Measuring the Efficiency of Wheat Production of Western Australian Growers[1].

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Abstract

Using stochastic frontier analysis, efficiency of production of wheat in Western Australia was studied. The production function model used was a relatively simple input model, consisting of wheat yield, effective rainfall, fertilizer application rates and year of study. Inefficiency was captured in a second model that incorporated machinery capital investment, opening equity level, and year of study. Data covered the production years 2004 through to 2007. The results demonstrated that inefficiency was present in wheat production in Western Australia and that inefficiency increased over the period from 18% in 2004 to 29% in 2007. Higher machinery investment per hectare and opening equity levels reduced inefficiency, due to producers having sufficient capacity, mechanical or financial, to adapt to variability within the production season. The results demonstrated the stochastic nature of efficiency and that for some firms improving efficiency may not be possible or feasible due to limitations within the firm. This also holds for firms that are relatively efficient in some years and that the reasons for the inefficiency are not necessarily production related, hence, programs targeted to improve efficiency may not be very successful. On the other hand firms that are consistently inefficient provide an ideal target audience for programs to improve efficiency. However, these programs must be conditioned on adequately identifying the source(s) of inefficiency and the producer having access to resources to increase efficiency. Similar analyses could be undertaken in different crops or different geographic locations, to identify if and why inefficiencies are present in other production systems.
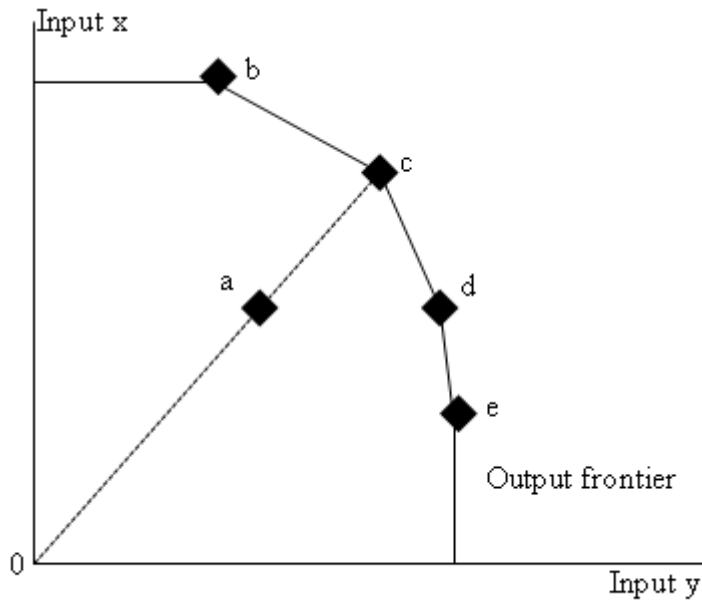

Introduction

Grain producers are continually asked to be more "efficient" in the production of crops. The term "efficient" is in some cases not well defined, but in the context of the current research it is defined as the ability to produce at the potential level of the farm business. Alternatively, "efficiency" is the ability to produce more output with the same level of inputs or producing the same level of output with fewer inputs. (Coelli et al., 2005). Efficiency in economic terms is relative to the base scenario or year being examined and implies that producers are achieving the economic optimal level of production, i.e. where profits are maximised or costs minimized. Operating at levels less than optimal imposes on the producer higher costs or losses in revenue. Figure 1 presents a simple example of efficiency and inefficiency in input/input space. Other approaches such as input/output and output/output space can also be used (Kumbhakar and Lovell, 2000). However, given the context of this research is input oriented this figure is in input/input space. The production function combines two inputs, x and y to produce an output. The most efficient producers, represented by b, c, d, and e, are on the production frontier, these producers have different levels of production and combine inputs x and y in different ways to achieve these levels of production. However, producer a, is less efficient than producers on the frontier and the level of the inefficiency is determined by the ratio of actual yield and potential yield. In this example producer a is on a ray from the origin that intersects the efficient frontier at c, hence producer a can be compared directly to producer c. For producer a the ratio of $0a/0c$ defines the efficiency of producer a relative to producer c. Alternatively, $(1 - 0a/0c)$ is the level of the inefficiency of producer a in the production system.

French and Schultz (1984a, b) studied water use efficiency (WUE) of grain production in South Australia and concluded that potential yields of 20kg of grain per mm of transpiration was possible in the Mediterranean climatic production zones of south-eastern Australia. They also discussed the limitations to achieving this potential yield. These limitations include management ability and nutrient availability to the crop. Water use efficiency has become a standard benchmark in determining the efficiency of crop production; see for example Sadras and Angus (2006) or Jalota et al., (2007). However, few studies have examined the role of multiple inputs on the efficiency of

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grain production systems and the factors that impact on the efficiency of systems under multiple input combinations.

Figure 1: A two input production function diagram showing the output frontier and showing efficient producers (b, c, d, and e) and an inefficient producer (a).

There are two main methods that can be used to measure the efficiency of a production system that utilises multiple inputs: data envelopment analysis (DEA) and stochastic frontier analysis (SFA). Data envelopment analysis is a non-parametric method that estimates the efficiency of production of a group of firms, sometimes called decision-making units (DMU). However, as DEA is a non-parametric method no information is provided by the analysis as to the reasons or sources of inefficiencies (Coelli et al., 2005). Also, DEA does not make allowance in the analytical method for measurement error or missing data or information in estimating the efficiencies of production. On the other hand, SFA is a parametric method of analysis that is estimated using maximum likelihood , which is similar to standard ordinary least squares (OLS) analysis. The use of this approach enables missing information or data and measurement errors to be captured in the error term (Coelli et al., 2005).

The objectives of this research were to examine the efficiency of wheat production of growers in Western Australia at the farm level to provide information that may be useful in identifying factors causing inefficiencies that can be used by growers and or

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extension personnel to improve the efficiency of grain production. Inefficiency was defined as the difference between the actual wheat yield achieved and the yield achieved by peer producers on the production frontier for each cropping year.

Materials and Methods

Model

Stochastic Frontier Model

As noted by Coelli et al (2005), the stochastic frontier production function was developed independently by Aigner, Lovell, and Schmidt (1977) and Meeusen and van den Broeck (1977). The model is similar to a standard linear regression model except for the addition of one extra parameter. The additional parameter is a stochastic error term that captures inefficiency in the system of interest. The model chosen to represent the production function is selected such that the function envelops all data observations, this in contrast to a typical regression analysis where the model is selected to best fit through the means of the data rather than the frontier or perimeter of the data. After reviewing the relationships between the variables in the data the analyst selects the functional form that best represents the input-output process. Functional forms that have been used previously include the Cobb-Douglas and transcendental logarithm (translog) functions (Coelli 1996). In this research we utilise the technical effects Cobb-Douglas formulation of Battese and Coelli (1995). The stochastic frontier model has the following form:

$$\ln(q_{it}) = \beta \ln(x_{it}^{'}) + v_{it} - u_{it} \tag{1}$$

where q_{it} is the output of the *i*th firm in time period *t*, $x_{it}^{'}$ is the vector of inputs used by firm *i* to produce q in period *t*, β is a vector of unknown parameters to be estimated, v_{it} is a normally distributed error term with mean 0 and variance σ_v^2, i.e. $v_{it} \sim N(0, \sigma_v^2)$, u_{it} is a non-negative random variable that measures inefficiency and has a normal distribution, truncated at 0, with mean $z_{it}\delta$ and variance σ_u^2, i.e. $u_{it} \sim N^+(z_{it}\delta, \sigma_u^2)$ (Battese and Coelli, 1995). Hence,

$$u_{it} = z_{it}\delta + w_{it} \tag{2}$$

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where z_{it} is a vector of variables that explain inefficiency of firms over time, δ is a vector of unknown coefficients that are to be estimated in the model, and $w_{it} \geq -z_{it}\delta$, to ensure that $u_{it} \geq 0$, Battese and Coelli (1995). Following from equations 1 and 2, technical inefficiency is estimated as:

$$TE_{it} = \exp(-u_{it}) = \exp(-z_{it}\delta - w_{it}) \tag{3}$$

In the results that follow inefficiency is measured as the ratio of estimated efficiency for a firm, from equation 3, to the frontier efficiency as shown in Figure 1, this yields inefficiency values as a ratio. Adding the variance terms for each of the error terms yields, $\sigma_u^2 + \sigma_v^2 = \sigma_s^2$, and $\gamma = \sigma_u^2 / \sigma_s^2$ measures how much of the total variance of the error term is due to the inefficiency term (Coelli et al. 2005). A high value for γ indicates that much of the variance in the error term is due to the inefficiency component. However, there is no critical value for γ that determines whether inefficiency is significant or not as it is a relative measure. Significance of the inefficiency estimates is captured through the parameter estimates of the inefficiency model. The model also determines whether γ is significantly different from 0.

Empirical Model

As we were interested in estimating inefficiency effects in a crop production model at a per hectare level the variables included in the model were effective rainfall (RF) measured in millimetres (mm), and nitrogen (N) and phosphorus (P) inputs in kilograms per ha. Machinery investment per hectare was initially included in the model but due to the poor statistical fit of this variable was dropped from the final model, as shown in Table 2. Effective rainfall was an adjusted rainfall measure with an allowance made for evaporation in both the summer (SRF) and during the growing season (GSR) and was measured as:

$$RF = 0.3 * SRF + (GSR - 50) \tag{4}$$

where summer was January through April, and the growing season was May through October. Equation 4 is based on French and Schultz (1984a) and adapted to account for

higher evaporation rates during the growing season in Western Australia. Effective rainfall was used rather than total water availability, as data on soil water content or soil water availability were not available. Average summer rainfall, January to April, for all producers in the four years of the study was approximately 60mm. Rainfall data was that recorded by each farm in the analysis.

Year (Yr) was included in the stochastic frontier model to capture the effects of scale neutral technological change, such as new varieties or chemicals. For the inefficiency model, as shown in previous research (Nasr, Barry, and Ellinger 1998), capital structure did affect efficiency of production, and in the context of this model capital structure was measured using the business's equity ratio. Also, measuring productive capital was a machinery variable, machinery investment per ha (PHA) measured in $/ha. This variable captured efficiencies or inefficiencies in production due to machinery constraints or capacity. The year variable in the inefficiency model described how efficiency changed over the period of study. Therefore, the stochastic frontier crop production model estimated was:

$$\ln Y_{it} = \beta_0 + \beta_1 \ln RF_{it} + \beta_2 \ln N_{it} + \beta_3 \ln P_{it} + \beta_4 Yr_{it} + v_{it} - u_{it} \qquad (5)$$

and the inefficiency effects model was:

$$u_{it} = \delta_0 + \delta_1 PHA_{it} + \delta_2 Equity_{it} + \delta_3 Yr_{it} + w_{it} \qquad (6)$$

Other variables were tested in preliminary analysis of the efficiency models, these included rainfall and models without one or more of the three included variables. The model with the three variables presented in equation 6 yielded the best fit based on likelihood ratio tests, see Table 2. The models were fitted using the maximum likelihood simultaneous solution method in the program FRONTIER 4.1 (Coelli 1996).

Data

Data from 50 farms were sourced from a farm management consultant's database and were selected from a database of 400 farms based on the availability of four continuous years of data from 2004 to 2007. Farm businesses were located throughout the

wheatbelt of Western Australia. The wheatbelt of Western Australia covers much of the south-western corner of Western Australia, with the exception of the far south-western portion that lies south of Perth. Because of the geographical range of farms included in the sample, the data covers low, medium and high rainfall production zones. The number of producers from each region were 11 from the low rainfall zone, 35 from the medium rainfall zone, and four from the high rainfall zone. The stochastic frontier model was designed to allow for this type of variability and this variability is captured by the two error terms. The data collected includes numerous, production and financial variables such as total farm area, total crop area, individual crop yields and area, fertilizer and chemical inputs, fuel usage, gross income, fixed and variable costs, equity level and return on capital and equity.

Table 1: Summary statistics for wheat yield, effective rainfall, nitrogen and phosphorus fertiliser inputs, opening equity, and machinery investment per hectare in the period 2004-2007.

Year	Yield (t/ha)	Effective Rainfall (mm)	Nitrogen applied (kg/ha of crop)	Phosphorus applied (kg/ha)	Opening Equity (%)	Machinery investment per crop ha ($A/ha)
2004						
Mean	2.00	200	46	10	83	387
s.d.	0.56	54	14	3	10	144
Min	0.99	119	23	4	54	138
Max	3.07	374	104	19	100	965
2005						
Mean	2.21	258	47	10	82	421
s.d.	0.51	59	14	3	10	169
Min	1.08	134	25	5	56	194
Max	3.73	502	84	16	100	1153
2006						
Mean	1.33	130	28	8	85	508
s.d.	0.49	37	15	3	9	192
Min	0.35	37	7	2	55	238
Max	2.26	227	69	16	100	1214
2007						
Mean	1.85	168	33	8	83	456
s.d.	0.87	68	19	3	10	261
Min	0.30	40	3	0.3	55	188
Max	3.31	387	86	16	99	1919

Continuity of data is not essential for stochastic frontier analysis (Greene, 1997), but for the purposes of this research and for ease of interpretation of results continuity of farms in the data set was considered essential. Additional observations, or farms, provide more information regarding the overall efficiency of the industry, i.e. through the estimation of the parameters (Greeene, 1997). Increasing the number of observations per farm increases the consistency of the estimated efficiency level for each farm (Kumbhakar and Lovell, 2000). Given that many businesses in the sample had one or two observations over the four years, consistency of the efficiency estimation would have been poor, hence the requirement for four years of continuous data. Also, identifying year to year changes in efficiency requires continuity of data.

Figure 2: Effective rainfall (mm) and wheat yield (t/ha) across years 2004 to 2007 for all farms.
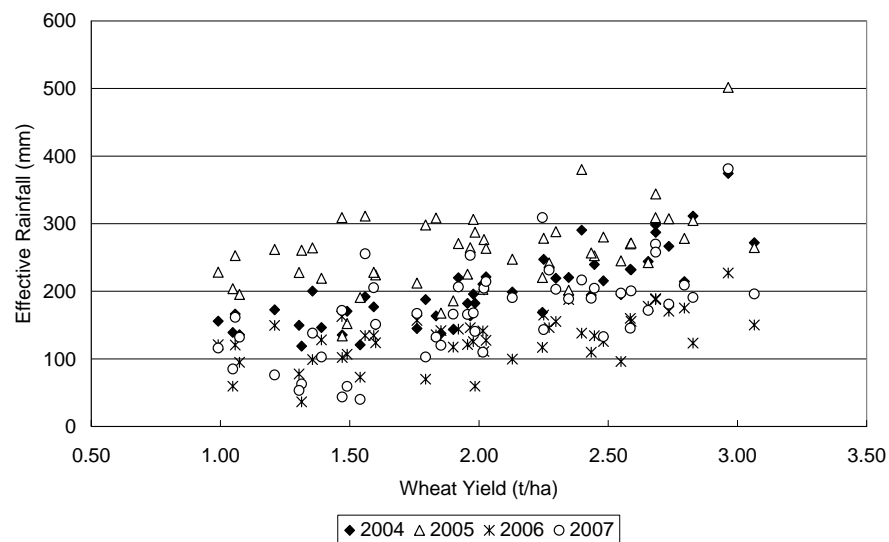
Summary information for the variables used in the model is presented in Table 1 and Figures 2 and 3. From the table it is possible to see the variability in effective rainfall within a year and across the four years represented in the model. Typically, Western Australia has a Mediterranean-type weather pattern with hot dry summers and mild wet winters. Total average rainfall in summer (January – April) totals 61mm, and average growing season rainfall is 309mm (BOM, 2009). The seasonal break is a trigger point for producers to begin sowing operations, and is assumed to occur when more than 25 mm of cumulative rainfall over three days is received after April 15.

Rainfall in 2006 was the lowest on record for Western Australia and also the seasonal break was extremely late; this is the reason for the low application rate of nitrogen in 2006. Many producers delayed sowing crops until late in the growing season and if they did sow crops, then low levels of nitrogen were applied to reduce the potential economic losses in the event that crop failure resulted from lack of rain later in the season. Hence, there was a correlation between rainfall and nitrogen application, but this level of correlation did not significantly affect the parameter estimates and the related standard errors as would be expected with multicollinearity. The first year, 2004, was a "typical" year for the representative farms. The year 2005 was an above average year, and 2007 was a below average year, in terms of rainfall and wheat yield across the wheat production zone of Western Australia. The correlation of rainfall and year was relatively low and negative at -0.42.

Figure 3: Nitrogen application rates (kg/ha of N) and wheat yields (t/ha) across years 2004-2007 for all farms.
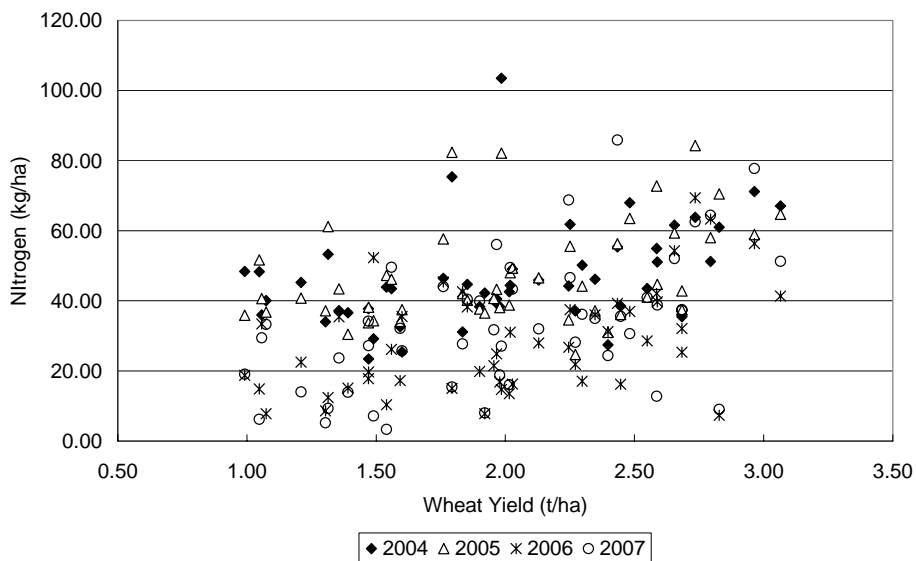
Two graphs showing yield to rainfall and nitrogen application rates for each farm and in each year are shown in Figures 2 and 3. The response to rainfall is relatively linear as would be expected. However the response to nitrogen application is not as clear with some farms in some years applying little nitrogen but achieving relatively high yields, and other producers applying higher rates and achieving lower yields.

The data also showed that equity levels did not vary markedly across the four years of study, but investment in machinery did, particularly when comparing 2005 and 2006. The above average yields and returns for 2005 produced an increase in machinery investment in 2006. From this we can see that producers in the sample invested in new machinery up until 2006, and in 2007 machinery investment per ha declined, as a consequence of poor yields and returns from the below average 2006 season, mostly due to depreciation.

Results and Discussion

Given the form of the production function, the parameter estimates generated from the production model were used as response or elasticity measures. This means that the estimated parameters indicated the responsiveness of output to a change in inputs. Table 2 presents the parameter estimates for the stochastic frontier model and the technical inefficiency model. From this table we see that the value of the intercept term, $\beta_0 = -3.34$ indicating, as expected, negative output with zero inputs. The value of the input parameters, β_1, β_2 and β_3 were all less than 1, indicating that for a 1% increase in any of these inputs, wheat yield would increase by 0.59%, 0.19%, and 0.14%, respectively. This suggests that the frontier was in the decreasing marginal returns region of the production function. Parameter β_4 measured the level of neutral technological change over the period of study. The value of $\beta_4 = 0.08$ showed that output increased, due to new varieties, chemicals or other scale neutral technological innovations, at an annual rate of approximately 2%/yr. This value is the annual productivity gain of producers and is in line with previous studies of productivity gains in broadacre agriculture in Australia (ABARE 2007). Productivity gains and efficiency increases are required by producers to combat rising input prices and falling real grain prices. The value of $\gamma = 0.99$ indicates that a very large proportion of the total variance of the error term was due to inefficiency.

The production response model can also be used to determine the average response to various inputs in the crop production process. For example, using the parameter for effective rainfall, β_1, and the rainfall of individual producers in year 1 showed that average water use efficiency (WUE) was approximately 12 kg of wheat per mm of effective rainfall; this level of WUE is consistent with that reported in French and

Schultz (1984a). A similar process was also carried out for nitrogen response analysis; this analysis demonstrated a response to nitrogen of approximately 27 kg of grain per kg of nitrogen at the frontier, which is consistent with the results shown in Brennan and Boland (2009).

Table 2: Parameter estimates for the final and preliminary stochastic frontier production functions and the technical inefficiency models, variance estimates, and likelihood function values

Parameter	Parameter value	s.e.	Parameter value	s.e.	Parameter value	s.e.
Stochastic Frontier Model						
	Final Model		Preliminary Model		Preliminary model with machinery	
β_0	-3.34***	-0.22	-3.49***	0.57	-0.15	0.25
β_1	0.59***	0.05	0.62*	0.38	0.19***	0.03
β_2	0.19***	0.03	0.20	0.73	0.02	0.02
β_3	0.14***	0.03	0.11	0.19	0.05**	0.02
β_4	0.08***	0.01	0.06	0.08	-0.01	0.03
β_5					0.01	0.01
Technical Inefficiency Model						
δ_0	0.87	0.86	0.15	0.98	1.49***	0.26
δ_1	-0.25*	0.16	-0.06	0.16	0.03	0.05
δ_2	-0.93**	0.47	-0.41	1.00	-0.04	0.09
δ_3	0.12**	0.07			-0.70***	0.02
Variance Estimates						
σ_s^2	0.18**	0.06	0.19*	0.12	0.02***	0.00
γ	0.99***	0.01	0.97***	0.14	0.80***	0.04
Log-Likelihood Function						
	17.43		8.67		180.84	

Inefficiency Model

The parameter estimates for the technical inefficiency model show that higher investment in crop machinery per hectare and higher opening equity levels lead to lower inefficiency, or conversely higher efficiency, but overall inefficiency increased by approximately 13% over the period of study, or 3.25% per year, as indicated by the positive coefficient for the year variable δ_3. As shown, lower inefficiency is due to higher investment in machinery capital and higher opening equity levels. An interpretation is that producers with higher investment in machinery have the machinery capacity to undertake operations at the optimal time in the crop growing cycle. Also, higher equity levels imply that producers have the financial reserves to wait for the optimal timing of crop operations rather than undertake operations at suboptimal times due to either machinery or capital constraints.

Several tests were undertaken to test for the presence of inefficiency in the model and whether the parameters of the inefficiency model were significantly different from zero. As the model was estimated using maximum likelihood the appropriate test was a likelihood ratio test of a restricted and unrestricted model. The critical value for each of these tests was derived from Kodde and Palm (1986) as they were adjusted χ^2 values to a take into account the mixed nature of the likelihood ratio test. The first test for $\gamma = \delta_0 = \delta_1 = \delta_2 = \delta_3 = 0$, tests for significant inefficiency effects in the model. This test does not provide any indication as to what variables were contributing to the inefficiency in the model; hence, the need for two subsequent tests. The second test, $\gamma = 0$, determined whether the inefficiency effects were stochastic. If the null hypothesis of this second test is not rejected then the model collapses to a standard mean response function in which the machinery capital and equity variables are included in the production model and the values of the parameters β_0 and β_3 are equal to zero, hence the critical value has three degrees of freedom (Battese and Coelli, 1995). The third and final test in Table 3 was a test of the whether the inefficiency effects were a linear function of the three variables, machinery investment, equity level and year of study.

Table 3: Generalised likelihood ratio tests of hypothesis for parameters of stochastic frontier model and technical inefficiency model.

Null hypothesis	Test statistic	d.f.	Critical χ^2 value[1]	Decision
$\gamma = \delta_0 = \delta_1 = \delta_2 = \delta_3 = 0$	55.9270	5	10.371	Reject H_0
$\gamma = 0$	32.3675	3	7.045	Reject H_0
$\delta_1 = \delta_2 = \delta_3 = 0$	23.5596	3	7.045	Reject H_0

[1] Critical χ^2 values from Table 1 of Kodde and Palm (1986) $\alpha = 0.05$.

Results from the hypotheses tests are presented in Table 3 and the conclusion that derived from these was that all parameters were statistically different from zero. The results from the first test which indicated that inefficiency was absent from the model was rejected at the 5% level, indicating that some or all of the variables in the inefficiency model were contributing to the inefficiency observed. From the second test it was possible to conclude that inefficiency was present in the model and it was

stochastic. Finally, the results of the third test support the conclusion that inefficiency effects were a function of the three variables, machinery investment per hectare, equity level, and year.

Increasing inefficiency over the period of study seems to suggest that there were problems in producer tactical decision making. If producers were consistent in their decision making over time, then some stochastic elements would affect efficiency, i.e. rainfall variability, but the efficiency of producers would be relatively consistent. The inconsistency of decision making was apparent when comparing the average efficiency over the 4 years. In 2004 average efficiency was 82%, falling to 74% in 2005, and falling further to 69% in 2006, with a small increase to 71% in 2007. The systematic problems and low efficiencies may have been due to producers attempting to predict rainfall events or adapting fertiliser application tactics to match rainfall forecasts that did not eventuate, rather than waiting for the event to occur, even though they have the machinery capital to allow them to make the most favourable production decisions.

Wheat producers in Western Australia utilize various crop management tactics that are made based on the forecast growing season rainfall. For example, the amount of fertilizer applied at sowing varies based on forecast rainfall, and because of this producers may apply fertilizer, principally nitrogen, in different forms and or at different times during the growing season. This approach is taken for risk management reasons and optimal productivity of the crop; however, success is contingent on the operation being taken at the optimal time of the crop's growth stage. Hence, mistiming the operation will reduce the efficiency of the fertilizer applied.

The number of producers from each rainfall zone in the top and bottom 20% of the efficiency rankings was consistent with the sample population. There were seven producers from the medium rainfall zone, two from the low, and one from the high rainfall zones. In the bottom 20% there were eight from the medium rainfall zone and two from the low rainfall zone, with no producers from the high rainfall zone in the lower rankings. This would indicate although there may be differences in rainfall and other production technologies; in this case efficiency is not affected by rainfall zone.

Examining the relative rankings of producers provides further information. Using a Spearman rank correlation test, the rank correlations between years ranged from -0.02 to 0.54. When comparing consecutive years the Spearman rank correlation coefficient ranged from 0.20 to 0.32. These relatively low correlation coefficients demonstrate that rankings and inefficiency levels were very sensitive to within year and within farm effects. One factor driving these low correlation coefficients is that in each correlation calculation there are several producers who have significantly different ranks. For example, when comparing rankings from 2004 and 2005 one producer, Farm 29, improved their ranking by 42 places, and 4 producers had rank changes of 30-33 places. Deleting these 5 producers increased the Spearman rank correlation from 0.32 up to 0.60. These effects were observed within other year comparisons and demonstrate that firm specific factors other than those captured in the parameters of the model affect the production function. Figure 4 demonstrates that efficiency scores for many producers were in a relatively narrow range, i.e. <20%. However, for others this range increased to greater than 40%.

Firm specific factors that may affect efficiency within and across years could include risk preferences and avoidance, or strategic planning goals that may be inconsistent with efficiency. For example, the top ranked producer in 2004 was ranked 34th in 2005 and it appears from the data that the only major difference between the two years was a substantial change in the cash position of the business. This may indicate that the producer was using cash to reduce debt and as a consequence this reduces the ability of the business to purchase inputs at the optimal time for crop production. However, one other group of producers were relatively consistent within the rankings and these were the bottom 10 producers or 20% of the sample. These low ranking producers consistently had efficiency scores below 70% and in some cases below 40%. This is shown in Figure 4, where farms 9, 26, 27, and 45 had efficiency scores in all years below 70%. These inefficiencies are driven by various factors; Farm 9 had lower than average yields, but received average rainfall, applied average levels of fertilizers, but had lower than average equity and machinery investment levels ; whereas Farms 26 and 27 generated average yields, but Farm 26 applied excess amounts of fertilizer and Farm 27 was substantially over capitalized in machinery per hectare.

Due to the nature of the data it is not possible to identify the types of machinery and age of machinery included in the machinery capital value. Therefore, simply increasing the investment in machinery may not lead to higher efficiency of production due to the purchase of machinery that is incompatible with a goal of efficiency improvement. Hence, machinery purchases need to be considered in a strategic manner if efficiency is to be improved.

Figure 4: Technical efficiency scores for each farm for each year 2004 to 2007.
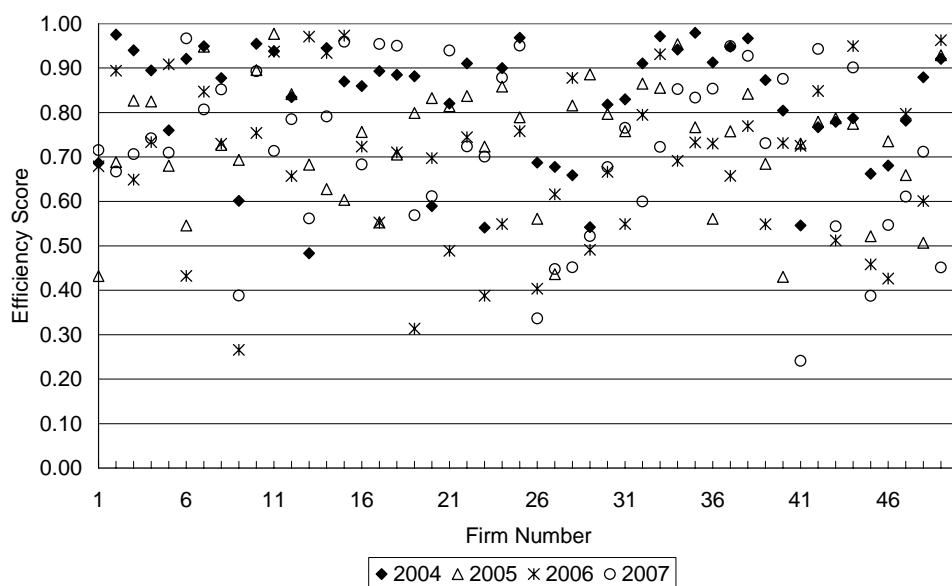
These results demonstrate the stochastic nature of efficiency and that for some firms improving efficiency may not be possible or feasible, due to limitations within the firm, for example, the lack of available cash or other sources of equity to finance the purchase of additional machinery capacity. This holds for firms that are relatively efficient in some years, and that the reasons for the inefficiency of these firms is not production related, and that programs targeted to improve efficiency may not be very successful. On the other hand firms that are consistently inefficient provide an ideal target audience for programs to improve efficiency. However, these programs must be conditioned on adequately identifying the source(s) of inefficiency. These sources may be production related, i.e. application of fertilizer at non-optimal times, or capital related, such as inadequate machinery capacity to complete operations in an optimal manner.

Conclusions

Using stochastic frontier analysis approach inefficiency in the production of wheat in the wheatbelt of Western Australia was studied. The production function model used was a relatively simple input model, consisting of wheat yield, effective rainfall, fertilizer application rates and year of study. Inefficiency was captured in a second model that incorporated machinery capital investment, opening equity level, and year of study. The results generated from these two models show that the responses from the production function are consistent with expectations and that the output responses to changes in any of the inputs increased at a decreasing rate and that over the period of study output had increased due to scale neutral technological change by approximately 8%. However, overwhelming this increase in output due to technological change was an increase in inefficiency in wheat production over the four years studied. Inefficiency levels of 18 to 31% indicate that producers have reduced yields when compared to those producers on the estimated frontier. These indicate that producers were losing revenue or increased the costs of production and thereby suffering reduced profits over the study period. In Australia, and increasingly other countries where subsidies to agriculture are being removed, the only way for producers to remain financially viable is through efficient production and or productivity gains. Hence, increasing inefficiency is reducing the competitiveness and financial viability of Australian grain producers, even though productivity is increasing.

An implication of this research is that one potential solution to increase efficiency in crop production is to alter, not necessarily increase, the investment per hectare in machinery. This suggests that there exists some optimal level of machinery investment and machinery type per unit area, not necessarily an optimal level of total machinery investment. However, this investment must be considered in the context of the overall business goals and financial position of the farm business.

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