologies, there is evidence that rainfall ($Z_3$), land ($Z_8$), age ($Z_1$) and education ($Z_6$) are positively and significantly related to farm-level technical efficiency. On the other hand, there is evidence that no-till farming has a more detrimental effect on technical efficiency, compared with minimum till farming.

**Table 10**: SFA inefficiency model results.

| Variable | Parameter | Value | Standard Error | t- ratio |
|---|---|---|---|---|
| **1997** | | | | |
| Constant | $\delta_0$ | 1.46E+00 | 8.66E-01 | 1.69E+00 |
| Age ($Z_1$) | $\delta_1$ | -1.69E-02 | 3.74E-02 | -4.51E-01 |
| Age$^2$ ($Z_2$) | $\delta_2$ | 1.72E-04 | 3.88E-04 | 4.44E-01 |
| Rainfall ($Z_3$) | $\delta_3$ | -1.50E-04 | 3.18E-04 | -4.73E-01 |
| Min till D ($Z_4$) | $\delta_4$ | 1.40E-02 | 8.63E-02 | 1.62E-01 |
| Direct drill D ($Z_5$) | $\delta_5$ | 1.33E-01 | 1.09E-01 | 1.22E+00 |
| Education ($Z_6$) | $\delta_6$ | -8.62E-02 | 6.89E-02 | -1.25E+00 |
| Land ($Z_7$) | $\delta_8$ | -3.60E-04 | 7.57E-05 | -4.75E+00[a] |
| **1998** | | | | |
| Constant | $\delta_0$ | 2.87E+00 | 1.30E+00 | 2.20E+00[b] |
| Age ($Z_1$) | $\delta_1$ | -1.12E-01 | 5.71E-02 | -1.95E+00[c] |
| Age$^2$ ($Z_2$) | $\delta_2$ | 1.04E-03 | 5.73E-04 | 1.81E+00[c] |
| Rainfall ($Z_3$) | $\delta_3$ | 5.24E-05 | 3.83E-04 | 1.37E-01 |
| Min till D ($Z_4$) | $\delta_4$ | -3.48E-02 | 1.60E-01 | -2.18E-01 |
| Direct drill D ($Z_5$) | $\delta_5$ | 2.46E-01 | 1.65E-01 | 1.49E+00 |
| Education ($Z_6$) | $\delta_6$ | -1.85E-01 | 1.02E-01 | -1.81E+00[c] |
| Land ($Z_8$) | $\delta_8$ | 4.79E-05 | 8.03E-05 | 5.97E-01 |
| **1999** | | | | |
| Constant | $\delta_0$ | 2.13E+00 | 1.65E+00 | 1.29E+00 |
| Age ($Z_1$) | $\delta_1$ | -3.69E-02 | 6.23E-02 | -5.93E-01 |
| Age$^2$ ($Z_2$) | $\delta_2$ | 3.41E-04 | 6.21E-04 | 5.50E-01 |
| Rainfall ($Z_3$) | $\delta_3$ | -4.09E-03 | 1.29E-03 | -3.16E+00[a] |
| Min till D ($Z_4$) | $\delta_4$ | 2.27E-01 | 4.19E-01 | 5.41E-01 |
| Direct drill D ($Z_5$) | $\delta_5$ | 6.01E-01 | 4.42E-01 | 1.36E+00 |
| Education ($Z_6$) | $\delta_6$ | -2.82E-01 | 1.43E-01 | -1.97E+00[c] |
| Land ($Z_8$) | $\delta_8$ | 1.44E-05 | 8.89E-05 | 1.63E-01 |

[a], [b] and [c] denote t-statistics significant at the 1 per cent, 5 per cent and 10 per cent levels of significance.

The findings have some implications for research, development and extension (R,D&E) investment in the study region. For example, R,D&E efforts might be more effective if they focused on developing policies to improve the education level of farmers, and also if they targeted smaller farms run by young farmers. It might also be worth focusing extension efforts in drier areas and also, promoting research into establishing whether minimum tillage has truly persistent benefits that would allow it to be the preferred method of crop establishment for this region.

### Allocative Efficiency Findings

Using a DEA profit function, measures of economic or profit efficiency can be decomposed into allocative and technical components through inclusion of the directional distance function. Because the profit function considers inputs, outputs and their respective prices, allocative efficiency, a measure of how well farmers combine both inputs and outputs given their respective prices, can be estimated.

The outline of this sub-section follows that of the sub-section on technical efficiency. Table 11 shows the main source of economic or profit inefficiency in each year is the result of allocative rather than technical inefficiency. Allocative inefficiency accounts for 75, 81 and 79 per cent of the profit inefficiency estimated in the years 1997, 1998 and 1999 respectively. This indicates that far more gains in farm profitability will come from improving the selection of inputs and outputs given their respective prices, rather than boosting technical performance.

**Table 11:** Mean profit, technical and allocative inefficiency scores.

| Years | PIE | TIE | AIE |
|---|---|---|---|
| 1997 | 0.312 | 0.079 | 0.233 |
| 1998 | 0.388 | 0.073 | 0.315 |
| 1999 | 0.308 | 0.066 | 0.242 |

The mean profit inefficiency scores range from 0.308 to 0.388 with the year 1998 showing the highest overall inefficiency level, while similar and lower scores are observed in 1997 and 1999. The same pattern is observed with mean allocative inefficiency but not with mean technical inefficiency, where the highest level of inefficiency is observed for 1997, and 1999 has the lowest. Mean profit and allocative inefficiency scores both follow a similar yearly pattern because the overwhelming cause of inefficiency is allocative rather than technical.

These results have important implications, because they suggest that more gains in economic efficiency (i.e. profit) can be made through policy and R,D&E measures that address allocative rather than technical inefficiency.

Table 12 displays distributions of the profit, allocative and technical inefficiency scores in each year. The distributions of allocative inefficiency differ markedly with the technical inefficiency distributions. The pattern of difference is similar across all three years, where allocative inefficiency is relatively normally distributed, with the greater proportion of farms being found in the 0.1-0.4 inefficiency ranges. Technical inefficiency distributions are skewed much further toward the lower inefficiency levels. These differences are the least marked in 1997. The profit inefficiency distributions contain more observations in the higher ranges of inefficiency, which is no surprise given that profit inefficiency is the additive combination of allocative and technical inefficiency.

**Table 12**: Inefficiency distributions in 1997, 1998 and 1999.

| IE Range | PIE | TIE | AIE | PIE | TIE | AIE | PIE | TIE | AIE |
|---|---|---|---|---|---|---|---|---|---|
| | | *1997* | | | *1998* | | | *1999* | |
| 0.0 | 3 | 33 | 3 | 1 | 37 | 1 | 2 | 36 | 2 |
| 0.0 – 0.1 | 6 | 23 | 15 | 6 | 26 | 8 | 7 | 34 | 16 |
| 0.1 – 0.2 | 19 | 29 | 29 | 9 | 21 | 20 | 24 | 14 | 34 |
| 0.2 – 0.3 | 20 | 6 | 9 | 13 | 8 | 27 | 21 | 6 | 14 |
| 0.3 – 0.4 | 18 | 2 | 8 | 26 | 1 | 12 | 15 | 3 | 10 |
| 0.4 – 0.5 | 12 | | 5 | 17 | | 10 | 11 | | 8 |
| 0.5 – 0.6 | 11 | | 2 | 6 | | 5 | 1 | | 3 |
| 0.6 – 0.7 | 3 | | | 6 | | 3 | 6 | | 2 |
| 0.7 – 0.8 | | | | 5 | | 4 | 3 | | 1 |
| 0.8 – 0.9 | | | | 1 | | | 1 | | 1 |
| 0.9 – 1.0 | | | | 1 | | 1 | 1 | | 1 |
| 1.0 – 1.1 | 1 | | 1 | 2 | | 2 | | | |
| 1.1 – 1.2 | | | | | | | 1 | | 1 |

Table 13 displays the changes in inputs and outputs that would be required for the average farm to become economically efficient in each year. Looking first at outputs; to increase economic efficiency, the average farm would have needed to increase its production of crops in all three years, while increasing livestock production in two of the three years (1997 and 1998). In both 1997 and 1999, greater increases in the production of crops than livestock needed to be made in order to maximise profits. These results are interesting, because in WA and other Australian States, prices for sheep and wool have been in decline relative to crop prices during the study period, 1997 to 1999. In response many farmers were shifting their resource allocation from livestock to cropping enterprises. According to these results greater changes in this direction were required if farmers during the period were to raise their profit levels and attain economic efficiency.

**Table 13:** Changes in the levels of inputs and outputs necessary to achieve economic efficiency for the average farm.

| | Crop | Livestock | Capital | Labour | Material | Services |
|---|---|---|---|---|---|---|
| **1997** | | | | | | |
| Original levels | 2.250 | 0.799 | 0.961 | 0.773 | 1.035 | 1.425 |
| EE levels | 5.168 | 0.816 | 0.962 | 0.931 | 1.565 | 1.968 |
| **1998** | | | | | | |
| Original levels | 1.890 | 0.563 | 0.875 | 0.643 | 1.097 | 1.415 |
| EE levels | 5.086 | 0.390 | 1.043 | 0.573 | 1.716 | 2.019 |
| **1999** | | | | | | |
| Original levels | 2.547 | 0.438 | 0.700 | 0.720 | 1.267 | 0.862 |
| EE levels | 4.286 | 0.682 | 0.766 | 1.038 | 1.429 | 0.897 |

Overall, input usage increased in each year. This is not surprising, because, in order to maximise profits much larger quantities of crops needed to be grown, which also entails increasing the overall scale of production. While it is possible, it would take most farms some years to alter both their production mix and scale of operation to the extent suggested by the results in table 13. A proper practical perspective of the results is that they should relate more to medium term suggested changes for the farm businesses than short-run changes. This is partly due to the fact that all of the inputs in the model were treated as variable inputs. However, in practice some of the inputs (e.g. capital) or components of the inputs are more fixed in nature and so their alteration is more a medium term or long-run decision.

### *Are DEA efficiency rankings consistent?*

To test if farms that perform well technically also perform well economically and allocatively, Spearman coefficients of rank correlation were calculated. The hypothesis tested was:

$H_0$: $r_s = 0$, i.e. there is no significant correlation between the two series of ranks.
$H_1$: $r_s \neq 0$, i.e. there is significant correlation between the two series of ranks.

Results are presented in table 14.

**Table 14:** Rank agreement between efficiency series.

| Years | $r_s$ | t - test statistic | Decision |
|---|---|---|---|
| 1997 | | | |
| TIE vs PIE | 0.414 | 4.340[a] | Reject $H_0$ |
| TIE vs AIE | -0.020 | -0.192 | Accept $H_0$ |
| PIE vs AIE | 0.846 | 15.130[a] | Reject $H_0$ |
| 1998 | | | |
| TIE vs PIE | 0.277 | 2.753[a] | Reject $H_0$ |
| TIE vs AIE | -0.109 | -1.049 | Accept $H_0$ |
| PIE vs AIE | 0.872 | 17.024[a] | Reject $H_0$ |
| 1999 | | | |
| TIE vs PIE | 0.386 | 3.994[a] | Reject $H_0$ |
| TIE vs AIE | -0.043 | -0.410 | Accept $H_0$ |
| PIE vs AIE | 0.825 | 13.941[a] | Reject $H_0$ |

[a] and [b] denote t-statistics significant at the 1 per cent and 5 per cent levels of significance.

The profit and allocative efficiency rankings are positively correlated at a very high level of significance in each year. The technical efficiency rankings are also positively correlated with profit efficiency rankings at a high level of significance in each year. However, there is no significant correlation between technical and allocative efficiency in any of the years examined.

These results indicate the top technical performers are different to the top allocative performers. This finding has important implications for policy and R,D&E activities. If these activities solely target technically inefficient farmers, they may be misguided where these farms already display profit and allocative efficiency. Further, using R,D&E to solely improve farmers' technical efficiency does not necessarily ensure improvement in their allocative and profit efficiency; yet it appears that farmers have most to benefit from improvement in these latter two.

***Do 'economically efficient' farms remain efficient?***

The stability of PIE and AIE ranks over time is assessed by calculation of Spearman coefficients of rank correlation. Results are presented in Table 15. Again it is important, from a policy and R,D&E point of view, to see whether or not the top performers in the sample can be consistently identified from year to year. The statistical test for the following hypothesis was the Spearman coefficient of rank correlation:

$H_0$: $r_s = 0$, i.e. there is no significant correlation between the two series of ranks.
$H_1$: $r_s \neq 0$, i.e. there is significant correlation between the two series of ranks.

The efficiency rankings in each series were significantly similar across the consecutive years 1997-1998 and 1998-1999, as well across the three years, 1997-1999 at the 1 per cent level of significance (see table 6.7). This is a positive result because it demonstrates that both the directional distance function and profit efficiency DEA models consistently identify both good and poor performers with regard to economic, technical and allocative efficiency.

**Table 15:** Rank agreement between inefficiency series over consecutive years, 1997 - 1998, and 1998 – 1999 and 1997 – 1999.

| Years | $r_s$ | t - test statistic | Decision |
|---|---|---|---|
| 1997 – 1998 | | | |
| PIE | 0.646 | 8.076[a] | Reject $H_0$ |
| TIE | 0.375 | 3.865[a] | Reject $H_0$ |
| AIE | 0.676 | 8.741[a] | Reject $H_0$ |
| 1998 – 1999 | | | |
| PIE | 0.575 | 6.712[a] | Reject $H_0$ |
| TIE | 0.424 | 4.464[a] | Reject $H_0$ |
| AIE | 0.697 | 9.277[a] | Reject $H_0$ |
| 1997 – 1999 | | | |
| PIE | 0.449 | 4.793[a] | Reject $H_0$ |
| TIE | 0.278 | 2.765[a] | Reject $H_0$ |
| AIE | 0.567 | 6.558[a] | Reject $H_0$ |

[a] denotes t-statistics significant at the 1 per cent level of significance.

The movement of 'best-practice' farms from one year to the next was also examined. Only farms in the 'efficient set' (i.e. those fully efficient farms comprising the frontier) were examined. The findings are limited because they do not reveal the magnitude of the decline in efficiency of farms that move out of the efficient set. For example, a farm may move out of the efficient set but still be relatively efficient, hence its overall rank won't differ markedly.

None of the farms that were allocatively or economically efficient remained so after even a single season. This is not surprising given that a maximum of 3 out 93 farms were found to be fully efficient in any year. One reason why so few farms are found to be economically efficient is because this is dependent not only on being efficient in production (i.e. being technically efficient), but also on having an optimal combination of inputs and outputs given their respective prices (i.e. being allocatively efficient). Also, a farmer's potential to perform well in an allocative capacity is likely to be confounded by yearly or seasonal variation in the prices of inputs and outputs.

### *What influences economic efficiency?*

Indicative results from the regressions on farm-specific variables on PIE and AIE are presented in table 16. Only results for 1999 are presented, to save on space.

**Table 16**: Tobit regression results (1999).

| IE/Variable | Parameters | Coefficient | Standard error | t-ratio |
|---|---|---|---|---|
| **TIE** | | | | |
| Intercept | $\delta_0$ | 6.062 | 3.654 | 1.659 |
| Age ($Z_1$) | $\delta_1$ | -0.220 | 0.152 | -1.452 |
| Age$^2$ ($Z_2$) | $\delta_2$ | 2.32E-03 | 1.56E-03 | 1.484 |
| Rainfall ($Z_3$) | $\delta_3$ | -2.98E-03 | 1.31E-03 | -2.269[b] |
| Min till D ($Z_4$) | $\delta_4$ | 0.325 | 0.379 | 0.857 |
| Direct drill D ($Z_5$) | $\delta_5$ | 0.463 | 0.400 | 1.154 |
| Education ($Z_6$) | $\delta_6$ | 7.41E-02 | 0.2471 | 0.300 |
| Land ($Z_8$) | $\delta_8$ | 1.13E-04 | 1.19E-04 | 0.953 |
| Log likelihood | | 13.576 | | |
| **AIE** | | | | |
| Intercept | $\delta_0$ | 0.13978 | 3.4594 | 4.04E-02 |
| Age ($Z_1$) | $\delta_1$ | 0.13727 | 0.14543 | 0.944 |
| Age$^2$ ($Z_2$) | $\delta_2$ | -1.34E-03 | 1.49E-03 | -0.900 |
| Rainfall ($Z_3$) | $\delta_3$ | -2.17E-04 | 1.31E-03 | -0.165 |
| Min till D ($Z_4$) | $\delta_4$ | -0.53068 | 0.35706 | -1.486 |
| Direct drill D ($Z_5$) | $\delta_5$ | -0.55195 | 0.38114 | -1.448 |
| Education ($Z_6$) | $\delta_6$ | -0.29097 | 0.23329 | -1.247 |
| Canola ($\delta_7$) | $\delta_7$ | -1.2401 | 0.8292 | -1.496 |
| Land ($Z_8$) | $\delta_8$ | -5.81E-04 | 1.19E-04 | -4.869[a] |
| Log likelihood | | 26.692 | | |
| **PIE** | | | | |
| Intercept | $\delta_0$ | 2.6581 | 3.4629 | 0.768 |
| Age ($Z_1$) | $\delta_1$ | 4.75E-02 | 0.14503 | 0.327 |
| Age$^2$ ($Z_2$) | $\delta_2$ | -4.13E-04 | 1.49E-03 | -0.277 |
| Rainfall ($Z_3$) | $\delta_3$ | -1.47E-03 | 1.32E-03 | -1.114 |
| Min till D ($Z_4$) | $\delta_4$ | -0.37629 | 0.35597 | -1.057 |
| Direct drill D ($Z_5$) | $\delta_5$ | -0.28243 | 0.37954 | -0.744 |
| Education ($Z_6$) | $\delta_6$ | -0.30537 | 0.23334 | -1.309 |
| Canola ($\delta_7$) | $\delta_7$ | -1.2239 | 0.82906 | -1.476 |
| Land ($Z_8$) | $\delta_8$ | -4.87E-04 | 1.17E-04 | -4.161[a] |
| Log likelihood | | 26.692 | | |

[a], [b] and [c] denote t-statistics significant at the 1 per cent, 5 per cent and 10 per cent levels of significance.

In 1999 land ($Z_8$) was the only significant variable identified in regressions on both AIE and PIE scores. Regressions on TIE in 1999 only identified one significant variable, rainfall. As was the case in both 1997 and 1998, $Z_8$ was significantly and positively related to AIE and PIE at the 1 per cent level.

Drawing on the results from the regressions on the allocative efficiency scores across all years (see Henderson 2002), there is evidence that direct drill D ($Z_5$), minimum till D ($Z_4$), education ($Z_6$) and land ($Z_8$) all have a positive and significant effect on efficiency.

The results from the profit efficiency models tell a similar story, with land ($Z_8$) having the most consistent significant impact on economic efficiency. This result is almost entirely related to its impact on allocative rather than technical inefficiency. In none of the three years did canola ($Z_7$) explain a significant amount of the variation in AIE or PIE. This suggests that despite farmers receiving a historically high price for this crop over the period of this study, and although its impact was positive, it did not *significantly* affect the profitability of these farms.

### *A Cautionary Note*

It is worth noting that unless the difference between maximum and actual farm profit is positively related to farm size, then the normalisation required for PIE may favour the larger farms in the sample. Recall that PIE is the difference between maximal and actual profit ($\pi(p,w)-(py-wx)$), normalised by the sum of actual costs and revenues ($pg_y+wg_x$). Table 17 displays the relationship between farm size, $\pi(p,w)-(py-wx)$ and $pg_y+wg_x$ in each year.

In 1997 the difference between maximum and actual profit declines over the first 3 size categories then increases substantially in the final size category. The corresponding normalisation values increase with each size category but again more substantially in the last one. This result is somewhat disconcerting, because it shows that the normalisation does favour farms in the larger size categories. In 1998 a similar pattern is observed. The 1999 results are the most alarming; here there is very little difference in $\pi(p,w)-(py-wx)$ in each category, while there are substantial increases in $pg_y+wg_x$ as farm sizes increase. Consequently, the highly significant relationships found between land ($Z_8$) and PIE (and AIE) in each year should be viewed with some skepticism. Perhaps using the value of input and output prices, which would also permit PIE to be invariant to proportional changes in prices, would have been more appropriate.

**Table 17:** Relationship between farm size, $\pi(p,w)-(py-wx)$ and $pg_y+wg_x$.

| | < 1500 (ha) | 1500-2000 (ha) | 2000-3000 (ha) | >3000 (ha) |
|---|---|---|---|---|
| $\pi(p,w)-(py-wx)$ | | | | |
| 1997 | 228,241 | 229,879 | 229,252 | 343,162 |
| 1998 | 258,581 | 291,381 | 285,087 | 435,553 |
| 1999 | 216,735 | 221,278 | 240,942 | 252,790 |
| $pg_y+wg_x$ | | | | |
| 1997 | 526,299 | 814,047 | 1,005,507 | 1,618,576 |
| 1998 | 509,988 | 807,374 | 106,2454 | 1,490,857 |
| 1999 | 539,694 | 789,904 | 1,060,877 | 1,518,857 |

## Section 3: Concluding Remarks

An examination of mean technical efficiency scores using DEA and SFA revealed that technical inefficiency in a southern agricultural region of Western Australia decreasing over the years 1997 to 1999. A comparison of mean DEA and SFA scores revealed that the SFA approach identified higher levels of technical inefficiency than the DEA approach. The distributions of inefficiency revealed by each method were found to be heavily skewed toward lower levels, becoming increasingly skewed over time as more farms moved closer to the frontier.

To achieve technical efficiency the average farm was calculated to require its output levels to increase by 6.4, 6.5 and 6.0 per cent in the years 1997, 1998 and 1999 respectively, while input levels needed to be reduced by 16.4, 15.1 and 10.7 per cent in the same years. The results indicated that most of this reduction is achievable through reducing the use of capital. The SFA results, on the other hand, predict more optimistic estimates for potential gains in output, which is not surprising given that it only considers the expansion of outputs and not the contraction of inputs

Rank agreements between the DEA and SFA scores were assessed using Spearman coefficients of rank correlation, and significant rank agreement was found between each series in each year. This result should give practitioners the confidence that, regardless of which method is employed, efficient farms can be identified.

The stability of the efficiency rankings identified by each approach over time also was investigated. Spearman coefficients of rank correlation were used to assess the stability of efficiency rankings over time. The ranks identified by DEA were more stable over time than the SFA ranks. Results suggest that DEA is superior at identifying farms that persist in technical efficiency. Conditional probabilities were also calculated to examine the durability of farm efficiency. These results also indicated that DEA produced more temporally stable efficiency rankings. It is also possible, however, that the farms' relative efficiency levels vary significantly from year to year and that the SFA approach reflects this.

The degree to which some farm specific factors can explain variation in technical efficiency also was investigated using Tobit regressions. Farmers engaging in no-till cropping were less efficient than those farmers reliant on minimum tillage practices to prepare seedbeds. This suggests that at least a small amount of tillage produces benefits, such as pest control and more rapid growth, that outweigh the improvements in soil sustainability and reduced time and capital requirements that come with no-till farming (at least in the short term). Analysis of the same variables to explain variation in the technical inefficiency effects in the SFA model identified a different set of significant variables. This demonstrates that there is some disparity between the scores from each method, despite their rankings being significantly alike. Here, farm size, farmer age, education levels and rainfall were all found to be positively and significantly related to technical efficiency. There was also some evidence to support the life-cycle hypothesis; where farmer productivity increases first as middle age approaches and then decreases again at a similar rate.

Although technical inefficiency declined consistently from 1997 to 1999, profit and allocative inefficiency peaked in 1998, with 1997 and 1999 recording similar levels. The overwhelming source of profit inefficiency was attributable to allocative rather than technical inefficiency. This finding has important policy and R,D&E implications, because it suggests that policies and R,D&E activities that target allocative rather than technical performance of farmers may more effectively improve their profitability. One explanation for the poor allocative performance of the sample firms is that because the prices of commodities and factors of production are subject to yearly variation beyond the control of farm managers, it is often more difficult to perform as well allocatively as it is technically. However, a valid alternative explanation is simply that this finding is due to the restrictive nature of the analysis. When there is little variation in farm prices, the DEA problem identifies very few allocatively efficient points on the frontier.

There was no rank agreement found between the AIE and TIE rankings across the three years. This also has important implications, because policies and R,D&E activities that target technically inefficient farms may be somewhat misguided if these farms perform well in an allocative capacity. The rankings of all three efficiency series were found to be stable over time which demonstrates not only the persistence of characteristics (e.g. 'best-practice' management) that beneficially affect technical and allocative efficiency, but also that DEA is a reliable technique for identifying this efficient set of farms.

Tobit regression results identified land and minimum tillage as two variables that explained most of the variation in AIE across each year. Education and direct drill technology also had a significant and positive impact on AIE in one of the three years. The findings on the impact of crop establishment are interesting when viewed in conjunction with the results from the TIE regressions, where no-till farming proved to have a significant positive relationship with TIE. This latter finding suggests that the benefits, such as weed control and soil aeration, associated with at least a minimum level of tillage, are more beneficial to productivity than the benefits that come with no-till farming, e.g. reduced labour and soil improvement. However, the evidence from this analysis suggests that both minimum tillage and no-tillage operations are related to higher levels of allocative efficiency than conventional or multiple tillage practices. This could be due to minimum and no-till farming practices requiring less expensive items such as capital and labour, providing greater flexibility in crop sowing, and also because they provide farmers with more time to focus on other areas of production.

Farm size was found to have a positive and consistent significant relationship with allocative efficiency. However, as mentioned in the cautionary note, the normalisation underpinning the PIE measure downwardly biases the inefficiency scores for larger farms. The gains from rearrangement of inputs and outputs to achieve allocative efficiency should also be viewed with caution because if a farm changes its proportion of inputs and outputs its level of technical efficiency is also likely to change (Farrell 1957). In addition, because the production mix of farms is often adjusted to expected future prices rather than actual prices, farms may be identified as being inefficient when they are actually, in prospect at least, efficient.

## Appendix One

Crops

The crops variable comprises an aggregation of seven crop types: wheat, barley, oats, lupins, canola and other crops (such as faba beans and field peas). Crop prices could not be obtained simply by deflating the value of crop sales by the quantity harvested, because not all of the harvested quantity is sold in each year. Harvested crops are sold sequentially by commodity boards, in a system known as pooling. Farmers receive a stream of payments, known as pool payments, from the sale of their harvested grain. Although farmers receive the bulk of these payments in the year following the harvest, these payments can extend over a few years. Accordingly, crop prices are estimated as State cash-equivalent prices minus district freight charges.

Livestock

The livestock quantity variable is an aggregate of sheep and cattle numbers and products sold. However, very few farms in the sample run cattle enterprises. Beginning with the sheep quantity variables, there are two different outputs: the first of these consists of sheep sold plus any positive change in the livestock inventory. The second is the quantity of wool produced in the production year.

The prices corresponding to these quantity variables were calculated in the following way: the value of sheep sold was simply divided by the number of sheep sold. Positive changes in the inventory between the beginning and end of the season were priced using the farm's average sale price of sheep sold that year. These are commonly referred to as positive operating gains.

Occasionally the value for wool sales listed on the farmer's balance sheet did not necessarily match the quantities of wool produced, according to the farm physical record. This is because wool is not always sold soon after shearing. It can be warehoused. Fortunately though, the prices for wool sold directly by each farmer were available from the farmer records.

For cattle the only product is the number of cows sold. This output was computed in exactly the same manner as for sheep, i.e. numbers sold plus positive operating gains.[11]

Capital

The capital variable is an aggregate of five items: land, buildings and structures, plant (machinery and vehicles), sheep and cattle.

The first three of these five items were converted from stock into flow variables by calculating their user costs. These variables were converted into user costs simply by taking the average of their opening and closing values and multiplying this average by the market real rate of interest for that year. Thus the user cost could be interpreted as the cost to the farmer of not selling her on-farm assets and putting her money into a high interest savings account.

[11] Where there were no sales, and hence no prices available for cattle and sheep, average State prices from the ABARE farm survey for that year were used.

The land item was classified as total hectares of land and its price was derived simply by dividing its user cost by this quantity[12]. Unfortunately it was not possible to separate buildings and structures from land and hence, estimate depreciation on these items. Because they are included in the land category, their cost is captured partly by the user cost of land. According to ABARE statistics on the average WA broadacre farm, depreciation on buildings and structures represents a much smaller fraction of costs than depreciation on plant (vehicles and machinery) (ABARE 1999). Depreciation on plant items is included in the capital variable. For the plant item the user cost was calculated following the approach outlined above and then depreciation was added[13]. This total value was then deflated using a price index taken from ABARE's annual farm survey results, to obtain quantity estimates. This price index represents the average price for these items for WA farms in each year. Unfortunately, applying this index necessitates the assumption that all farms have equal unit costs for these items. This is an unavoidable distortion given that both quantity and price information are required to calculate technical and allocative efficiency, respectively.

The livestock inputs, sheep and cattle comprise two components. The first is purchases plus the absolute value of negative operating gains (i.e. when closing numbers less opening numbers is negative), which can be interpreted as capital stock depletion to produce output. Rather than using the purchase price to value the decrease in the livestock inventory, the sale price for that year was used. This is because the average purchase price is usually inflated by the purchase of rams that are considerably more expensive than ewes, lambs or wethers. The second component of the livestock inputs is their user costs which are calculated by multiplying the value of the opening numbers of livestock by the real rate of interest for the relevant year.

Labour

The labour variable consisted of three items: operator/family labour, hired labour and shearing expenses.

The farm records from which these variables were constructed contained information on the number of weeks worked by the farm operator and family members. The market rate for labour, obtained from ABARE farm survey results, was used as a notional price for operator/family labour.

The numbers of weeks worked by hired employees was also recorded, along with money paid in wages for hired labour. A price for hired labour was easily obtained by dividing wages paid by the number of weeks worked.

Shearing expenses for each farm were taken from the farm financial records. Corresponding quantity indexes for each year were drawn from ABARE's annual farm survey results.

Materials

Materials is an aggregation of five items; crop chemicals, fodder and agistment, fertiliser, seed, and fuel. Only costs were available for these items, and once again the average price indices for these items were taken from ABARE survey results from WA broadacre farms and

[12] Total land area rather than effective hectares was used.
[13] A depreciation rate of 8 per cent was assumed to be appropriate. This was taken from the PlanFarm survey for the 1999 year (pp. 26) (PlanFarm 2000).

were used to obtain quantity estimates by deflating their respective costs. By applying an average price it was necessary, once more, to make the assumption that all the items were of equal unit value and of homogenous quality.

Services

Like materials, the items that make up services are only reported as costs on the farm financial records. The service cost items include: rates and taxes, administrative costs, miscellaneous livestock costs, total contract costs, total repairs costs, net insurance costs, other costs (e.g. general freight, fertiliser freight and spreading, electricity and gas). Again, average price indices were taken from ABARE WA farm survey results and quantities were obtained by deflating costs.

The materials and services variables are the least perfect because they make the assumption that all farms face the same price for these inputs. The same is true of capital, but to a lesser extent. Given the quality of the data available, these variables were seen to give the best representation of the farm production structure. Ideally enterprise-specific variables should be used to characterise the farm production processes. However, this was not possible given that the farm records did not contain enterprise-specific input data. For example, the capital items and overheads are not reported as enterprise specific inputs and can only be partitioned with difficulty, and with the need to make further restrictive

A SFA production frontier based on a Cobb-Douglas functional form with two different distributional assumptions is used to estimate technical efficiency effects. One assumes a truncated-normal distribution, while the other assumes that the technical efficiency effects are a linear function of a number of farm and farmer-specific variables. Hypothesis tests reveal that the latter specification is preferred.
To answer this question, the technical performance of 93 broadacre farm businesses from 1997 to 1999 was examined using two new techniques, data envelopment analysis (DEA) and stochastic frontier analysis (SFA). The main preliminary findings revealed that:

- Most farms demonstrated high levels of technical efficiency.
- Technical efficiency improved over the three years.
- The distribution of technical efficiency among farms was uneven - of concern was the small, yet diminishing portion of farms displaying relatively low levels of technical efficiency.
- Both analytical techniques, DEA and SFA, generated consistent rankings of farm technical efficiency.
- Farms identified as being very efficient tended to remain so.
- A range of factors influenced technical efficiency, including rainfall, farm size, tillage method, formal education level of the farmer, and their age.

The survey examined three types of farm efficiency, although only *technical efficiency* has been reported on here. A business is technically efficient if its inputs cannot be reorganised to generate more output. In a cropping context this would mean an efficient farmer has combined his inputs such as machinery, labour, fertilisers and herbicides in such a way that he achieves the maximum production possible in that season. A technically efficient farmer is getting the maximum output from a given set of inputs.

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