Efficiency and Scale Economies in the Western Australian Wheatbelt

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The production performance of wheatbelt farms in Western Australia is analysed to determine whether potential to exploit scale economies and improve technical efficiency has driven the trend towards increased farm size. An input-orientated stochastic frontier model is used to estimate technical efficiency and scale economies using an unbalanced panel dataset provided by BankWest for the period 1995/1996 to 2005/2006. Differences in the relative efficiency of farms are explored by the simultaneous estimation of a model of inefficiency effects. The results show the majority of wheatbelt farms operate at high levels of technical efficiency and experience increasing returns to scale. Over the study period farms became bigger to benefit from economies of scale, however average farm technical efficiency declined. More specialised farms on average are more technically efficient and have less potential to exploit scale economies. Technical efficiency and scale economies are significantly affected by farm location. The farmer/farm family characteristics do not significantly affect technical efficiency although attending an agricultural college and having a child with a strong interest to return to the farm has a positive effect on scale economies.

Keywords: *stochastic frontier, technical efficiency, scale economies, farm size, agriculture*

1. Introduction

In the past few decades there have been significant changes to the structure of the Australian agricultural sector. Improvements in technology and farming practices along with policy decisions have led to a decline in the rural population as average farm size has increased. The decline in rural population has had significant social impacts on country communities and the economic sustainability of family farms has become a concern. Alston (2004) suggested globalisation, international policies such as farmer subsidies in the U.S. and E.U., and continued deregulation in Australian agriculture has left Australian farm families more vulnerable in the global market. These forces have provided an incentive for Australian farms to improve their economic efficiency to remain globally competitive.

Past literature suggests that farms may improve productivity by improving their coordination of inputs and outputs, expanding to benefit from economies of scale, or adopting new technologies (Henderson 2001; Morrison *et al*. 2004). Accordingly, technical efficiency, scale economies and technical change are often used as performance indicators.

Technical efficiency (TE) is a measure of a farmøs ability to transform inputs into outputs at a constant level of technology (Rougoor *et al.* 1998). An improvement in TE infers that the farm was able to produce a given level of output using a lower level of inputs or that the farm was able to increase output with a given level of inputs. The measurement of TE has developed from the work of Farrell (1957), who drew upon Debreu (1951) and Koopmans (1951). Since this fundamental work, researchers have developed methods of measuring the TE of a particular firm by measuring the distance between the efficient frontier and where the actual firm lies (Sickles 2005). Efficiency is most commonly measured relative to an estimated frontier that can be deterministic or stochastic (Rezitis *et al.* 2002). The stochastic method creates a frontier that accounts for statistical noise in the data. Coelli (1995) suggested that if farm level data was used, where measurement error and missing variables such as weather play a significant role, then the stochastic method was likely to be a better estimator of the efficient frontier than deterministic non-parametric methods. For this reason the stochastic production frontier (SPF) approach was used in this study.

Scale or size effects refer to the effect of farm size on the level of outputs and inputs. For example, scale economies (SEC) and scale efficiency are measures of size effects. SEC refer to the decrease in average cost of a firm due to an increase in production. Scale efficiency is a measure indicating whether or not a farm is operating at an optimal scale. A farm smaller than the scale efficient size experiences increasing returns to scale and so could become more productive by increasing its scale of operation. A farm larger than the scale efficient size experiences decreasing returns to scale and so could become more productive by decreasing its scale of operation (Coelli *et al.* 2005).

Technical change is measured by the movement in the production frontier over time. It represents improvements in technology and management practices. Movements in the production frontier will affect the efficiency score of a farm. For example, a positive technical change will move the production frontier outwards indicating the farmer can achieve a higher level of output with the same level of inputs. In this case if the input-output bundle of the farm does not move by the same proportional shift in the frontier, the farm will be more technically inefficient.

This paper examines the performance of Western Australian wheatbelt farms using stochastic frontier analysis based on farm business data supplied by BankWest. The predominant hypothesis tested is whether the potential to improve TE and exploit significant SEC has driven the trend towards increased farm size in the wheatbelt. An investigation into significant determinants of TE and SEC was also conducted.

The paper continues by describing stochastic frontier and inefficiency effects models. Section 3 describes the data and variables used in the analysis. Sections 4 and 5 present the results and discussion, and conclusions are made in the final section.

2. Models and Estimation Approach

2.1 Stochastic frontier model

A SPF considers that deviations from the frontier result from technical inefficiency and statistical noise. Statistical noise arises from the omission of relevant variables in the input vector, and from measurement errors associated with the functional form of the model (Coelli *et al.* 2005). SPFs are derived through estimation of input parameters and include a non-negative random error representing technical inefficiency and a symmetric random error that accounts for noise.

Figure 1 illustrates a SPF model of one output and one input with input-orientated efficiency measures. An input-orientated efficiency measure is interpreted in terms of using lower input levels to produce a given output level. This is derived using an input-distance function. An input-distance function was used in this paper as broadacre dryland farmers typically have more control over their inputs than outputs. The figure shows the positive or negative nature of the noise effect and the corresponding inefficiency of the firm.

In Figure 1, farm A has a positive random error *de*. This resulted in the stochastic frontier of farm A being situated left of the deterministic frontier, the curved line in Figure 1. Farm A can achieve the same level of output for a lower input due to the positive noise effect. The inefficiency of farm A is given by *df*, the distance between the farm and the stochastic frontier. Farm B in Figure 1 has experienced a negative noise effect *ab*, resulting in the stochastic frontier being situated right of the deterministic. The inefficiency of farm B is represented by *bc*.

Figure 1 also illustrates size effects. Any point along a frontier assuming constant returns to scale, a straight line from the origin, represents a scale efficient farm. Point X represents the optimal scale efficient farm as it is at the point of tangency between the constant returns to scale frontier and the frontier assuming variable returns to scale. At point X the farm is fully technically and scale efficient. Farm A is smaller than the scale efficient size and experiences increasing returns to scale and so could become more productive by increasing its scale of operation, moving along the SPF towards point X. Farm B experiences decreasing returns to scale as it is larger than the scale efficient size and so could become more scale efficient by decreasing its scale of operation. Scale efficiency can be implied by SEC as at point X both scale efficiency and SEC will be equal to one (Ray 1998).

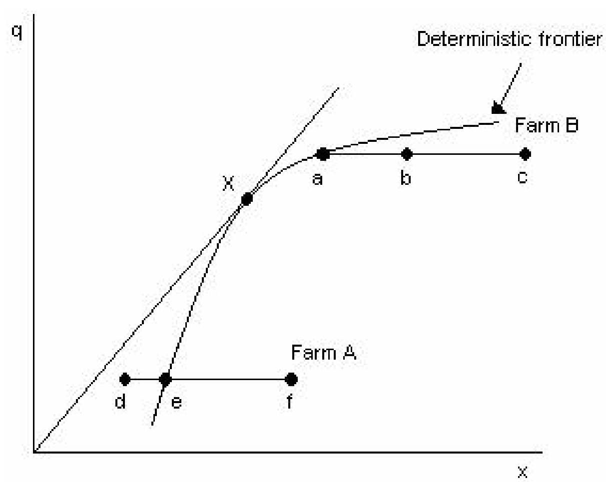

Figure 1: A Stochastic Production Frontier (Input-orientated)

Distance functions are used to estimate the efficiency levels or production characteristics for multiple-output frontiers (Coelli *et al.* 2005). The SPF measurement in this study involved econometric estimation of an input distance function $D^I(\mathbf{X},\mathbf{Y},\mathbf{R})$ where; **X** and **Y** are input and output vectors and **R** represents time as an external production determinant. This required first imposing the condition that $D^I(\mathbf{X},\mathbf{Y},\mathbf{R})$ be homogeneous of degree one in inputs. This was achieved through normalisation:

$$D^I(\mathbf{X,Y,R})/X_1 = D^I(\mathbf{X}/X_1,\mathbf{Y,R}) = D^I(\mathbf{X^*,Y,R}) \quad (1)$$

where **X*** is a vector of inputs normalised by X_1. The resulting input-distance function identifies minimum possible input levels to produce a given output level (Morrison *et al*. 2004). A flexible translog functional form was used to estimate the stochastic frontier. This form allows analysis of SEC as there are no restrictions imposed on returns to scale of individual farms or elasticities of substitution.

The translog model of the production frontier estimation was as follows:

$$-\ln D^I_{it}/X_{1,it} = \beta_0 + \sum_m \beta_m \ln X^*_{it} + 0.5\sum_m \sum_n \beta_{mn} \ln X^*_{mit} \ln X^*_{nit} + \beta_y \ln Y_{it} + \sum_m \beta_{ym} \ln Y_{it} \ln X^*_{mit} + \delta R_t \quad (2a)$$

$$-\ln D^I_{it}/X_{1,it} = \mathrm{TL}(\mathbf{X^*,Y,R}) \quad (2b)$$

$$-\ln X_{1,it} = \mathrm{TL}(\mathbf{X^*,Y,R}) - \ln D^I_{it} \quad (2c)$$

where i denotes farm, t denotes time period, m, n, are inputs, there is one output and δ is the parameter for a time variable. If X_1 is land for example, the function is essentially specified on a per hectare basis.

Estimation of this equation by SPF methods, as initially developed by Aigner *et al*. (1977), involves characterising the distance from the frontier, $-\ln D^I_{it}$, as a negative error associated with technical inefficiency, $-u_{it}$. This error is then combined with a random error component v_{it}, representing factors that may generate noise in the data (Morrison *et al*. 2004). Following the work of Aigner *et al*. (1977) the inefficiency term was assumed half-normally distributed and the error term was normally distributed. The parameters of the input-distance function were estimated using maximum likelihood methods. The frontier model allowed a farmộs efficiency level to vary through time, a time-invariant model was found to be inappropriate. From the frontier model a radial input-orientated measure of TE was derived as:

$$\mathrm{TE} = \exp^{-u} \quad (3)$$

SEC were calculated from the estimated frontier model as the scale elasticity by differentiating the input-distance function with respect to output (Y):

$$\mathrm{SEC} = -\partial \ln D^I(\mathbf{X,Y,R}) / \partial \ln Y \quad (4)$$

SEC = 1 implies the farm is scale efficient (Ray 1998). If SEC are less than one, it implies the farm has potential to exploit SEC and become more productive by increasing its scale of production. If SEC are greater than one, it implies the farm is experiencing decreasing returns to scale. A farm experiencing increasing or decreasing returns to scale is scale inefficient.

To evaluate the appropriateness of the technological form assumed in the SPF model the input and output elasticities were examined:

$$\varepsilon_{DIY} = -\partial \ln D^I(\mathbf{X,Y,R}) \,/\, \partial \ln Y \quad (5)$$

$$\varepsilon_{DIXm} = -\partial \ln D^I(\mathbf{X,Y,R}) \,/\, \partial \ln X_m \quad (6)$$

The output measure indicates the increase in input use when output expands, this should be positive (ie. like the slope of the production frontier). The input elasticities represent input shadow shares of the *m*th input relative to X_1, and should be negative (ie. like the slope of an isoquant). This gives an indication of how inputs can be substituted to produce a given output (Coelli *et al*. 2005).

Movement in the frontier through time was indicated by including a time variable in the frontier production function as an external determinant **R**. Technical change is then the differentiation of the input-distance function with respect to time (*YEAR*):

$$\mathrm{TC} = \partial \ln \mathrm{D}^I(\mathbf{X,Y,R}) \,/\, \partial YEAR \quad (7)$$

2.2 Inefficiency effects model

Explanation of cross-farm variation in TE involved stochastic frontier specifications that incorporated a model for the technical inefficiency effects. All parameters were estimated in a one stage procedure. The technical inefficiency effects in the stochastic frontier model are assumed to be independently distributed non-negative variables (Battese and Coelli, 1995). Battese and Coelli define the technical inefficiency effects by:

$$u_{it} = z_{it}\delta + w_{it} \quad (8)$$

where z_{it} is a vector containing a constant and the firm-specific and time-specific variables, δ is a vector of parameters to be estimated, and w_{it} are unobservable random variables.

A time variable was included in the inefficiency effects model to pick up the change in efficiency of the average farm through the period analysed. Including time in the inefficiency effects model indicates the extent the average farm is keeping up with the frontier (Hadley 2006). It is important to note that yearly variations in efficiency scores may not follow a smooth trend due to various short-term exogenous factors in addition to technical change

(Morrison *et al*. 2004). Thus, changes in TE between years capture a combination of technical and environmental changes over time.

3. Data

The farm level data used to construct the panel dataset for this study were obtained from BankWest for the period 1994/1995 to 2005/2006. The BankWest data are from an annual survey of their farming clients in Western Australia. The survey has been running for eleven consecutive years and each year approximately 500 farmers complete the survey. The Australian Bureau of Statistics records 11,876 farms as being in operation in Western Australia in 2004 (AusStats 2005). However, there are only around 6,400 farms that deliver grain to Cooperative Bulk Handling (Ian Wilkinson, pers. comm., 2006). So the BankWest sample represents approximately 4 per cent of the entire stateǿs farm population or close to 8 per cent of the grain farmer population. The BankWest data is collected primarily in the wheatbelt region of Western Australia, bounded by Geraldton to the north, Merredin and Esperance to the east and Albany to the South. Cereal and livestock operations are the predominant farm type through this region. The BankWest dataset is the largest annual survey of individual farms in Western Australia.

The survey collects financial and production data of Western Australian farm Businesses. The data are whole farm records for individual farms and in total 1,458 farms have taken part in the survey. Financial information collected includes sources of income and expenses, both on-farm and off-farm, categorised into particular enterprises such as grain or livestock production. Also farm physical data are recorded including farm area, crop yields, number of sheep shorn, wool production and rainfall.

Retention rates of farms within the survey were not high and some information was not recorded for a number of farms. Table 1 shows the length of time farms have been present in the survey sample after farms with missing or incomplete data were eliminated. The table shows 903 of the total 1458 farms were used in the analysis. It is also important to note that farms may not be in the survey in consecutive years. For example a farm that has responded five times may have done so over a period longer than five years. Table 1 shows 80 per cent of farms are in the survey sample for four or less years. Therefore the BankWest dataset is a large unbalanced panel.

Table 1: Duration of farms in the survey sample

No. of years in survey	No. of farms	% of farms	Cumulative %
1	362	40.1	40.1
2	172	19.1	59.1
3	112	12.4	71.5
4	76	8.4	80.0
5	62	6.9	86.8
6	54	6.0	92.8
7	34	3.8	96.6
8	16	1.8	98.3
9	13	1.4	99.8
10	2	0.2	100.0
11	0	0.0	100.0
Total	**903**	100	

A major weakness of the dataset is that values of income and expenditure have not been adjusted to take into account changes in inventories. For example, when a farm sells stockpiled wool, the income from this wool will be counted in the year the wool is sold, rather than in the year the costs for producing the wool have been incurred. A similar effect occurs with grain, as payments for grain produced in one year can extend across a number of production years. These lags in payments cause distortions in the annual performance indicators.

Another weakness is the robustness of the survey. A survey sample bias may exist because the survey includes mainly farm businesses that have borrowed funds from BankWest during the season. Thus the survey may include more farmers looking to expand their operation and exclude farmers with low levels of debt. Also the number of farms in each region that are present in the survey may differ between years. This can distort the annual performance measures if a significantly different region has a greater than average response rate to the survey in a particular year. It can be assumed however that in the majority of cases there should be a sufficient number of farms surveyed in each region to allow comparisons of farm performance.

The dataset provided by BankWest is not ideal for production frontier analysis as it was not designed for this purpose. A better dataset for the analysis would be a balanced panel that includes levels of production in terms of yearly output and input quantities. Depreciating monetary variables to a comparable level would then not be a problem and there would not be inaccuracies due to low farm retention rates. However the BankWest dataset is one of the few large datasets on Western Australian farms, and every effort has been made to transform the data into a useable form.

3.1 Stochastic frontier model

Table 2 lists descriptive statistics of variables used in the frontier model. There were six input variables and Y_{it} was the only output variable. All input variables were normalised by $LAND_{it}$ so the input-distance function is essentially specified on a per hectare basis. All variables measured in monetary terms were adjusted to 1997/1998 values using price indexes provided by the Australian Bureau of Agricultural and Resource Economics (ABARE 2005). The indexes were based on prices paid and received by Australian farmers, and so may vary from prices received by Western Australian farms. Burggraaf (2006) for example, compiled price data for a range of animal classes (cattle, sheep, pigs and goats) over the period 2003 to 2006 and found consistent and persistent differences with Western Australian sale yard prices being well below those of the Eastern States for all stock classes.

Table 2: Descriptive statistics for variables used in the frontier model

Variable	Explanation	Unit	Mean	Std. Err.	Min	Max
Y_{it}	total annual farm income	$	533,214	7,734	35,007	4,339,066
L_{it}	annual labour expenditure	$	21,033	546	8	335,362
K_{it}	book value of on-farm assets	$	1,558,748	20,852	610	15,500,000
$RAIN_{it}$	annual rainfall	mm	267	2	40	900
$CROP_{it}$	annual crop expenses	$	267,998	4,187	7,922	2,342,903
$LIVE_{it}$	annual livestock expenses	$	36,337	1,033	35	983,858
$LAND_{it}$	total land area farmed	ha	3,120	44	200	35,400

The labour input variable is not ideal for production analysis as it is measured in terms of annual labour expenditure. This would not give a true indication of the amount of labour used on the farm as farm family members are not likely to be included. A better estimator of labour use on a farm would be one based on full time labour equivalents.

External factors affecting technical change in the frontier, such as the adoption of an improved wheat variety, were not included in the efficient frontier model. This is because the analysis focuses on one predominant farming type, cereal and livestock, and so these factors are consistent for the entire data set. Also the dataset was not detailed enough to include significant events such as floods, droughts and frost that could be accounted for by dummy variables. Time was included as an external factor affecting movements in the frontier however its effect was not significant (p = 0.45) and so was excluded. This means that changes in a farmȏs TE were assumed due to movements in farm observations rather than shifts in the frontier due to technological change and external factors.

3.2 Inefficiency effects model

Independent variables used in the inefficiency effects model to explain between-farm variation in TE scores included; time, farm specalisation and region dummies. The time variable included in the model (*YEAR*) was a linear time trend.

The Herfindahl index (*HI*) was used to determine the level of farm specialisation (Purdy *et al.* 1997). The index lies between zero and one; a value near one indicates a highly specialised farm whilst a value near zero indicates a highly diversified farm. The index was calculated as the sum of the squares of the proportion of farm income from crops, livestock and other sources.

$$\mathrm{H}_{it} = \sum_{i=1}^{n} (I_j / Y)_{it}^{\;2} \qquad (9)$$

where I_j is the value of income derived from source j (j = cropping, livestock or other) and Y is total farm income. Table A1 summarises the farm specific variables measured in the survey that were aggregated into income from crop, livestock and other sources.

Farm location was based on the regions and districts assigned to the wheatbelt by BankWest. They divided the wheatbelt into seven regions consisting of eighteen districts illustrated in Figure A1.

3.3 Farm size

Farm size was measured in two ways; firstly as effective land area and secondly in terms of annual turnover. Sutherland (1983) suggested efficiency studies need to use differing measures of farm size due to the combined effects of farm size and farm type impacting on efficiency measures. For example, farms of different output composition can be different in land area but have the same value of output. Sutherland (1983) also reports a similar effect through differing land quality. Farm size by land area was measured by total hectares farmed and farm size by turnover was measured by total farm income (Y_{it}). Farm size was not included as a variable in the inefficiency effects model because the effects of farm size had been included in the stochastic frontier model ($LAND_{it}$ and Y_{it}).

3.4 Farmer/farm family characteristics

To complement the BankWest dataset, 133 farms were sent separate surveys to collect information on specific farmer/farm family characteristics. There was a 60% response rate resulting in an unbalanced panel dataset comprised of 80 different farms with 291 observations running across 5 years (2000/2001 to 2004/2005). Definitions of the farmer/farm family variables used to explain TE, SEC and farm size, is provided in Table 3.

Table 3: Definitions of farmer/farm family variables used to explain TE, SEC and farm size

Variable	**Explanation**
AgSchool	A dummy variable taking a value of one if any farm operater has attended an Agricultural College
IntChild	A dummy variable taking a value of one if a farmer's child has a strong interest in returning to the farm
NoFarmers	Number of farmers directly involved in the farm business

4. Results

4.1 TE and SEC for the wheatbelt

Table 4 lists the estimated TE and SEC for the BankWest dataset. The estimated mean TE indicates on average farms in the sample are operating close to the efficient frontier. The mean level of SEC indicates the majority of farms are operating at increasing returns to scale. This suggests many farms have significant potential to increase in scale and improve their productivity. In fact, only one farm was found to be experiencing decreasing returns to scale.

Table 4: Summary statistics of TE and SEC for farms that are BankWest clients

	No. of farms	No. of Observations	Mean	Std.Err.	Min	Max
TE	903	2483	0.885	0.001	0.361	0.972
SEC	903	2483	0.537	0.001	0.257	1.014

Figure 2 shows estimated mean annual TE and SEC for farms in the sample from 1995/1996 to 2005/2006. Average TE of the farms declined over the 11 years while mean SEC remained relatively constant. Estimated mean annual TE and SEC for each region were also plotted through time, shown in Figure A2. This was to determine whether there were differences between regions in the trends of TE and SEC. There were no major variations in trends between regions with the exception of the Northern >350mm, which had a strong upward trend in TE over a three year period (1999/2000 to 2001/2002). Apart from this exception, all regions followed a similar trend to that of the average TE and SEC for the entire wheatbelt.

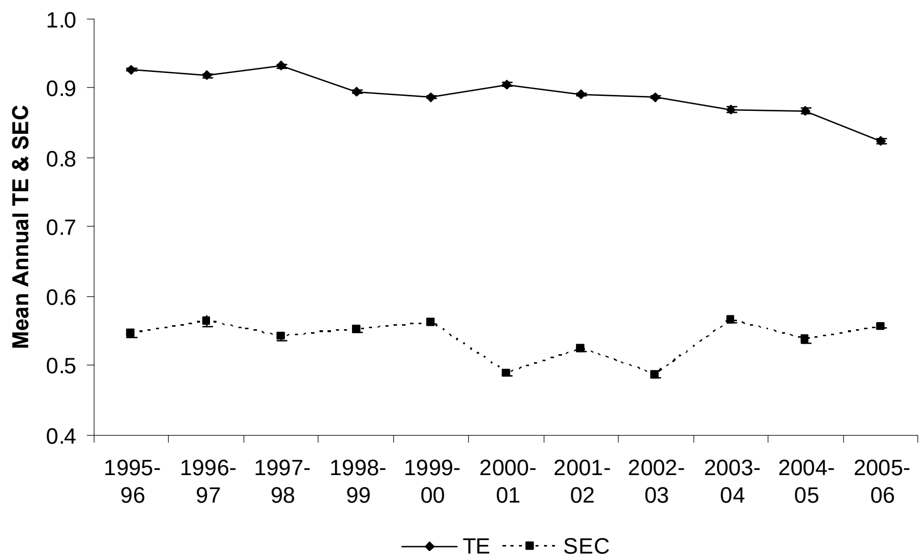

Figure 2: Mean annual TE and SEC for the sample of farms with standard errors

The distribution of estimated TE and SEC of individual farms for the 11 year period is illustrated in Figure 3. The TE of farms had a skewed distribution with the majority of farms operating at close to the technically efficient point. There was a relatively wide distribution in TE however, with few farms operating at low levels of TE. The SEC of individual farms were distributed symmetrically around the mean.

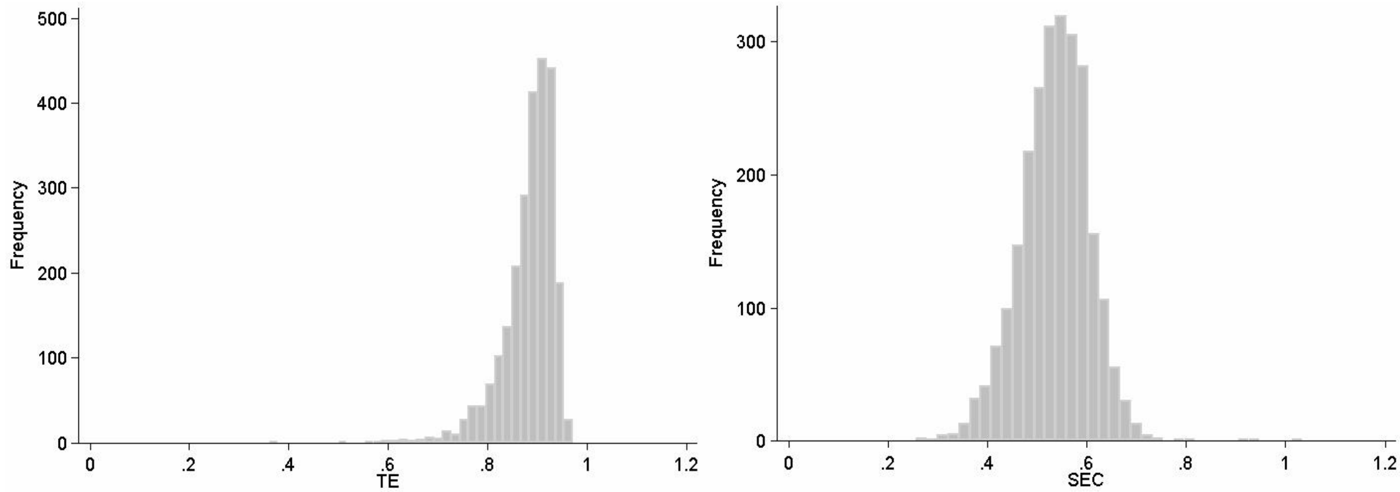

Figure 3: Distributions of estimated TE and SEC for the sample of farms

When TE and SEC of individual farms were regressed against each other, the relationship was significant (p = 0.001) with TE being positively related to SEC. The elasticity of TE with respect to SEC was derived from the regression and found to be 0.029. If farms exploited SEC by 1% the TE of the farm would increase by 0.029 on average. So farms closer to the optimal scale efficient size (point X in Figure 1, Section 2) were likely to be more technically efficient than other farms in the sample.

The parameter estimates of the SPF and the inefficiency effects model are given in Table A2. The noise term v_{it} was significant implying divergence from the frontier was not only due to the inefficiency effect. The first order elasticity measures are presented in Table A3. Average output elasticities were positive and average input elasticities were negative indicating the technological form of the estimated SPF was appropriate for the dataset.

4.2 Inefficiency effects model parameters

Table 5 shows parameter estimates for the inefficiency effects model with their t-test probabilities of being significantly different from zero. The results indicate time had a significantly positive effect on the inefficiency of individual farms implying TE was declining through time. The same result was illustrated in Figure 2 and indicates that over the study period the average farm was falling further behind the frontier. This is implied because the frontier was not significantly affected by time. It appears farms with high levels of TE, near the frontier, are remaining relatively technically efficient. However, farms at lower levels of TE are moving further away from the frontier becoming less technically efficient. This is supported by the distribution of TE becoming less skewed through time with more inefficient farms in the later years; however the mode remained relatively constant at around 0.91. Note however that this interpretation may be somewhat flawed due to the unbalanced nature of the data set.

Table 5 also shows the Herfindahl index had a negative effect on the inefficiency of individual farms and was significantly different from zero ($p < 0.05$). This indicates more specialised farms were generally more efficient. Parameters estimated for the region dummies were interpreted in relation to the omitted region, Great Southern. The region dummy parameters indicate that the Northern >350mm, Northern <350mm, Central Midlands and South Coast regions were significantly different ($p < 0.05$) in efficiency compared to the Great Southern, and all had a positive impact on inefficiency. The North Eastern and South Eastern regions were not significantly different from the Great Southern ($p < 0.05$). The South Eastern region was excluded from the model as it had a probability value around 0.8 and adversely affected the model.

Table 5: Parameter estimates for the inefficiency effects model

Variable	**Coefficient**	**Std. Err.**	**Prob.**
YEAR	0.169	0.0006	0.000
HI	-0.467	0.0047	0.047
NWG350	0.550	0.0042	0.009
NWL350	0.394	0.0037	0.031
CENMID	0.536	0.0045	0.016
NEAST	0.220	0.0034	0.196
SCOAST	0.331	0.0033	0.044

4.3 Region effects on TE and SEC

Figure 4 illustrates the impact of farm location on TE and SEC, showing mean TE and SEC of the regions. For TE, Figure 4 shows the regions can be split into two groups. Farms of the North Eastern, South Eastern and Great Southern regions appear to be operating at a higher level of TE than the others. This is supported by results of the region dummies in the inefficiency effects model. In terms of SEC, Figure 4 suggests that average SEC varied significantly with region. The Northern >350mm has the least potential to exploit SEC by increasing the scale of production. Central Midlands has the largest potential to exploit SEC by increasing the scale of production.

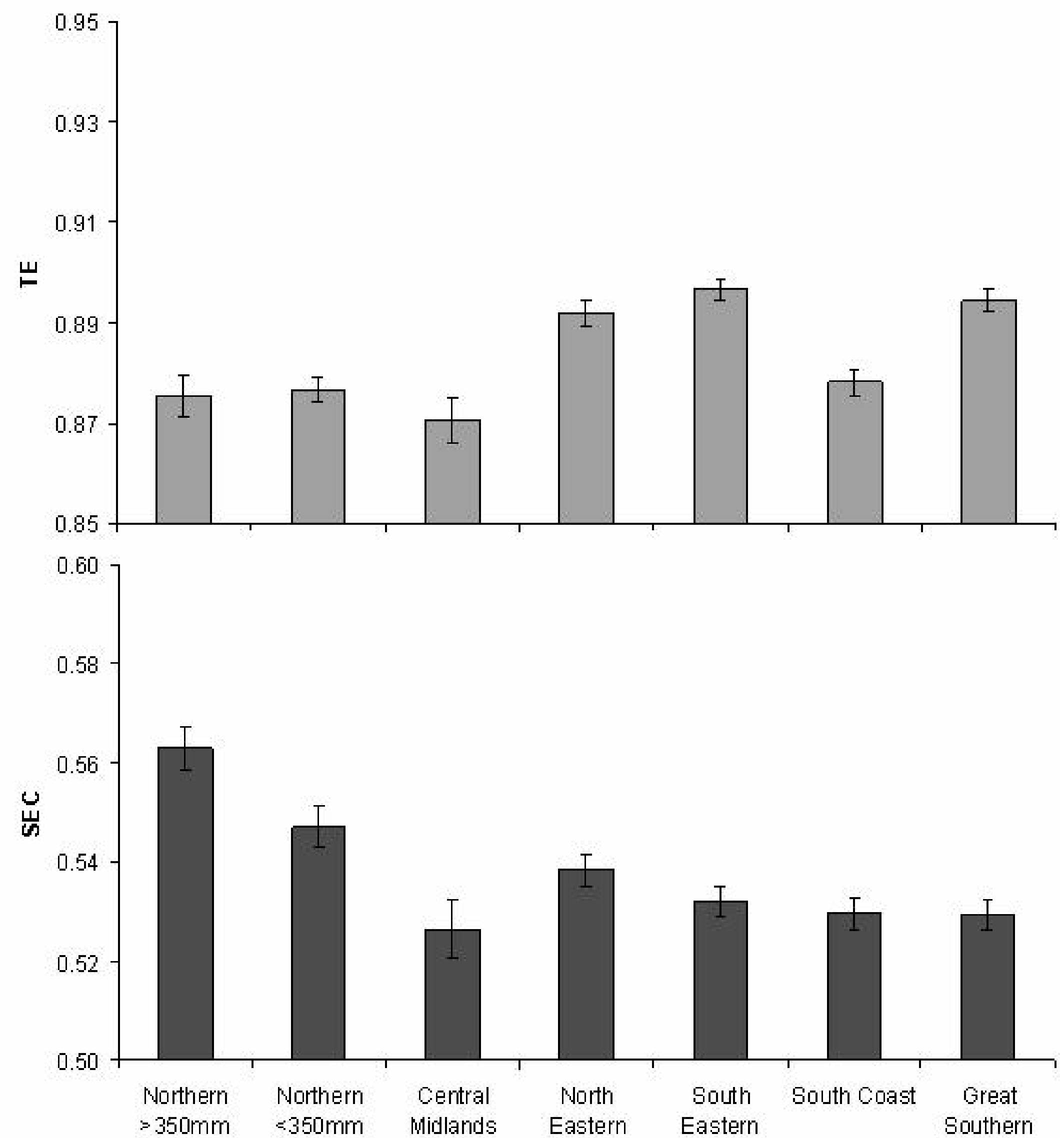

Figure 4: Regional means of TE and SEC for the period 1995/1996 to 2005/2006 with standard errors

4.4 Farm specialisation effects on TE and SEC

The effect of farm specialisation on TE and SEC of wheatbelt farms is illustrated in Figure 5 with simple regressions. Note that TE and SEC were not normally distributed ($p < 0.001$ for both using Shapiro-Francia test for normality), violating an assumption of simple regression. However to determine a trend between TE, SEC and other explanatory variables, simple regression is adequate. The Herfindahl index had a significantly positive relationship ($p < 0.001$) with TE. This suggests that more specialised farms were more technically efficient, which is supported by the findings of the inefficiency effects model. The Herfindahl Index also had a significantly positive impact ($p < 0.001$) on the SEC of individual farms suggesting that more specialised farms have less potential to exploit SEC. The R^2 values indicate that there is a large amount of variation around the line. This is expected in a dataset with such a large scope.

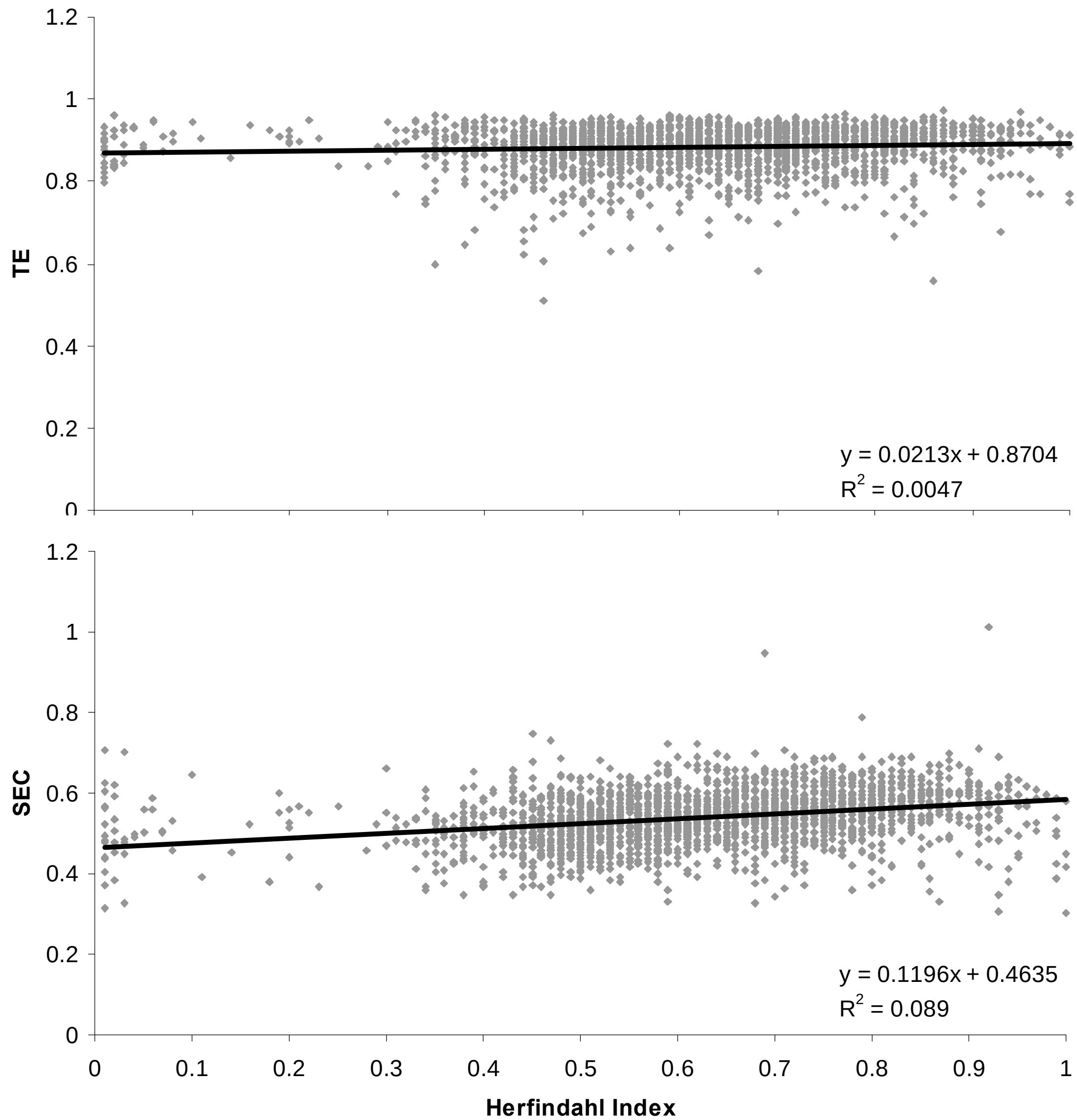

Figure 5: Relationship between farm specialisation (HI) and TE ($F_{1, 2168}$ = 11.99; p < 0.001) and SEC ($F_{1, 2168}$ = 217.92; p < 0.001) excluding outliers

4.5 Farm size effects on TE and SEC

Figure 6 shows the effects of farm size, when measured in terms of land area farmed (hectares), on TE and SEC. A log linear regression was estimated to show the relationship between SEC and land area as it was a better fit of the data than simple regression. Land area had a significantly negative relationship ($p < 0.001$) on the TE of individual farms and a significantly positive relationship ($p < 0.001$) on SEC. This suggests larger farms were less technically efficient and had less potential to exploit SEC.

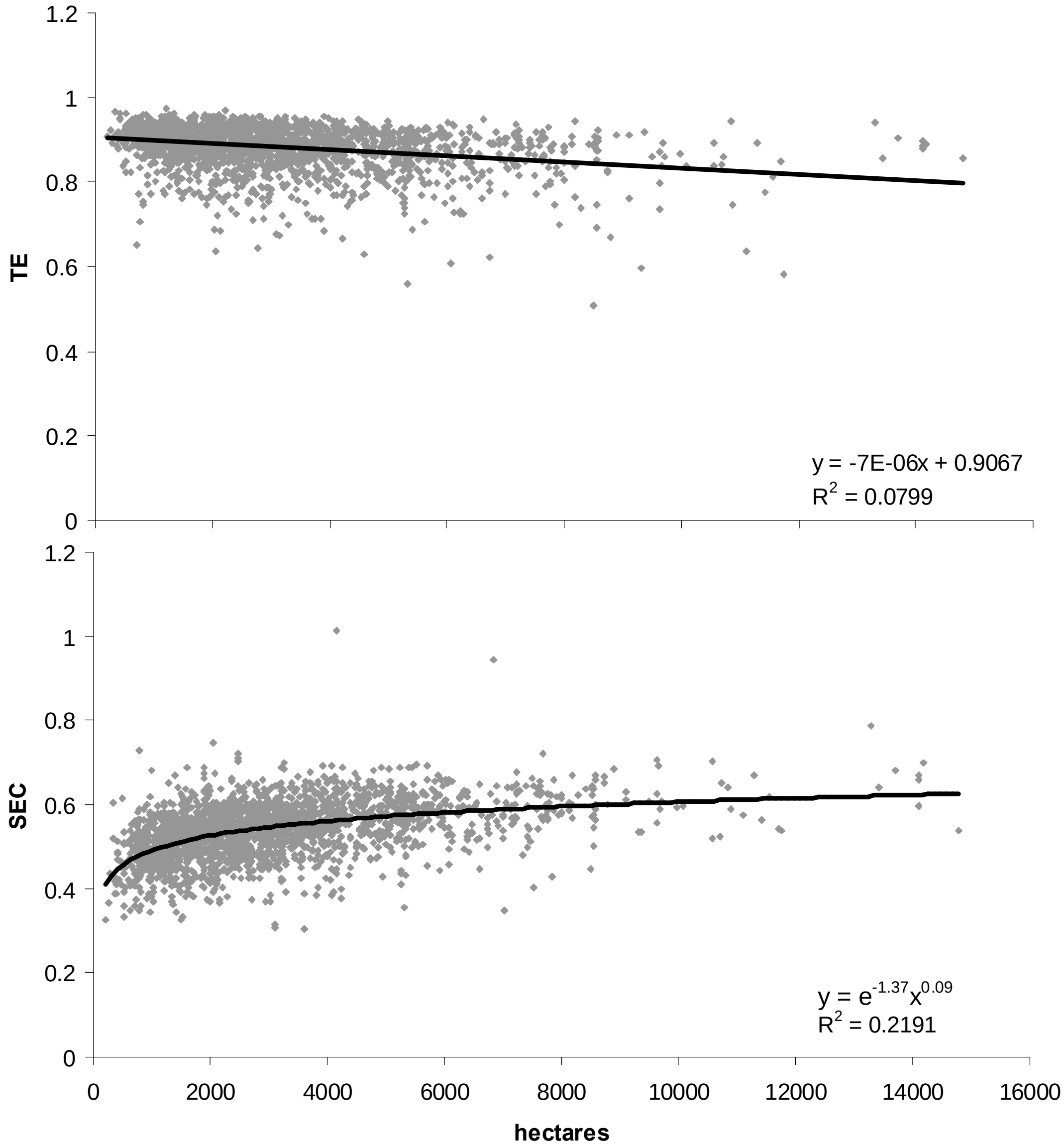

Figure 6: Relationship between farm size (hectares of farmed land) and TE ($F_{1, 2479} = 228.68$; $p < 0.001$) and SEC ($F_{1, 2479} = 605.75$; $p < 0.001$) excluding outliers

Figure 7 shows the effects of farm size, when measured by annual turnover (in farm revenue), on TE and SEC. A log linear regression was used to show the relationship between SEC and annual turnover. An R^2 value of 0.62 indicates the log linear regression was a very good estimator of the data. The relationship between annual turnover and TE was not significant ($p = 0.23$). However annual turnover had a significantly positive effect ($p < 0.001$) on the SEC of individual farms. This suggests larger farms had less potential to exploit SEC, and were not significantly disadvantaged with inefficiencies.

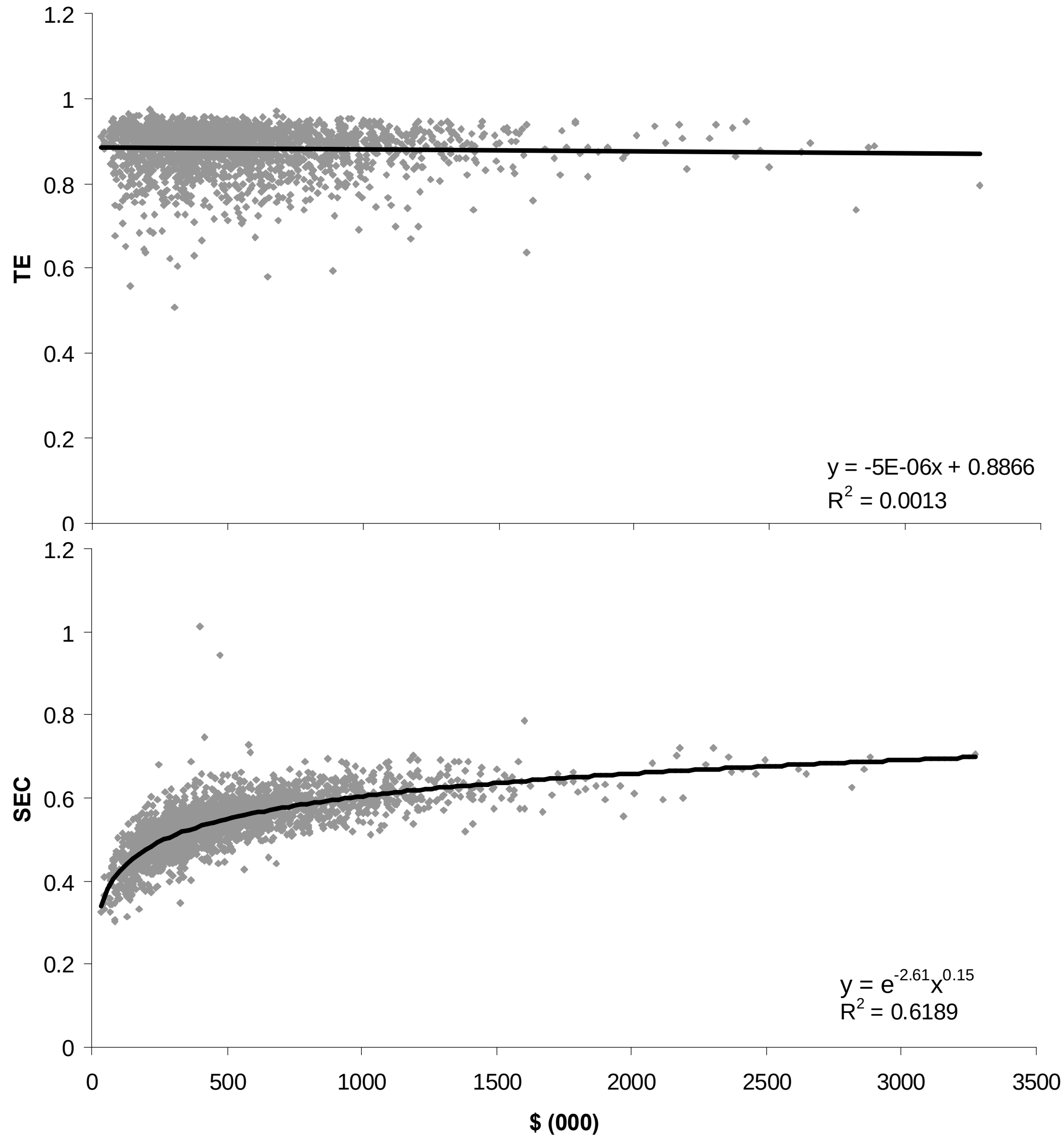

Figure 7: Relationship between farm size (total annual farm revenue) and TE ($F_{1, 2478} = 1.44$; $p < 0.23$) and SEC ($F_{1, 2478} = 3518.40$; $p < 0.001$) excluding outliers

4.6 Trends in farm size and land prices

Figure 8 illustrates the trends in average farm size for the sample of farms in terms of land area and annual turnover. Average farm size by land area increased relatively consistently over the 11 year period. However no similar steady trend is observed for annual turnover. Figure 8 shows that average annual turnover decreased in years 1998/1999 to 2000/2001 and remained relatively low through the period 2000/2001 to 2002/2003. This is likely to be due to a number of external factors. For example, there was widespread drought affected crop production in the wheatbelt in 2000/2001 to 2002/2003 (BOM 2006). Also low prices were experienced by broadacre farms in 1998/1999 and 1999/2000 in predominant cereals such as wheat, barley and lupins, and sheep and wool (ABARE, 2005). Geometric means (Lucht 1995) for the 11 years were calculated with land area increasing by 3.2 per cent per year on average and annual turnover growing by 5 per cent per year on average.

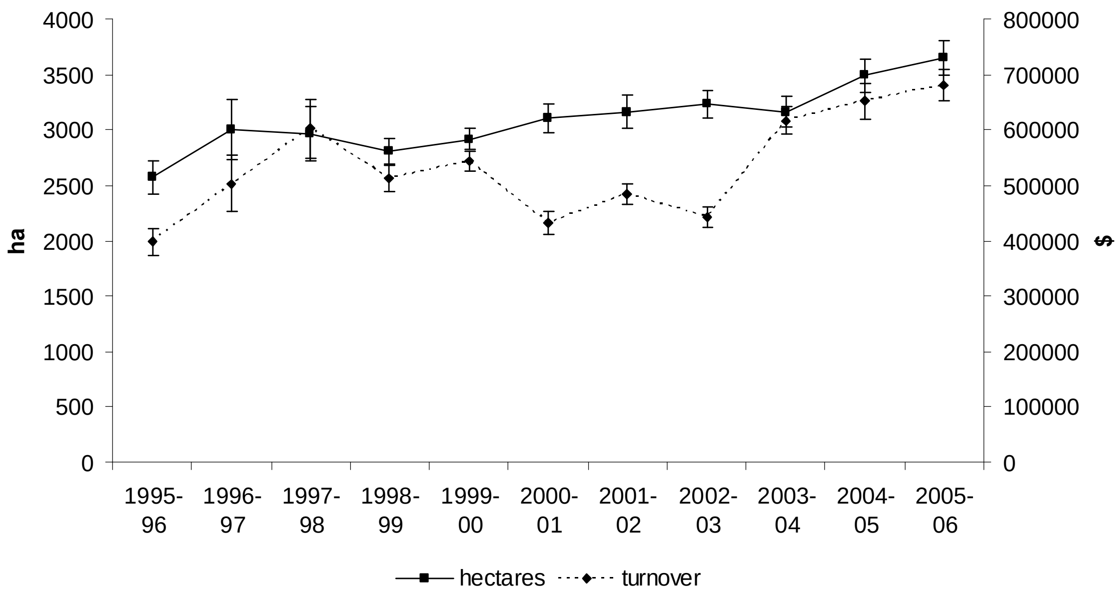

Figure 8: Mean farm size in terms of land area farmed (hectares) and annual turnover (dollars) from 1995/1996 to 2005/2006; including standard errors

Average growth in farm size in terms of effective land area was also evaluated for each region and results are listed in Table A4. The Northern >350mm region had the lowest average growth per year in terms of land area at 2 per cent. The Great Southern, Northern <350mm and North Eastern regions had the greatest average increase in land area per year at 5.9, 5.3 and 4.8 per cent respectively.

Average land prices in dollars per hectare were also considered for each region (see Table A4). Information on land prices was gathered from the 2005 Rural Value Watch provided by the Department of Land Information. Land prices increased by 9.3 per cent per year on average for the entire wheatbelt.

4.7 Farmer/farm family characteristics

Table 6 shows the results of the estimated inefficiency effects model of data collected on farmer/farm family characteristics. The variables did not significantly affect the efficiency level of farms ($p > 0.05$). However from the estimated coefficients it can be implied that attending an agricultural college and having a child with a strong interest to return to the farm reduced inefficiency. Also farms with a large number of farm operators tended to be less efficient.

Table 6: Parameter estimates of farmer/farm family characteristics in the inefficiency effects model

Variable	Coefficient	Std. Err.	Prob.
AgSchool	-0.401	0.273	0.141
IntChild	-0.170	0.259	0.512
NoFarmers	0.076	0.121	0.529

The results of a simple regression with SEC as the dependent variable and farmer/farm family characteristics as independent variables are presented in Table 7. The AgSchool and IntChild variables had a significantly positive impact ($p < 0.05$) on SEC. The estimated coefficient for the NoFarmers variable was not significant ($p > 0.05$) although implies a slightly positive relationship existed between the number of farmers and SEC.

Table 7: Parameters of a simple regression between SEC and farmer/farm family characteristics

Variable	Coefficient	Std. Err.	Prob.
AgSchool	0.020	0.008	0.009
IntChild	0.017	0.007	0.019
NoFarmers	0.005	0.004	0.171

Table 8 presents the estimated coefficients of farmer/farm family characteristics in a simple regression with farm size in terms of land area as the dependent variable. The AgSchool and IntChild variables did not have a significant relationship ($p > 0.05$) with farm size. The number of farmers was positively related with farm size and was significant ($p < 0.05$).

Table 8: Parameters of a simple regression between land area and farmer/farm family characteristics

Variable	Coefficient	Std. Err.	Prob.
AgSchool	-130.982	254.637	0.607
IntChild	52.192	245.692	0.832
NoFarmers	858.903	122.602	0.000

Summary statistics of the dataset used for farmer/farm family analysis is reported in Table A5. Estimated parameters of the SPF and inefficiency effects model are given in Table A6.

5. Discussion

The results of this study suggest Western Australian wheatbelt farms have expanded to exploit SEC, however average TE has declined. Morrison *et al*. (2004) used an input-distance function to derive a translog functional form similar to the SPF used in this paper. Their paper found cereal and livestock farms were growing to benefit from both SEC and TE in the Heartland region of the United States. Larger farms had lower average costs and were more technically efficient. In this study, it appears the trend in average TE is due to inefficient farms moving further behind the frontier, while the majority of farms continued to operate at high levels of TE. This result suggests the decline in TE may not be directly associated with increases in farm size but rather other factors such as poor management or location.

The results show that on average, all farms in the wheatbelt of Western Australia have been operating at a high level of TE for the past 11 years. 93 per cent of all observations in the data sample had TE of 0.8 or above. Many recent studies have reported high levels of TE in cereal and livestock farms of the developed world (Hadley 2006; Henderson 2001; Morrison *et al*. 2004; Wilson *et al*. 2001). Henderson (2001) found that Western Australian farms were operating at an average TE level of 76 per cent using stochastic frontier analysis. However the close proximity of the majority of farms to the production frontier is a result contrasting to the findings of Titmanis (2005). He used a translog functional form and found that Western Australian wheatbelt farms had an average TE of 51.7 per cent. However, he used an output-orientated translog functional form and his model did not include cropping or livestock expenses as inputs. His model also assumed TE for a farm was constant through time and the inefficiency term was modelled as a truncated-normal random variable multiplied by a specific function of time. These modelling differences help explain the contrasting results.

The mean level of SEC suggests the majority of farms have significant potential to exploit economies of scale by expanding production. The distribution of SEC supports this with only one farm in the entire data set experiencing decreasing returns to scale. Henderson (2001) also found the majority of Western Australian broadacre farms were operating at increasing returns to scale using data envelopment analysis. The results of this study indicate the average SEC of wheatbelt farms has not varied substantially through time. So the incentive for farms to grow in production to decrease their average costs has been relatively consistent through time. This result suggests that gains from SEC may be underpinning the trend towards increases in farm size. Importantly however, the BankWest dataset may suffer some selection bias as farm businesses enter the sample because they anticipate gains from SEC and turn to the bank to finance their farm expansion. This bias may explain why SEC did not increase through time with average farm size.

Technical change did not appear to be significant in the wheatbelt over the 11 year period. When time was included as a variable in the SPF model it was not significant, suggesting that there were no substantial movements in the frontier through time due to technical change. Seasonal variations were accounted for to some degree by the inclusion of an annual rainfall variable in the efficient frontier model. However, there may be other environmental factors such as disease and frost that have off-set technical improvements in the short time period analysed.

Farm location appears to have a significant impact on TE levels of farms through the wheatbelt. The North Eastern, South Eastern and Great Southern regions had a significantly greater level of average TE than the other four regions of the wheatbelt. Given TE is a measure indicating a farmõs ability to transform inputs into outputs at a constant level of technology (Rougoor *et al*. 1998), this result draws some interesting hypotheses for further research. For example, the Great Southern region is likely to have the highest occurrence of farms with income predominantly received from livestock rather than cereals. Perhaps farms with a greater tendency towards livestock production are on average more technically efficient than farms more specialised in cereal production. Latruffe *et al*. (2004, 2005) found that livestock farms were more technically efficient than cropping farms in Poland. This result was also found by Hadley (2006) for farms in England and Wales. However, it should be noted that the high TE of farms in the Great Southern region could be an artefact of the modelõs dependence on national output prices compiled by ABARE. Buggraaf (2006) found that for almost all livestock classes Western Australian prices were consistently lower than prices in the eastern states and this is less true for grains. Hence, livestock output prices would have been more inflated than crop prices. This is likely to cause livestock predominant farms to be assessed as more efficient.

Another interesting result was that the North Eastern and South Eastern regions were found to have relatively high levels of TE. These regions would be considered more marginal than other regions of the wheatbelt as seasonal variations are greater. For example rainfall is less consistent and they have a greater risk of frost. Due to this, it is likely farms in this region require higher TE to remain profitable. Farms in regions with more consistent rainfall may have higher input levels to try and achieve crop yield potentials, lowering TE. Titmanis (2005) found greater levels of TE resulted in farms being more profitable. There is scope for further analysis into relationships between profit, profit variability and TE and variability in TE in various agricultural regions.

Farm location also appears to have a significant impact on economies of scale in wheatbelt farms. The Northern >350mm rainfall region had the least potential to exploit SEC while the Central Midlands region had the most. Some insights about the relative contributions of individual inputs embodied in the SPF SEC elasticities may be gained from the first order elasticity measures in Table A3 (Morrison *et al*. 2004). The marginal cost, in terms of overall input increases as output expands, is lower for the Central Midlands region. Relative input savings with the expansion of output appears to be driving the greater potential for Central Midland farms to exploit SEC. In terms of contributions of inputs to output, labour was the most inelastic and rainfall was the most elastic in wheatbelt farms. The latter finding is expected in dryland farming systems, particularly when growing season average rainfall in many parts of the wheatbelt is less than 300 millimetres.

Visser (1999) and Lund and Hill (1978) suggest that farms of different regions will have a different optimal scale efficient point. In a study of U.S. farms, Visser (1999) concluded that farm area should increase as the distance to market increases and/or soil fertility decreases. This allows the farm to take advantage of SEC spreading their transportation costs and input costs over a larger area and larger scale of production. Analysis in this study considers a single optimal scale efficient point for the entire wheatbelt, and so differences in SEC between regions is expected according to Visser (1999) and Lund and Hill (1978).

The scale elasticity of TE with respect to SEC suggests that TE increases when farms exploit economies of scale. This elasticity is supported by the region results as the Great Southern and North Eastern regions had high average growth in farm size over the 11 years. These regions also had high levels of TE. The results suggest that by increasing farm size and exploiting economies of scale, farms in these regions have improved their efficiency.

Trends in average farm size (in land area) and land prices give further insight into average SEC of the regions. The average farm of the Northern >350mm region has had the least potential to exploit SEC over the 11 year period. This was reflected by the Northern >350mm region having had the lowest expansion of land area. The Central Midlands region had the most potential to exploit SEC and so it would be expected to have the strongest growth in farm size. However land availability maybe restricting farm growth in this region which is suggested by the strong increase in land values (see Table A4). Returns to farming and land price expectations are the predominant factors affecting land prices (Just and Miranowski 1993) where expectations often reflect future land scarcity. Land availability and land prices may restrict a farm from exploiting SEC.

Analysis of farmer/farm family characteristics on Western Australian wheatbelt farms suggests farmers with some high school education in agriculture have tended to expand production and exploit economies of scale. Latruffe *et al*. (2005) found farmer education was an important indicator in determining scale efficiency of farms in Poland as farmers became aware of increasing or decreasing returns to scale. This study also found farms with a high likelihood of family succession tended to be more likely to expand their operation and benefit from SEC.

The results of the inefficiency effects model and regression analysis indicate that farm specialisation had a significantly positive effect on the level of TE in wheatbelt farms. This is consistent with the findings of Bagi (1982) who found farms that focused on crop production were more technically efficient than mixed enterprise farms in West Tennessee. However, Fraser and Hone (2001) reported that mixed enterprise farms were more efficient than specialist wool producers in Victoria, possibly gaining from scope efficiency or diversity advantages. Hadley (2006) also found more specialised farms to be less efficient than farms that were less specialised, perhaps due to increased flexibility of farms to adapt to changing market and seasonal conditions. The analysis in this study does not consider gains from scope specifically. However the results suggest that advantages associated with farm specialisation outweigh possible benefits of diversification. This could be due to much of the wheatbelt being unsuitable for production other than cereal and livestock. Therefore it becomes difficult to achieve significant advantages through output scope.

When farm size was measured by land area, there was a significantly negative relationship between farm size and TE. This suggests that there are significant inefficiencies associated with larger farms. This is in contrast to many studies that found larger farms to be more technically efficient than smaller farms (Aly *et al*. 1987; Dawson 1985; Helfand and Levine 2004; Latruffe *et al*. 2004; Morrison *et al*. 2004; Rezitis *et al*. 2002). Analysis on farmer/farm family characteristics suggests large numbers of farmers, associated with larger farms, has a negative impact on TE (although not significant). This may be due to labour or managerial inefficiencies. Farms may also find it difficult to find skilful workers due to the seasonality of labour demand, making it unattractive for skilled workmen. Another inefficiency associated with larger farms is that the land may not be managed as effectively. However improvements in technology such as yield mapping and variable fertiliser rates will help to rectify these inefficiencies in the future.

The same significant relationship was not seen between farm size and TE when farm size was measured by turnover. It is likely this is due to the decrease in annual turnover experienced by wheatbelt farms in years 1998/1999 to 2002/2003. This would have adversely affected the relationship between annual turnover and TE.

The log linear relationship between SEC and farm size suggests that farms of the wheatbelt are reaching a size threshold. It is expected the threshold would occur when farms are close to reaching the optimally scale efficient size (where SEC = 1), however this is not the case. The results of this study may imply that large farms are not exploiting further SEC as increased costs associated with inefficiencies may be out-weighing the cost savings gained through economies of scale.

6. Conclusions

The aim of this study was to examine the performance of Western Australian wheatbelt farms to determine if their potential to exploit SEC and improve TE has driven the trend towards increased farm size. From the analysis it appears wheatbelt farms over the last 11 years have grown to benefit from SEC. However, farm growth has been accompanied by a decline in average TE. Some of this decline can be attributed to inefficient farms falling further behind the frontier whilst the majority of farms continued to operate at high TE. Henderson (2001) supports this paperǿs finding that the majority of Western Australian cereal and livestock farms operate at high levels of TE and increasing returns to scale.

Results indicate that a variety of farm characteristics were significantly related to the TE and SEC of wheatbelt farms in Western Australia. In terms of farm location, the North Eastern, South Eastern and Great Southern regions had significantly greater TE than the rest of the wheatbelt. It is likely the SEC of regions is impacted to some degree by land prices and availability. The Northern >350mm region had the least potential to exploit SEC while the Central Midlands region had the most. Farm specialisation was associated with higher TE and a lower potential to exploit SEC. There were no farmer/farm family characteristics significantly affecting TE however this may be a consequence of the small data size. SEC were positively impacted by a farmer attending an agricultural college and having a child with a strong interest to return to the farm.

There is scope for further investigation into the relationship between farm profitability and TE and SEC. An integration of the findings in Titmanis (2005), on farm profitability and their key determinants in Western Australian farms, and this paper would be worthwhile. Research into impacts of greater farm size on Western Australian farm businesses would be useful to determine inefficiencies. Also a more comprehensive analysis of farmer/farm family characteristics including managerial ability would be useful in determining inefficiencies. Analysis into factors affecting land prices of Western Australian farms and how this affects farm expansion would be beneficial to gaining a better understanding of farm growth.

Western Australian wheatbelt farms have been successful in lowering average cost by growing in size and exploiting significant SEC and there is scope for further growth in farming operations. However this dataset implies that farm growth can result in increased farm inefficiencies in terms of optimal inputs to achieve an output level. The future of farm growth in Western Australian cereal and livestock farms will depend on a balance between exploiting significant SEC and remaining highly technically efficient. Additionally, this will be affected by farm specific characteristics such as location, specialisation, farmer managerial ability and family structure.

7. Appendix

Table A1: Income from farm specific variables measured in the BankWest survey aggregated into income from crop, livestock and other sources.

Income Group	Survey Data Aggregated
Income Crop	Wheat
	Barley
	Lupins
	Chickpeas
	Canola
	Other Crop
Income Livestock	Sheep
	Wool
	Cattle
	Pigs
	Other Livestock
Income Other	Other
	Rebates

Figure A1: The Western Australian wheatbelt divided into regions specified by BankWest. Following are the REGIONS with their associated districts; NORTHERN WHEATBELT >350mm, Geraldton, Carnamah/Mingenew; NORTHERN WHEATBELT <350mm, Dalwallinu, Morawa; CENTRAL MIDLANDS, Northam, Moora; NORTH EASTERN WHEATBELT, Koorda/Nungarin, Merredin, Narembeen; GREAT SOUTHERN, Narrogin, Katanning/Kojonup, Wagin; SOUTH EASTERN WHEATBELT, Lake Grace, Corrigin/Bruce Rock, Kondinin/Hyden; SOUTH COAST, Esperance, Albany, Jerramungup/Ongerup

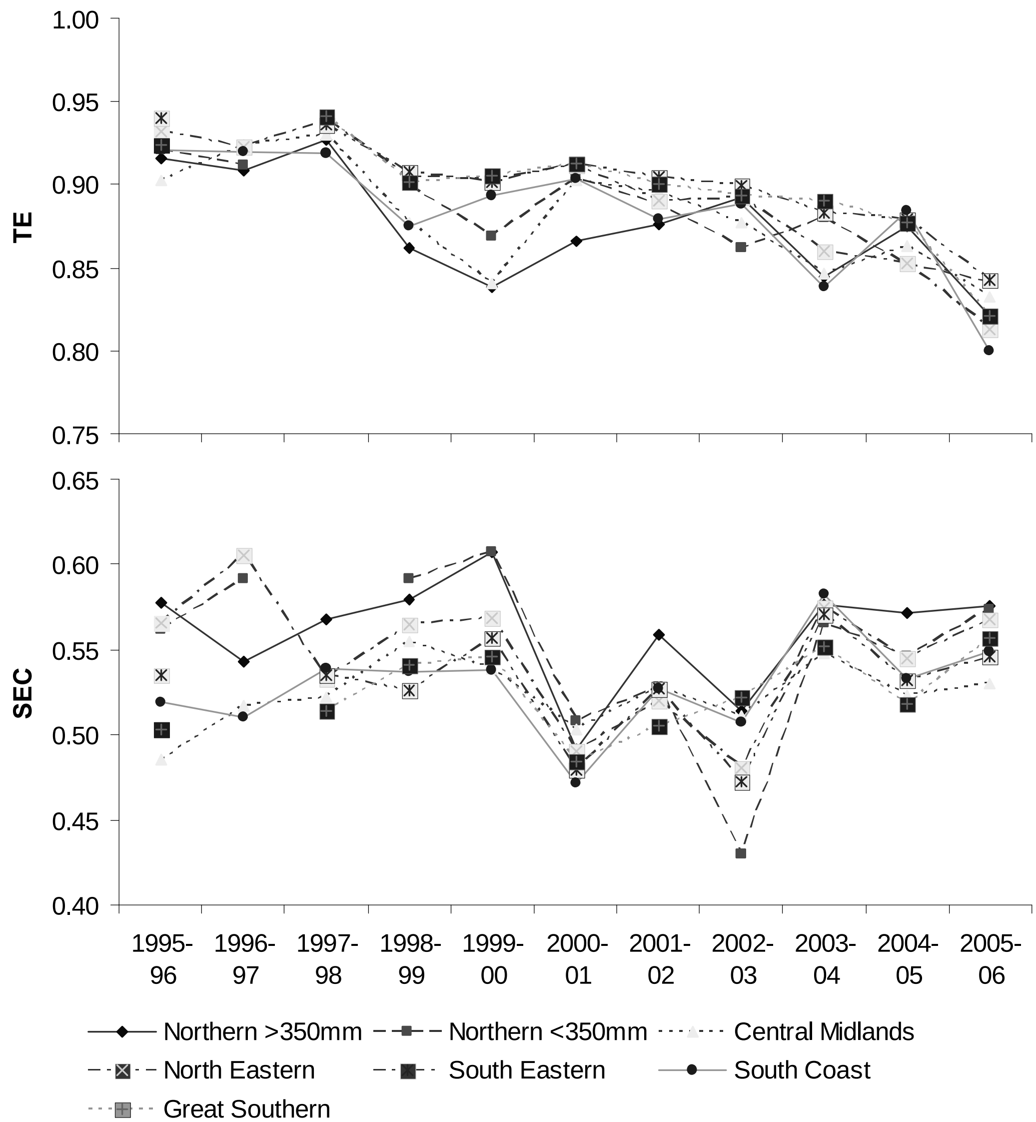

Figure A2: Mean annual TE and SEC of regions through time

Table A2: Parameter estimates for the stochastic production frontier and inefficiency effects model (log likelihood = 716.133; p < 0.001)

Model	Variable	Coefficient	Std. Err.	Prob.
-ln*LAND*				
	ln*Y*	0.513	0.0047	0.028
	ln*L*	-0.052	0.0016	0.510
	ln*K*	-0.681	0.0036	0.000
	ln*RAIN*	1.099	0.0030	0.000
	ln*CROP*	0.341	0.0052	0.186
	ln*LIVE*	0.096	0.0017	0.260
	$\ln Y^2$	-0.061	0.0002	0.000
	$\ln L^2$	0.004	0.0000	0.011
	$\ln K^2$	0.016	0.0001	0.000
	$\ln RAIN^2$	0.003	0.0002	0.752
	$\ln CROP^2$	0.046	0.0004	0.022
	$\ln LIVE^2$	0.009	0.0000	0.000
	ln*Y*ln*L*	0.009	0.0001	0.196
	ln*Y*ln*K*	0.068	0.0004	0.000
	ln*Y*ln*RAIN*	-0.064	0.0003	0.000
	ln*Y*ln*CROP*	-0.006	0.0005	0.813
	ln*Y*ln*LIVE*	-0.009	0.0002	0.304
	ln*L*ln*K*	0.001	0.0001	0.901
	ln*L*ln*RAIN*	0.004	0.0001	0.536
	ln*L*ln*CROP*	-0.018	0.0002	0.042
	ln*L*ln*LIVE*	0.005	0.0001	0.079
	ln*K*ln*RAIN*	0.000	0.0003	0.979
	ln*K*ln*CROP*	-0.058	0.0004	0.006
	ln*K*ln*LIVE*	-0.012	0.0001	0.076
	ln*RAIN*ln*CROP*	0.021	0.0004	0.294
	ln*RAIN*ln*LIVE*	-0.008	0.0001	0.235
	ln*CROP*ln*LIVE*	0.013	0.0002	0.230
	_cons	-5.540	0.0294	0.000
lnsig2*v*				
	_cons	-3.746	0.0015	0.000
lnsig2*u*				
	YEAR	0.169	0.0006	0.000
	HI	-0.467	0.0047	0.047
	NWG350	0.550	0.0042	0.009
	NWL350	0.394	0.0037	0.031
	CENMID	0.536	0.0045	0.016
	NEAST	0.220	0.0034	0.196
	SCOAST	0.331	0.0033	0.044
	_cons	-4.838	0.0078	0.000

Table A3: First order elasticities of the frontier model with standard errors and sample size by region

	Wheatbelt		**Northern >350mm**		**Northern <350mm**		**Central Midlands**	
	ε	**Std. Err.**	ε	**Std. Err.**	ε	**Std. Err.**	ε	**Std. Err.**
$-\varepsilon_{DIY}$	0.537	0.0014	0.563	0.0045	0.547	0.0040	0.526	0.0057
$-\varepsilon_{DIL}$	-0.004	0.0003	-0.002	0.0008	-0.001	0.0006	-0.010	0.0104
$-\varepsilon_{DIK}$	-0.120	0.0009	-0.128	0.0031	-0.129	0.0023	-0.113	0.0033
$-\varepsilon_{DIRAIN}$	-0.336	0.0009	-0.330	0.0030	-0.325	0.0021	-0.351	0.0031
$-\varepsilon_{DICROP}$	-0.262	0.0009	-0.273	0.0029	-0.263	0.0022	-0.256	0.0044
$-\varepsilon_{DILIVE}$	-0.026	0.0004	-0.020	0.0012	-0.023	0.0009	-0.029	0.0017
No. of observations	2483		206		387		166	
	North Eastern		**South Eastern**		**South Coast**		**Great Southern**	
	ε	**Std. Err.**	ε	**Std. Err.**	ε	**Std. Err.**	ε	**Std. Err.**
$-\varepsilon_{DIY}$	0.538	0.0033	0.532	0.0031	0.530	0.0032	0.530	0.0030
$-\varepsilon_{DIL}$	-0.002	0.0005	-0.001	0.0006	-0.005	0.0007	-0.009	0.0006
$-\varepsilon_{DIK}$	-0.125	0.0018	-0.122	0.0021	-0.109	0.0023	-0.112	0.0020
$-\varepsilon_{DIRAIN}$	-0.328	0.0018	-0.333	0.0021	-0.345	0.0022	-0.345	0.0020
$-\varepsilon_{DICROP}$	-0.258	0.0019	-0.262	0.0018	-0.266	0.0025	-0.262	0.0021
$-\varepsilon_{DILIVE}$	-0.024	0.0009	-0.024	0.0010	-0.030	0.0009	-0.032	0.0008
No. of observations	518		367		428		411	

Table A4: Mean land area and land prices for the period 1995/1996 to 2005/2006 with their average growth in each year (geometric mean) for regions of the wheatbelt

	Land Area (ha)		**Land Prices ($)**	
	Mean	**% average growth per year**	**Mean**	**% average growth per year**
Wheatbelt	3120	3.2	808	9.3
Northern >350mm	3258	2.0	771	11.6
Northern <350mm	4108	5.3	398	10.9
Central Midlands	2054	3.9	953	10.1
North Eastern	4022	4.8	366	10.9
South Eastern	3159	2.5	579	9.1
South Coast	2497	2.9	961	9.1
Great Southern	2025	5.9	1150	8.2

Note: Northern <350mm, South East and Great Southern regions did not have any farms recorded for one year, so the % average growth of farms per year in terms of land area in these regions is over 9 years.

Table A5: Summary statistics of TE and SEC for farms surveyed on farmer/farm family characteristics

	No. of farms	**No. of Observations**	**Mean**	**Std.Err.**	**Min**	**Max**
TE	80	291	0.872	0.004	0.623	0.971
SEC	80	291	0.502	0.003	0.349	0.998

Table A6: Parameter estimates for the stochastic production frontier and the inefficiency effects model of farms in the farmer/farm family characteristic survey (log likelihood = 148.187; p < 0.001)

Model	**Variable**	**Coefficient**	**Std. Err.**	**Prob.**
-ln*LAND*				
	ln*Y*	-0.052	0.648	0.936
	ln*L*	0.151	0.236	0.521
	ln*K*	-0.332	0.378	0.379
	ln*RAIN*	0.481	0.401	0.230
	ln*CROP*	0.066	0.643	0.919
	ln*LIVE*	0.223	0.336	0.507
	$\ln Y^2$	-0.027	0.031	0.376
	$\ln L^2$	0.010	0.005	0.071
	$\ln K^2$	0.012	0.007	0.076
	$\ln RAIN^2$	0.013	0.024	0.571
	$\ln CROP^2$	0.069	0.060	0.253
	$\ln LIVE^2$	0.011	0.008	0.156
	ln*Y*ln*L*	-0.003	0.022	0.886
	ln*Y*ln*K*	0.067	0.049	0.170
	ln*Y*ln*RAIN*	-0.001	0.043	0.983
	ln*Y*ln*CROP*	-0.004	0.071	0.949
	ln*Y*ln*LIVE*	-0.025	0.027	0.346
	ln*L*ln*K*	0.016	0.018	0.354
	ln*L*ln*RAIN*	0.012	0.019	0.530
	ln*L*ln*CROP*	-0.042	0.026	0.104
	ln*L*ln*LIVE*	0.004	0.012	0.719
	ln*K*ln*RAIN*	0.039	0.045	0.381
	ln*K*ln*CROP*	-0.101	0.053	0.055
	ln*K*ln*LIVE*	-0.024	0.026	0.360
	ln*RAIN*ln*CROP*	-0.033	0.060	0.579
	ln*RAIN*ln*LIVE*	-0.037	0.025	0.143
	ln*CROP*ln*LIVE*	0.032	0.042	0.438
	_cons	-3.487	0.421	0.000
lnsig2*v*				
	_cons	-4.535	0.273	0.000
lnsig2*u*				
	AgSchool	-0.401	0.273	0.141
	IntChild	-0.170	0.259	0.512
	NoFarmers	0.076	0.121	0.529
	_cons	-3.487	0.421	0.000

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