Technical Efficiency of Australian Wool Production: Point and Confidence Interval Estimates

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Abstract

A balanced panel of data is used to estimate technical efficiency, employing a fixed-effects stochastic frontier specification for wool producers in Australia. Both point estimates and confidence intervals for technical efficiency are reported. The confidence intervals are constructed using the Multiple Comparisons with the Best (MCB) procedure of Horrace and Schmidt (2000). The confidence intervals make explicit the precision of the technical efficiency estimates and underscore the dangers of drawing inferences based solely on point estimates. Additionally, they allow identification of wool producers that are statistically efficient and those that are statistically inefficient. The data reveal at the 95% level that twenty of the twenty-five wool farms analysed may be efficient.

KEY WORDS: Technical Efficiency, Multiple Comparisons with the Best, Wool Production.

JEL CLASSIFICATION NUMBERS: C12, C23, D24

1. Introduction

Despite an extensive literature concerning estimation of farm-level efficiency in Australian agriculture (e.g., Coelli, 1995, Coelli, Prasada Rao, and Battese, 1998, and Fraser and Cordina, 1999), there is a dearth of research devoted to the Australian wool industry. The absence of research into farm-level efficiency is somewhat surprising given the size and importance of the wool industry to the Australian agricultural sector. The wool industry contributed almost ten percent of gross value of agricultural production that, in turn, generated $4 billion in export income in 1997-98 (Australian Bureau of Agriculture and Resource Economics (ABARE), 1999).

To date the only studies to address efficiency in the wool sector are Battese and Corra (1977), Lawrence and Hone (1981), Chapman, et al. (1999) and Fraser and Hone (2001). Hence, there is little research devoted to estimation of farm-level efficiency for wool production in the Australian agricultural economics literature. Battese and Corra estimated frontier production functions for sheep production in the pastoral zone of Australia i.e. Queensland, New South Wales and South Australia. In keeping with other pioneering frontier studies (Aigner et al., 1977 and Meeusen and van den Broeck, 1977), the results in this paper focus on the difference between average and frontier production functions estimates as opposed to farm specific results. Battese and Corra found that Constant Returns to Scale could not be rejected. They do, however, indicate that caution is necessary in interpreting their results as the data used in this paper pools across diverse production units. Lawrence and Hone estimated technical efficiency for grazing properties in the high rainfall zone of New South Wales for 1975-1976 using a restricted profit function. As they could not reject absolute allocative efficiency based on size, they did not test for technical efficiency, and as such provided only limited insights into the farm-level efficiency of Australian wool producers. Chapman et al. used data drawn from ABARE's 1997-98 Australia wide specialist wool survey and employed Data Envelopment Analysis (DEA) to estimate technical efficiency, focusing on the regional distribution of technical efficiency across Australia. Not surprisingly they found technical efficiency to be highly correlated with seasonal weather conditions within specified production regions, but they did not report specific farm-level technical efficiency estimates. Fraser and Hone (2001) employed DEA to estimate farm level technical efficiency and Malmqvist Total Factor Productivity (TFP) for an eight-year balanced panel data set derived from the South-Western Victorian Monitor Farm Project (SWVMF) (Patterson, et al.1998). They found significant variation in technical efficiency estimates between the farms in the sample and no growth in TFP for the farms in the sample.

However, the results of Fraser and Hone (2001) need to be treated cautiously because of limitations with the data. A weakness of the their paper stemmed from the aggregate nature of some of the inputs. In this paper we employ an improved version of the data used by Fraser and Hone overcoming importance data weaknesses. By gaining access to more detailed farm level records we are able to dis-aggregate inputs and avoid unnecessary aggregation. For example, we include a measure of land used in wool production. Furthermore, we employ an econometric fixed-effect specification to analyse farm-level technical efficiency explicitly taking account of sampling error in the data.

Another important contribution of our paper is the construction and interpretation of confidence intervals for the point estimates of technical inefficiency for the sample of farms. A weakness of most efficiency studies (including Fraser and Hone, 2001) to date has been the lack of application of statistical inference techniques to the point estimates derived. In both the parametric and semi-parametric frontier literature there has been a recent burst of research activity that has attempted to address this weakness. In the stochastic frontier literature the possibility of conducting inference, although noted, has been implemented very infrequently. Exceptions to this are Simar (1992), Battese et al. (2000), and Horrace and Schmidt (1996, 2000) and Fraser and Kim (2001).[1]

Inference (construction of confidence intervals) on point estimates of technical efficiency differs based on the assumptions that one in willing to impose on the model. With strong (and often arbitrary) parametric assumptions on the distribution (shape) of technical efficiency, inference follows in a straight-forward, although non-standard, way.[2] With no distributional assumptions on technical efficiency Schmidt and Sickles (1984) introduce a fixed-effect frontier specification and point estimates based on the difference of the maximal value of the fixed-effects (the frontier) and the other effects in the sample. While the lack of a specific distributional assumption on technical efficiency may be appealing for point estimation, confidence interval construction becomes non-trivial due to the bias created by "max" operation, and, until recently, has rarely been performed.[3] When a fixed-effects specification is applicable, confidence intervals are constructed using a technique called *Multiple Comparisons with the Best* (MCB) introduced by Horrace and Schmidt (1996, 2000). MCB allows construction of joint confidence intervals for all differences from the unknown

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[1] Bootstrapping has been used to construct confidence intervals for DEA measures of technical efficiency. See Wilson and Simar (1998, 2000). There have also been recent Bayesian frontier studies that have examined inference results for measures of efficiency. See Koop et al (1977) and Kleit and Terrell (2001).

[2] Battese and Coelli (1988) show that under certain assumptions the conditional, *ex post* distribution of technical efficiency is truncated normal. Horrace and Schmidt (1996) detail confidence interval construction for this truncated normal distribution.

[3] The fixed-effects specification requires that technical efficiency be time-invariant. Time- varying specifications are discussed in Kumbhakar (1990), Lee and Schmidt (1993), Coelli et al (1998) and Kalirajan and Shand (1999).

maximal fixed-effect and the other effects. In the context of a fixed-effect frontier model this is the vector of differences between the intercept of the most efficient farm and those of the rest, the usual estimate of technical efficiency. MCB can tell the researcher, for a pre-specified level of confidence, which farms may be technically efficient, and it also provides upper and lower bounds on the deviations of all estimates from the maximal value.

In this paper we use MCB (and other multiple comparison techniques) to construct confidence intervals for point estimates of technical efficiency for the Australian wool industry between 1991 and 1998. We estimate and rank point estimates of technical efficiency for a sample of twenty-five wool farms. MCB confidence intervals reveal that only six of the farms may be relatively inefficient at the 95% confidence level, and the most efficient farm in the sample may have technical efficiency as low as 86.4% of the maximal efficiency in the population. Point estimates alone are incapable of uncovering this type of statistical detail and, indeed, often suggest that all but the single best farm in the sample are technically inefficient. Additionally, we perform alternative inference experiments, called Multiple Comparisons with a Control (MCC) and Marginal Comparisons with the Best (MgCB) on technical efficiency estimates to disentangle the sources of statistical uncertainty that confound the point estimates.

This paper is organized as follows. The next section discusses technical efficiency point estimation using a fixed-effects specification. Section 3 introduces MCB, MCC and MgCB for the construction of confidence intervals for technical efficiency. Section 4 describes the data for the empirical analysis. Section 5 presents the findings. Finally, Section 6 summarizes and concludes.

2. Fixed-Effects Stochastic Frontier Estimation

The stochastic frontier literature is based on Aigner et al. (1977) and Meeusen and van den Broeck (1977), where the stochastic frontier contains an error term that is composed of two elements: a random error (v) and a one-sided, non-negative error (u), representing technical inefficiency. By decomposing the error term into these two components the frontier production function can be expressed as,

(1) $$Y_i = \alpha + X_i \beta + v_i - u_i$$

where $i = 1, 2, ..., N$. Y_i is the logarithm of productive output and X_i is a $1 \times K$ vector of factors of production. Here, i indexes farms and α and β are parameters to be estimated. The v are *i.i.d.* random variates with mean zero, and are assumed to be independent of u and the X. The u are non-negative *i.i.d.* random variates, which are independent of v and X. To fully identify the parameters in this model, a truncated normal or exponential distributional assumption is typically imposed on the u.

The stochastic frontier of equation (1) was extended to accommodate panel data by Pitt and Lee (1981), and Schmidt and Sickles (1984). For a more recent treatment of panel data models see Cornwell and Schmidt (1995) and Greene (1997). The form of panel data model to be estimated in this paper is

(2) $$Y_{it} = \alpha + X_{it}\beta + v_{it} - u_i$$

where $i = 1, 2, ..., N$ and $t = 1, 2, \ldots, T$. T is the number of observed time periods. Thus, Y_{it} denotes the logarithm of output for the i^{th} farm in the t^{th} time period. X_{it} is a $(1\times K)$ vector of inputs, v_{it} are random errors as previously defined, and $u_i \geq 0$ is a time invariant measure of technical inefficiency.

For the logarithmic stochastic frontier described by equation (2), technical efficiency of the i^{th} farm is defined as $r_i = exp(-u_i)\in[0, 1]$, so that technical inefficiency is $(1 - r_i)$. When u_i is small, u_i is approximately equal to $1 - exp(-u_i) = 1 - r_i$, so that u_i is frequently used as a measure of technical inefficiency.

Assuming that the u are fixed (non-random) and letting $\alpha_i = \alpha - u_i$, equation (2) becomes the standard panel data model with time-invariant individual effects (fixed-effects),

(3) $$Y_{it} = \alpha_i + X_{it}\beta + v_{it}$$

It follows from $u_i \geq 0$ that $\alpha_i \leq \alpha$ and $u_i = \alpha - \alpha_i$. Interest centers on the technical inefficiency rankings. Let the rank order of the α_i be:

(4) $$\alpha_{[1]} \leq \alpha_{[2]} \leq \ldots \leq \alpha_{[N]}$$

so that $[N]$ is the index of the farm with the largest α_i (i=1,..., N) in the population. Given that $u_i = \alpha - \alpha_i$ it follows that we can then write u_i in the opposite ranked order,

(5) $$u_{[N]} \leq u_{[N-1]} \leq \ldots \leq u_{[1]}$$

Clearly, $\alpha_{[N]} = \alpha - u_{[N]}$ and farm $[N]$ has the largest α_i (smallest u_i) for all $i = 1, ..., N$.

Equation (3) can be estimated using either the so-called "within" or "least squares dummy variable" estimator, yielding parameter estimates

(6) $$\hat{\alpha} = \max_{j=1,\ldots,N} \hat{\alpha}_j, \quad \hat{u}_i = \hat{\alpha} - \hat{\alpha}_i \text{ and } \hat{r}_i = exp(-\hat{u}_i), \quad i = 1, ..., N.$$

Notice that the $\hat{u}_i$ will be constrained non-negative and the $\hat{r}_i$ are bound on the unit interval. The $\hat{u}_i$ ($\hat{r}_i$) are relative measures of inefficiency (efficiency) which are consistent as N and $T\rightarrow\infty$. Schmidt and Sickles (1984) note that in finite samples (small T) $\hat{\alpha}$ is likely to be biased upward which implies that efficiency is underestimated. This bias is larger when T is small relative to N, and is caused by the "max" operator in equation (6).

Fixed-effects estimation in this context is a semiparametric estimator insofar as the u_i are non-random and do not require a distributional assumption to be characterised. Additionally, it is not necessary to assume that the inputs to the production process (X) are uncorrelated with technical inefficiency (u). Consequently, this is a particularly appealing specification for point estimates of technical efficiency ($\hat{u}_i$). For a rigorous treatment of the econometric properties of the fixed-effects model see Park and Simar (1994).

The semi-parametric nature of the fixed-effect specification leads to fairly serious complications for the construction of confidence intervals on the u_i. With no *ex an*te distributional assumption on the u, no *ex post* distribution for the purposes of inference is readily available. Additionally, the estimator $\hat{u}_i$ is biased, so confidence interval construction necessarily involves some type of bias correction. Finally, the estimation of u_i in equation (6) hinges on the implicit rankings of equations (4) and (5), which are *multiple* statements about the relative rankings. As such, any inference on these parameters of interest will necessarily be *multivariate*, involving N simultaneous probability statements. These types of multivariate inference problems can be overcome with MCB, as described in the next section.

3. Multiple Comparisons with the Best

MCB was originally developed by Edwards and Hsu (1983). Horrace and Schmidt (2000) discuss MCB for econometrics applications and provide a rigorous treatment of the stochastic frontier model. Horrace and Schmidt used MCB to construct confidence intervals for estimates of technical efficiency derived from panel data employing a fixed-effects specification. Simply put, MCB allows the researcher to construct simultaneous confidence intervals for differences between the best population parameter and the rest. That is, MCB facilitates the construction of simultaneous confidence intervals for $u_i = \alpha - \alpha_i$, $i=1,..N$. It is not assumed that the index of the largest $\hat{\alpha}_i$ in the sample equals [N], the index of the largest α_i in the population, and part of the problem is to determine if any sample index is so identified at a pre-specified confidence level. These confidence intervals can be monotonically transformed to confidence intervals for $r_i=exp(-u_i)$.

The confidence intervals that are constructed by the MCB algorithm are unique in three respects:

1. The confidence intervals do not presume that the most technically efficient farm in the sample is known, which is implicitly presumed in the point estimate $\hat{u}_i$ in equation (6).

2. The confidence intervals are derived simultaneously and thus provide joint statements about which farms are efficient and which can be eliminated from contention for efficiency at a given confidence level.

3. As MCB is based on fixed-effect (within estimates) panel specification we do not require distributional assumptions about u_i to be made.

The MCB intervals reveal information about population ranking of the farms. If for a single farm, the upper and lower bounds on u_i are 0 (alternatively the lower and upper bounds of r_i are 1), then that farm is most efficient (best) at the pre-specified confidence level. However, the inference can also reveal that several (or all) farms are best (on the efficient frontier), which the point estimates of technical efficiency cannot. Point estimates from the fixed-effect specification imply that all but one farm is efficient, assuming no ties in the sample for the best. Indeed, the notion that only one producer is operating efficiently in a large market seems to contradict the stylised facts of microeconomic analysis. Moreover, the inference can also reveal those farms that are not on the frontier at the pre-specified confidence level.

A thorough discussion of MCB can be found in Horrace and Schmidt (2000). Here, we summarise the salient features of their notation. We begin with a discussion of confidence intervals called *multiple comparisons with a control* (MCC), which are the basis of the MCB intervals that are discussed in the sequel. Let $\hat{\Omega}$ be the estimated variance-covariance matrix of the vector parameter estimates $[\hat{\alpha}_1, \hat{\alpha}_2, \ldots, \hat{\alpha}_N]$, with typical element, $\hat{\omega}_{ij}$. Define the following notation:

(7) $$L_i^j = \hat{\alpha}_j - \hat{\alpha}_i - h_{ji}, \; U_i^j = \hat{\alpha}_j - \hat{\alpha}_i + h_{ji}$$

where $i, j = 1, \ldots, N$, and where $h_{ji} = d_j^*[\hat{\omega}_{ii} + \hat{\omega}_{jj} - 2\hat{\omega}_{ji}]^{1/2}$, and d_j^* is the solution to:

(8) $$\Pr(\max_{1 \le i \le N-1} |z_i| \le d_j^*) = 1 - \gamma.$$

Here, z is an N-1 dimensional random vector distributed as a multivariate t-distribution with covariance $\hat{\Omega}$ and $N(T-1)-K-1$ degrees of freedom, and $\gamma \in [0, 0.5)$. The L_i^j and U_i^j are lower and upper bounds of simultaneous $(1 - \gamma) \times 100\%$ MCC confidence intervals for all differences from a control index, j, which is pre-selected by the analyst. The h_{ji} are the usual allowance terms consisting of the product of a critical value, d_j^*, and a standard error, $[\hat{\omega}_{ii} + \hat{\omega}_{jj} - 2\hat{\omega}_{ji}]^{1/2}$. The difficulty in constructing the MCC intervals arises from the determination of the multivariate critical value, d_j^*, which captures the multiplicity inherent in the max "operator" (i.e. the max operator implies a ranking of the population parameters of interest which implies that multiple comparisons must be made). Fortunately, for economic applications where replications of empirical studies is not critical (*vis á vis* applications in medicine), the critical values can be simulated. Such a simulation algorithm can be found in Horrace and Schmidt (2000).

We can select **any** index as the control (j), but for the purposes of frontier estimation it makes sense to select the control index as the farm with the largest $\hat{\alpha}_i$, then the MCC intervals can be interpreted as intervals on u_i. When we do this, we are making the implicit assumption that the farm with the largest $\hat{\alpha}_i$ in the sample is the efficient farm in the population. That is, we have made the *ex ante* assumption that the estimation has revealed the most efficient farm with certainty. MCB intervals, on the other hand, relax this *ex ante* assumption and are, hence, less "parametric" and wider in general that their MCC counterparts. In doing so, MCB intervals recognize that uncertainty over the identity of the most efficient farm exists while MCC intervals do not.

The $(1 - \gamma)\times 100\%$ MCB intervals on the u_i follow directly. Define the further notation:

(9) $S = \{j \mid U_i^j \geq 0 \ \forall\ j \neq i\} = \{j \mid \hat{\alpha}_i \geq \hat{\alpha}_j - h_{ij} \ \forall\ j \neq i\}$

(10) $L_i = \max[0, \min_{j\in S} L_i^j] = \max[0, \min_{j\in S} (\hat{\alpha}_j - h_{ji}) - \hat{\alpha}_i]$

(11) $U_i = \max[0, \max_{i\neq j} U_i^j] = \max[0, \max_{i\neq j} (\hat{\alpha}_j + h_{ji}) - \hat{\alpha}_i]$

Then we have the MCB result: $\Pr[[N]\in S$ **and** $L_i \leq u_i = \alpha_{[N]} - \alpha_i \leq U_i \ \forall\ i] \geq 1 - \gamma$. That is:

With probability at least $(1 - \gamma)$, *the technical inefficiency of the* i^{th} *farm lies between* L_i *and* U_i, *when the true identity of the efficient farm* $[N]$ *is not known with certainty.*

(Notice the notational difference between the MCC bounds $[L_i^j, U_i^j]$and the MCB bounds $[L_i,U_i]$.) Since we have simultaneous confidence intervals the degree of interval overlap of the intervals gives a sense of how meaningful differences in the technical efficiency point estimates may be. Furthermore, the set S contains the indices of all farms that are on the efficient frontier with probability at least $(1 - \gamma)$. To see this, one need only recognize that the set S contains only those indices of farms with **all** positive MCC upper bounds, U_i^j (all farms that have statistically large α_j). When S is a singleton it will contain only the index of the farm with the largest $\hat{\alpha}_i$, and we can conclude that the estimation has revealed the identity of the efficient farm with probability at least $(1 - \gamma)$. In this case, the MCB intervals reduce to MCC intervals with the farm with the largest $\hat{\alpha}_i$ as the control (as described above). Also, any farm that has $L_i > 0$, is inefficient with probability at least $(1 - \gamma)$. That is, the lower bound of difference of the best farm and the i^{th} farm is positive (different from zero), implying that this difference (technical inefficiency) is statistically meaningful.

These are powerful inference statements that can only be made through confidence interval construction. It is interesting to note that, the MCB intervals are not centered on the point estimate $\hat{u}_i$ (as we shall see), because they account for the bias inherent in the estimate. The MCC intervals are centered on the point estimate and, therefore, implicitly assume that the estimate is unbiased, which could only occur if the best farm in the sample is the best farm with certainty. Finally, the MCB and MCC confidence intervals and inference can be transformed into those for r_i. In this case the probability statement becomes: $\Pr[[N]\in S$ **and** $\exp(-U_i) \leq r_i \leq \exp(-L_i) \ \forall\ i] \geq 1 - \gamma$, and all the inferences change accordingly.

One potential shortcoming of the MCB and MCC intervals is that they are simultaneous, which causes them to be wider than intervals associated with a single inference statement (think of the effects of multiplicity on the Bonferroni inequality). Interest may center on a *marginal* inference statement: a statement about the technical inefficiency of a *single* farm. In a recent paper Kim and Schmidt (1999) develop marginal confidence intervals for comparison with best: intervals for $\alpha_{[N]} - \alpha_i$, for a single i. These *Marginal Comparisons with the Best* (MgCB) intervals remove interval width associated with the multiplicity of the probability statement. The MgCB intervals still account for uncertainty over the true population best farm (like the MCBs and unlike the MCCs) and, as such, tend to be wider when there are many farms near the efficient frontier. The intervals are constructed around the elements in subset, S, thereby accounting for uncertainty over the best firm in the population, but use the usual univariate t-statistic, t^*, where t^* is the solution to:

(12) $\Pr(|\, z \,| \leq t^*) = 1 - \gamma/2$,

where z is the aforementioned random variable of equation (8) but with dimensionality 1. Then the $(1 - \gamma)\times 100\%$ MgCB confidence intervals are:

(13) $\mathrm{Mg}L_i = \max[0, \min_{j\in S} \{\hat{\alpha}_j - t^*(\hat{\omega}_{ii} + \hat{\omega}_{jj} - 2\hat{\omega}_{ij})\} - \hat{\alpha}_i]$

(14) $\mathrm{Mg}U_i = \max[0, \max_{i\neq j} \{\hat{\alpha}_j + t^*(\hat{\omega}_{ii} + \hat{\omega}_{jj} - 2\hat{\omega}_{ij})\} - \hat{\alpha}_i]$.

The MCC, MCB and MgCB confidence intervals imply different inference statements that complement each other well. Together they provide information about any particular data set that the individual confidence intervals cannot provide themselves. The MCB intervals can be thought of as capturing multiplicity, uncertainty over $[N]$, and sampling variability. The MCC intervals with the index of $max_i \hat{\alpha}_i$ as the control index capture only multiplicity and sampling variability, so differences between the MCB and MCC intervals "quantify" uncertainty over [*N*]. The MgCB intervals capture uncertainty over [*N*] and sampling variability, so differences between the MgCB and MCB intervals are due to multiplicity. Differences between the MgCB and the MCC are due to multiplicity and uncertainty over [*N*]. By making comparisons across the various intervals we are able to provide a complete picture of the nature of the uncertainty of the stochastic frontier point estimates of technical efficiency.

4. Data and Functional Form

The data are a balanced panel of wool producers drawn from the SWVMFP survey (Patterson et al., 1998). To conduct the analysis we constructed a balanced panel covering 8 years (T = 8), from 1990-91 up to 1997-98, for N = 26 farms. The survey focuses on wool farms with the average farm size being 895 hectares and carrying 5,712 sheep. The data available for each farm in each period are output (wool) and inputs (land, number of animals, contract labor, pasture costs, selling costs, and supplementary feed costs). Some of the farms in the sample are multiple output producers. For example, in addition to wool, some of the farms also produce lamb, beef and crops, and this product mix varies across time and across farms. In 1998 the average of wool revenues as a percentage of total revenues was 83%, while in 1991 wool represented 90% of revenues on average. However, in these years most farms in the sample produced *only* wool (i.e. the mode of wool percentage was 100%).

An attractive feature of the SWVMFP survey is that all the farms are drawn from a homogenous geographical region. Hence the sample of farms will be subject to relatively similar weather and agronomic conditions i.e., soils, digestible vegetation and weeds. Another strength of the data set is that it provides output-specific information. That is, for each output (e.g. wool), specific input use is recorded. Specifically, contract labor, pasture costs, selling costs, and supplementary feed costs are reported in total dollars spent. Land used in wool production is measured in hectares and the number of animals is measured in *dry sheep equivalents* (dse). We use dse to normalise for the age and the weight distribution of sheep in flocks. For example, a dry sheep, that is a ewe that is not pregnant or lactating or a weaned lamb, with body weight of 40 kilograms is given a dse rating of 0.8, whereas a ewe with body weight 50 kilograms is given a dse rating of 1.0.

For output, to cope with difference in wool quality (i.e. micron size) we employ the total dollar value of the wool clip (instead of kilograms). The micron size of the wool determines its potential uses, and as such the price paid for the wool reflects the derived demand for the various micron sizes. Hence, the producers' choice of micron size is an important variable influencing the economic performance of the farm, and it is necessary to incorporate this information into the analysis. Within the sample, there are significant differences in the wool micron size produced and the associated price paid for the wool (i.e., 18.5 to 28). It should be noted that with output measured in this way, the estimates of technical efficiency are interpreted as "total economic efficiency" (Coelli and Battese, 1996). A summary of the data used in the analysis is presented in Table 1.

(Approximate Position of Table 1}

In this paper the most flexible functional form of the stochastic frontier examined is the translogarithmic function allowing for non-neutral technical change

$$\text{(15)} \qquad \mathrm{Ln}Y_{it} = \alpha_i + \sum_{j=1}^{6} \beta_j X_{\mathrm{jit}} + \delta_t T + \tfrac{1}{2} \sum_{j=1}^{6} \sum_{k=1}^{6} \beta_{jk} X_{jit} X_{kit} + \sum_{j=1}^{6} \gamma_{jt} X_{jit} T + \tfrac{1}{2} \delta_{tt} T^2 + v_{it}$$

where $\beta_{jk} = \beta_{kj}$ $(k \neq j)$ and the subscripts i and t represent the i-th farm and the t-th year. Furthermore, Y represents the total value of the wool clip, X_1 is the logarithm of land, X_2 is the logarithm of pasture cost, X_3 is the logarithm of contract labor, X_4 is the logarithm of additional feed, X_5 is the logarithm of selling cost, X_6 the logarithm of the number of animals and T is a time trend.

With equation (15) it is possible to model neutral technical change if the interaction terms between the various inputs and time are set equal to zero i.e., $\gamma_{jt} = 0$. We can also model no technical change if all coefficients involving time are set equal to zero i.e., $\gamma_{jt} = \delta_t = \delta_{tt} = 0$. Finally, the Cobb-Douglas production function is a special case of the translog frontier in which all the second-order terms are equal to zero i.e., $\beta_{jk} = 0$.

5. Results

5.1 Point Estimates of Technical Efficiency

Given the data described in the previous section we estimated equation (15) using OLS and a "within" transformation of the data. To derive our preferred functional form we estimated ten specifications. Models 1 to 5 are variable returns to scale specifications and models 6 to 10 are constant returns to scale. To impose constant returns to scale we divided throughout by land. Models 1, 3, 6 and 7 are Cobb-Douglas functional forms and all the others are Translog. Models 1, 2, 7 and 9 include a time trend to capture technical change. Models 3, 4, 6 and 8 do not include the time trend. Finally, the translog models 5 and 10 allow for non-neutral technical change. The fixed-effect regression results for the specifications estimated are reported in Table 2

{Approximate Position of Table 2}

In Table 2 we see that many of the marginal effects in the translog specifications are statistically insignificant. However, given the choice of functional form it is highly likely that our data are collinear and this is revealed by the fact that although the Cobb-Douglas specifications yielded significantly lower log-likelihood estimates many of the parameter estimates were statistically significant.

Employing a generalised log likelihood ratio test, which is distributed $\chi^2_{(J)}$, where J is the number of restrictions under the null hypothesis, we were able to identify our statistically preferred functional form. First, we were able to reject Model 1 in favor of Model 2, and Model 7 in favor of Model 9, that is the null hypothesis that a Cobb-Douglas production function is an adequate representation of the data is rejected i.e., H_0: $\beta_{jk} = 0$. Second for the Translog we rejected Model 4 in favor of Model 2 and Model 8 in favor of Model 9, that is we are able to reject the null hypothesis of no technical change i.e., H_0: $\delta_t = \delta_{tt} = 0$. Third, we were able to able to reject Model 2 in favor of Model 5, and Model 9 in favor of Model 10, that is the null hypothesis of non-neutral technical change i.e., H_0: $\gamma_{jt} = 0$. However, we were not able to reject Model 10 in favor of Model 5, that is the null hypothesis of constant returns to scale i.e., H_0: $\sum_j\beta_j = 1, \sum_k\beta_{jk} = 0$ and $\sum_j\gamma_{jt} = 0$ (Kim, 1992). Thus, our statistically preferred functional form is a translog with constant returns to scale imposed and non-neutral technical change (Model 10).[4][5]

Interestingly, the marginal effect estimate for average annual technical progress in Model 10 is negative and statistically significant implying that there has been technical regress over the sample period. This result is in keeping with the findings of Fraser and Hone (2001). This is not altogether surprising given that our data are for the period immediately after the collapse of the wool Reserve Price Scheme (RPS).[6] The collapse of the RPS brought about a very hard financially period for wool producers. It is therefore of little surprise to find that during such a period the industry suffered technical regress.

Next we report the estimates of the fixed-effect estimates for our preferred specification (Model 10). These results are contained in Tables 3.

{Approximate Position of Table 3}

In Table 3 we see that all of the fixed-effect estimates were significantly different from zero. Although the significance of the $\hat{\alpha}_i$ provides a guide to the precision of the individual parameter estimates,

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[4] We were unable to reject Model 3 in favor of Model 1 or Model 6 in favor of Model 7, that is with a Cobb-Douglas specification we are unable to reject the null hypothesis of no technical change i.e., H_0: $\delta_t = 0$.

[5] In the frontier literature a restricted (simplified) translog has been used to try and avoid collinearity problems. Following Fan (1991) and Ahmad and Bravo-Ureta (1996) we also estimated this simplified translog which assumes that all inputs are separable from each other but not time. Employing the generalised log-likelihood test we were able to reject this specification in favor of Models 5 and 10 respectively.

it is of little use in understanding the precision of estimates of the *differences* of the α_i that are used in the estimation of u_i and ultimately the calculation of the MCB, MCC and MgCB intervals. The rank-order point estimates of technical efficiency (r_i) are also presented in Table 3.

The results show that the distribution of technical efficiency estimates is quite dispersed. These estimates seem to suggest that for this sample of wool producers there exist opportunities for improvements in technical efficiency. However, one might have anticipated that wool producers to be efficient. As noted, the industry experienced a significant period of turmoil as a result of the collapse of the RPS in 1991. Real wool prices fluctuated around record low levels and, consequently, wool production contracted significantly. In 1989, 1031 kilotonnes of wool was cut, this had fallen to 650 kilotonnes by 1997 (ABARE, 1999). Over a period of major adjustment such as this, it might be anticipated that the remaining wool producers would likely be those that are efficient. The spread of point estimates for technical efficiency derived here contradicts this conjecture and indicates that significant gains in technical efficiency still exist for wool producers. As we will find, however, when we examine the MCB confidence intervals, we have to be far less strident in terms of the conclusions that we draw concerning the lack of efficiency of the industry.

Before examining confidence intervals of our point estimates of technical efficiency it is sensible to check the robustness of our technical efficiency results. First, an examination of all sets of technical efficiency estimates reveals that irrespective of functional form the technical efficiency results are very dispersed. This is revealed by the fact that the difference between the most efficient farm and the second most efficient farm, and also that the technical efficiency estimate for the least efficient farm is similar irrespective of model specification.

Second, a simple test of whether the rank of farms for Model 10 is robust to different model specifications is to estimate the Spearman Rank Correlation coefficient (ρ) between the various models (i.e., 1 to 10). We estimated technical efficiency (r_i) for all the models and derived the rank of the farms. ρ was estimated for all pairs of models and the results are reported in Table 4.

{Approximate Position of Table 4}

As we can see from the estimates in Table 4 there is a very strong positive relationship across all the models estimated. Thus, despite there being a statistically significant difference between the different model specifications we are able to reject the null hypothesis that the rank of farms are mutually exclusive and instead assume that the order of efficient/inefficient farms tends to be the same across models.

[6] See Haszler et al (1996) for a detailed review of the Reserve Price Scheme collapse and policy response.

Hence, technical efficiency rankings are fairly robust to model specification for this particular data set. These results are consistent with the observations of Kumbhakar and Lovell (2000) in relation to existing findings in the frontier literature.

Finally, as was noted in Section 2, the fixed-effect specification assumes that technical efficiency is time-invariant. Given that data set spans eight years there may have been technological improvements and the assumption of time-invariant technical efficiency is not plausible. Again an effective statistical test of whether the technical efficiency estimates are time varying is to estimate the Spearman Rank Correlation coefficient (ρ) for various pairs of sub-sets of the data. We estimated technical efficiency (r_i) for the time periods 1991-1994, 1993-1996 and 1995-1998 (n=104 in all cases) with Model 10. For each of the time periods the rank of the farms was derived (i.e., most efficient to least efficient) and ρ was then estimated for the three pairs of data. For 1991-1994 and 1993-1996, ρ=0.472, for 1991-1994 and 1995-1998, ρ=0.554, and for 1993-1996 and 1995-1998, ρ=0.577. The critical value for a five percent significance level is 0.33. Hence, in all cases we are able to reject the null hypothesis that the rank of farms are mutually exclusive and instead assume that the order of efficient/inefficient farms in one sub-set tends to be the same as the other sub-set. This result is in keeping with the findings of Fraser and Hone (2001) who also concluded that the farms in this sample exhibited time-invariant technical efficiency.

5.2. Confidence Interval Estimate

Having estimated the $\hat{\alpha}_i$ and their (NxN) variance-covariance matrix, $\hat{\Omega}$, MCB, MCC and MgCB intervals can be constructed for a given confidence level, (1 - γ). To show how the choice of the confidence level impacts the width confidence intervals, we present result for (1 - γ) equal to 95 % and 75%. A very different interpretation of the estimation results is forthcoming when we examine the confidence intervals estimates for technical efficiency. We begin by examining MCB, MCC and MgCB 95% confidence intervals. These results are presented in Table 5.

{Approximate Position of Table 5}

The 95% critical values used for MCC and MCB ranged from 2.430 to 3.069. For MgCB the critical value used was 2.240. The 95% confidence intervals (MCB, MCC and MgCB) presented in Table 5 tell a very different story than the point estimates reported in Table 3. In general the confidence intervals for the technical efficiency estimates demonstrate that we need to be far more conservative about the interpretation we place upon point estimates. For example, although for farm 9 the MCB confidence interval is fairly narrow [0.864, 1], for farm 20 the confidence interval is very wide [0.399, 1]. The confidence intervals are just as wide for farm 25, the farm with the lowest estimate of technical efficiency [0.156, 1]. Wide confidence intervals are not atypical of these types of MCB analyses. For example see Horrace and Schmidt (2000).

Although the MCB confidence interval results in Table 5 are wide we are able to place the sample of farms in three distinct groups. The first group includes all farms in the set *S*, which *are* efficient (best) at the 95% level. This group includes farms 2, 7, 9, 13, 14, 16, 17, and 21. For all farms in this group, in terms of MCB they have an upper bound equal to one. The lowest lower bound for this group is 0.499 (farm 21). The fact that we were not able to identify a single best farm can partly be traced to the dimensions of the data set. As Horrace and Schmidt (2000) note, a single best farm is more likely to emerge when the number of time periods is long and the set of farms is small.

Notice in Table 5 that farm 16 and farm 23 have the same estimates of technical efficiency (r_i = 0.728), but farm 16 is in the set *S* while farm 23 is not. This is because for farm 16: $U_i^{16} > 0 \; \forall \; i \neq 16$, but for farm 23: $U_9^{16} < 0$, so farm 23 is excluded from *S*. Surprisingly it is also the case that the variance estimates for r_{23} and r_{16} are also identical: $\hat{\omega}_{9,9} + \hat{\omega}_{16,16} - 2\hat{\omega}_{9,16} = \hat{\omega}_{9,9} + \hat{\omega}_{23,23} - 2\hat{\omega}_{9,23}$. Therefore, the difference in the two farms' membership in the set *S* is strictly a function of the difference in the critical values for each farm ($d_{16}^{\ *}$ = 3.067 and $d_{23}^{\ *}$ = 3.031). The smaller $d_{23}^{\ *}$ makes for sharper inference on farm 23 so we can conclude with 95% certainty that farm 23 is not in the set of best farms. Again the width of the confidence interval means that we really need to be extremely careful when attempting to interpret the point estimates of technical efficiency.

The farms in the second group are those with MCB upper bound equal to 1 but not in the set, *S*. These farms *may* be efficient at the 95% level. Again the confidence intervals derived are large. The farms in the second group are interpreted in a conventional manner with regard to the confidence interval. That is, they will be technically efficient 95 times out of 100. Notice, in Table 5, that despite having the lowest estimate of technical efficiency, farm 25 has an MCB upper bound equal to 1. In contrast, farm 18 has a better efficiency score but has an MCB upper bound equal to 0.886, and does not fall into this second group of farms. This can be attributed to the fact that for farm 25 $Cov(\hat{\alpha}_{25} - \hat{\alpha}_i)$ tends to be small. making $Var(\hat{\alpha}_{25} - \hat{\alpha}_i)$ relatively large, so inferences on farm 25 are less sharp than for other farms in the sample.

The third and final group of farms, are those that are technically inefficient at the 95% level. The upper bound of the confidence interval for this group does not include one. The farms in this group are 6, 1, 12, 10, and 18. Yet again the size of the confidence intervals is such that we need to interpret the point estimates of technical inefficiency very carefully.

The second set of confidence bounds presented in Table 5, are the MCC confidence intervals. These estimates are derived by assuming that farm 9 is efficient ([N] = 9) and using farm 9 as the control index, j. Consequently, we constrain the MCC upper bound for r_i to be no greater that 1, since farm 9 has the largest α_i by assumption. The MCC results reduce the upper bound for a large number of the farms in the sample. (Notice that there are fewer upper bounds equal to 1 for MCC than for MCB.) This in turn produces a narrowing of the confidence intervals. For example, for farm 20 the confidence interval is now [0.399, 0.856]. This represents a reduction of about a quarter in the size of the confidence interval. This narrower confidence intervals derived using MCC represents a reduction in the noise associated with uncertainty over which farm is the best (we just assume farm 9 is best).

The remaining width of the intervals, demonstrate that estimation error and/or multiplicity are important sources of the width of the MCB intervals. The effect of multiplicity on the width of the confidence intervals can be considered by examining the MgCB. When comparing MCB and MgCB we find that the confidence intervals have only narrowed minimally (e.g. for farm 20, the MCB width is 0.611 and the MgCB width is 0.561.) From this we can conclude that the impact of multiplicity on the confidence intervals is small. When we compare MCC and MgCB we find that MCC yields narrower confidence intervals, showing that uncertainty over [N] (the frontier) is more important than multiplicity in terms of confidence interval width.

To see how the confidence level can impact the confidence intervals derived we present in Table 6 results for 75 % confidence level.

{Approximate Position of Table 6}

The 75% critical values for MCC and MCB ranged from 1.623 to 2.403, and that for MgCB was 1.535. It is, therefore, not surprising that the MCB confidence intervals are narrower. For example, for farm 9 the confidence interval is now [0.928, 1] and for farm 20 it is [0.436, 1]. In both cases the lower bound has increased.

The 75 percent level of significance also reduces the number of farms in group one to three farms: 2, 9 and 17. In addition, the number of farms in group three has increased by one (farm 26 no longer has an upper bound of 1). The impact on the MCC confidence intervals is also obvious. Take for example, farm 20, its MCC confidence interval is [0.436, 0.783] which represents a 20 percent reduction in the width from the 95 percent MCC intervals. Finally, the MgCB confidence intervals are all slightly narrower than the MCB but still the impact of multiplicity on the results is minimal.

6. Discussion and Conclusions

In this paper we have estimated technical efficiency for a panel of wool producers in Australia. We found that the point estimates of technical efficiency imply that there exists a large degree of variation in farming practice for the sample of farms. However, when we constructed MCB, MCC and MgCB confidence intervals, the point estimates of technical efficiency were found to be subject to a significant level of statistical uncertainty.

By comparing the MCB and MgCB confidence intervals we are able to deduce that multiplicity is not important in explaining the width of the confidence intervals derived. The narrowing of the confidence intervals derived when estimating MCC as opposed to MCB intervals suggests that uncertainty over [*N*] (the frontier) is a relatively important source of uncertainty. However, the main reason for the width of the confidence intervals is statistical noise. We are therefore, in agreement with Horrace and Schmidt (1996), in that we suspect that much of the apparent variation between firms in terms of technical efficiency estimates derived using stochastic frontier models is nothing more than sampling error. These results raise important questions about the usefulness of stochastic frontier models, and frontier models in general, for comparative analysis (benchmarking).

In terms of useful information derived from the study, we can at least be sure that at the 95% confidence level for MCB that eight farms are efficient and five farms are inefficient. At the 75% confidence level there are three efficient farms and six that are inefficient.

So what are the agricultural policy implication of these results? We can roughly differentiate between sets of farms that are efficient and inefficient, but to rank farms on an individual basis within these groups is, perhaps, a vacuous proposition. This still means that with additional farm level information we could investigate reasons for differences in performance between the groups. However, to identify one particular farm as best practice relative to all others is unrealistic.

The Australian wool industry has historically benefited from large expenditures on Research, Development and Extension (Kingwell et al. 1999), and yet there is still a group of farms that are inefficient. If we could identify the reasons why a group of farms is inefficient it might be tempting to argue for targeted expenditure on extension efforts to improve overall farm-level performance for the inefficient producers.

Alternatively, maybe it is time to consider some radical policy options for the wool industry. One example that has different budgetary implications (far less government expenditure) would be to induce the retirement of inefficient farms via the use of compensatory financial incentives. This policy option could be linked with biodiversity objectives (Hone, Edwards and Fraser, 1999). Land retirement would have the same effect as an (optimal) export wool tax, in that the total supply of wool would be reduced and those producers remaining in the wool sector would be better off. The export wool tax argument arises as a result of the fact that Australian wool producers face a downward sloping demand curve for their wool because of the market power Australia wields (Edwards, 1997).

Although the results presented in this paper are relatively pessimistic about the usefulness of farm-level efficiency point estimates, we can improve matters. An obvious improvement that could be made with the data set is to increase the number of years of data. As Horrace and Schmidt (2000) acknowledge the size of N relative to T is important in determining the strength of the statistical results derived. Although the benefit of this is improved statistical robustness for the estimates derived, the assumption of time-invariant technical efficiency becomes an issue.

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Table 1
Data Summary Statistics

	Output ($)	Land (ha.)	Pasture Cost ($)	Contract ($)	Additional Feed ($)	Selling Cost ($)	DSE (No.)
Mean	128557.4	868.5	12998.4	19624.8	15863.5	17445.1	8059.6
Median	113671.7	667.0	11232.6	16172.6	11847.9	15024.6	7117.1
Standard Deviation	77467.2	563.0	9498.0	13716.2	15384.2	10864.7	4213.1
Minimum	15973.0	198.1	17.6	1238.5	32.5	363.4	1485.4
Maximum	464304.5	3116.0	45052.2	73359.1	83479.0	63901.8	23242.3

Table 2
Fixed-Effect Regression Estimates

	Model 1		Model 2		Model 3		Model 4		Model 5	
Variable	β	T	β	T	β	T	β	T	β	T
Land	0.318	1.517	0.152	0.060	0.236	1.193	-1.046	-0.387	3.075	1.077
Pasture	0.004	0.248	-0.016	-0.071	0.014	0.928	0.104	0.433	0.244	0.864
Contract	0.119	1.623	-0.298	-0.278	0.141	1.991	0.005	0.004	0.387	0.311
Feed	0.059	3.490	-0.183	-0.503	0.062	3.631	-0.312	-0.792	0.202	0.528
Selling	0.132	2.984	-1.047	-1.132	0.116	2.750	-0.918	-0.925	-2.076	-1.868
DSE	0.232	1.972	0.687	0.294	0.247	1.939	0.764	0.301	-0.284	-0.120
Land*Land			-0.230	-0.371			-0.023	-0.034	-0.489	-0.776
Pasture*Pasture			0.037	1.895			0.039	1.904	0.047	2.119
Contract*Contract			-0.069	-0.331			-0.023	-0.104	-0.197	-0.888
Feed*Feed			0.005	0.401			0.012	0.809	0.004	0.289
Selling*Selling			0.223	1.786			0.261	1.946	0.418	3.092
DSE*DSE			-0.151	-0.246			-0.026	-0.039	-0.044	-0.073
Land*Pasture			-0.048	-0.714			-0.093	-1.291	-0.035	-0.408
Land*Contract			-0.125	-0.425			-0.004	-0.012	-0.104	-0.353
Land*Feed			-0.009	-0.235			-0.021	-0.503	0.032	0.804
Land*Selling			0.119	0.524			0.149	0.611	-0.041	-0.162
Land*DSE			0.258	0.609			0.136	0.296	0.249	0.585
Pasture*Contract			0.043	0.778			0.129	2.275	0.104	1.569
Pasture*Feed			0.004	0.262			-0.001	-0.065	0.003	0.161
Pasture*Selling			0.009	0.092			-0.107	-1.095	-0.253	-2.061
Pasture*DSE			-0.052	-0.476			0.003	0.026	0.121	0.926
Contract*Feed			-0.001	-0.023			-0.023	-0.361	-0.002	-0.038
Contract*Selling			0.042	0.214			-0.023	-0.108	0.076	0.359
Contract*DSE			0.121	0.389			-0.037	-0.112	0.090	0.284
Feed*Selling			-0.001	-0.025			0.025	0.425	0.094	1.378
Feed*DSE			0.027	0.328			0.046	0.525	-0.148	-1.645
Selling*DSE			-0.214	-0.864			-0.151	-0.567	-0.135	-0.476
T	0.010	1.177	-0.152	-4.645					-0.318	-1.608
T*T			0.019	5.277					0.027	5.855
T*Land									-0.044	-1.024
T*Pasture									0.000	-0.021
T*Contract									-0.044	-1.375
T*Feed									0.000	-0.011
T*Selling									0.141	3.667
T*DSE									-0.056	-1.017
Log likelihood	45.3		85.2		44.5		66.7		96.8	

Note: Critical value at the 5% level of significance for 160 degrees of freedom is 1.6545
Critical value at the 10% level of significance for 160 degrees of freedom is 1.975

	Model 6		Model 7		Model 8		Model 9		Model 10	
Variable	β	T	β	T	β	T	β	T	β	T
Pasture	0.015	1.011	0.003	0.196	-0.030	-0.214	-0.027	-0.214	0.079	0.449
Contract	0.140	1.982	0.114	1.569	-0.245	-0.384	-0.476	-0.809	0.019	0.031
Feed	0.064	3.812	0.061	3.593	0.077	0.796	0.081	0.915	0.055	0.599
Selling	0.114	2.718	0.134	3.038	0.107	0.203	0.079	0.164	-0.805	-1.432
DSE	0.256	2.007	0.235	1.987	0.530	0.564	0.398	0.459	0.596	0.673
Pasture*Pasture					0.038	1.909	0.037	2.008	0.039	1.865
Contract*Contract					0.0053	0.026	-0.051	-0.261	-0.142	-0.684
Feed*Feed					0.0168	1.1879	0.009	0.669	0.005	0.400
Selling*Selling					0.2281	1.754	0.212	1.748	0.375	2.911
DSE*DSE					0.118	0.2059	0.045	0.085	0.015	0.028
Pasture*Contract					0.1009	2.3255	0.039	0.945	0.080	1.588
Pasture*Feed					0.0063	0.4226	0.007	0.551	0.008	0.540
Pasture*Selling					-0.108	-1.184	-0.010	-0.119	-0.227	-2.066
Pasture*DSE					0.0076	0.0677	-0.043	-0.406	0.151	1.186
Contract*Feed					-0.026	-0.459	-0.005	-0.092	0.013	0.228
Contract*Selling					0.0983	0.5254	0.145	0.836	0.115	0.612
Contract*DSE					-0.036	-0.112	0.075	0.252	0.041	0.138
Feed*Selling					-0.007	-0.124	-0.035	-0.681	0.068	1.058
Feed*DSE					0.022	0.2797	0.028	0.392	-0.126	-1.579
Selling*DSE					-0.233	-1.024	-0.260	-1.240	-0.197	-0.808
T*Pasture									0.000	-0.021
T*Contract									-0.046	-1.501
T*Feed									0.001	0.144
T*Selling									0.127	3.517
T*DSE									-0.054	-1.041
T			0.012	1.439			-0.153	-4.907	-0.331	-3.043
T*T							0.020	5.522	0.026	5.947
Log likelihood	43.6		44.9		63.2		82.3		93.1	

Note: Critical value at the 5% level of significance for 160 degrees of freedom is 1.6545
Critical value at the 10% level of significance for 160 degrees of freedom is 1.975

Table 3
Technical Efficiency Estimates (Rank Order)

Farm	$\hat{\alpha}_i$	$\hat{u}_i$	$\hat{r}_i$
9	5.467	0.000	1.000
2	5.285	0.181	0.834
13	5.229	0.238	0.788
17	5.213	0.254	0.776
7	5.164	0.303	0.739
14	5.158	0.309	0.734
16	5.150	0.317	0.728
23	5.150	0.317	0.728
21	5.146	0.320	0.726
11	5.102	0.365	0.694
4	5.093	0.374	0.688
8	5.089	0.378	0.685
19	5.066	0.400	0.670
3	5.046	0.421	0.656
5	5.044	0.423	0.655
22	5.023	0.444	0.642
15	5.014	0.452	0.636
24	4.936	0.531	0.588
26	4.933	0.533	0.587
20	4.929	0.537	0.584
12	4.780	0.686	0.503
10	4.770	0.697	0.498
1	4.767	0.699	0.497
6	4.706	0.760	0.468
18	4.693	0.774	0.461
25	4.565	0.902	0.406

$\hat{r}_i$ = ranked technical efficiency estimates.

Table 4
Spearman Rank Correlation Coefficients

Model	2	3	4	5	6	7	8	9	10
1	0.89*	0.99*	0.81*	0.82*	0.91*	0.91*	0.93*	0.92*	0.92*
2		0.89*	0.86*	0.89*	0.84*	0.84*	0.92*	0.94*	0.94*
3			0.76*	0.81*	0.86*	0.86*	0.90*	0.89*	0.88*
4				0.83*	0.93*	0.92*	0.93*	0.90*	0.91*
5					0.86*	0.85*	0.88*	0.88*	0.90*
6						0.99*	0.96*	0.93*	0.94*
7							0.96*	0.93*	0.94*
8								0.98*	0.98*
9									0.99*

* - statistically significant at five percent level

Table 5
MCB, MCC and MgCB Results (95%)

Farm	r_i	Lower Bound MCB	Upper Bound MCB	Lower Bound MCC	Upper Bound MCC	Lower Bound MgCB	Upper Bound MgCB
9	1.000	0.864	1.000	1.000	1.000	0.938	1.000
2	0.834	0.601	1.000	0.601	1.000	0.653	1.000
13	0.788	0.584	1.000	0.584	1.000	0.629	1.000
17	0.776	0.548	1.000	0.548	1.000	0.597	1.000
7	0.739	0.546	1.000	0.546	0.999	0.589	1.000
14	0.734	0.538	1.000	0.538	1.000	0.581	1.000
16	0.728	0.525	1.000	0.525	1.000	0.570	1.000
23	0.728	0.538	1.000	0.538	0.986	0.580	1.000
21	0.726	0.499	1.000	0.499	1.000	0.548	1.000
11	0.694	0.503	1.000	0.503	0.958	0.545	1.000
4	0.688	0.513	1.000	0.513	0.923	0.552	1.000
8	0.685	0.502	1.000	0.502	0.936	0.542	1.000
19	0.670	0.496	1.000	0.496	0.906	0.534	1.000
3	0.656	0.459	1.000	0.459	0.938	0.502	1.000
5	0.655	0.461	1.000	0.461	0.932	0.503	1.000
22	0.642	0.437	1.000	0.437	0.942	0.481	1.000
15	0.636	0.445	1.000	0.445	0.910	0.486	1.000
24	0.588	0.382	1.000	0.382	0.905	0.426	1.000
26	0.587	0.416	1.000	0.416	0.827	0.453	1.000
20	0.584	0.399	1.000	0.399	0.856	0.439	1.000
12	0.503	0.363	0.968	0.363	0.698	0.394	0.890
10	0.498	0.339	0.984	0.339	0.731	0.373	0.899
1	0.497	0.355	0.949	0.355	0.696	0.386	0.875
6	0.468	0.312	0.954	0.312	0.701	0.345	0.864
18	0.461	0.318	0.886	0.318	0.669	0.349	0.812
25	0.406	0.156	1.000	0.156	1.000	0.198	1.000

MCB = Multiple Comparisons with the Best Intervals.
MCC = Multiple Comparisons with a Control (sample best) Intervals.
MgCB = Marginal Comparisons with the Best Intervals.

Table 6
MCB, MCC and MgCB Results (75%)

Farm	r_i	Lower Bound MCB	Upper Bound MCB	Lower Bound MCC	Upper Bound MCC	Lower Bound MgCB	Upper Bound MgCB
9	1.000	0.928	1.000	1.000	1.000	1.000	1.000
2	0.834	0.649	1.000	0.649	1.000	0.705	1.000
13	0.788	0.626	1.000	0.626	0.993	0.676	1.000
17	0.776	0.594	1.000	0.594	1.000	0.649	1.000
7	0.739	0.586	1.000	0.586	0.932	0.632	1.000
14	0.734	0.578	1.000	0.578	0.932	0.625	1.000
16	0.728	0.566	1.000	0.566	0.937	0.615	1.000
23	0.728	0.577	1.000	0.577	0.919	0.623	1.000
21	0.726	0.544	1.000	0.544	0.968	0.599	1.000
11	0.694	0.542	1.000	0.542	0.889	0.588	1.000
4	0.688	0.549	1.000	0.549	0.862	0.592	1.000
8	0.685	0.539	1.000	0.539	0.871	0.584	1.000
19	0.670	0.532	1.000	0.532	0.844	0.574	1.000
3	0.656	0.499	1.000	0.499	0.863	0.546	1.000
5	0.655	0.500	1.000	0.500	0.858	0.547	1.000
22	0.642	0.478	1.000	0.478	0.862	0.526	1.000
15	0.636	0.483	1.000	0.483	0.837	0.529	0.996
24	0.588	0.423	1.000	0.423	0.819	0.471	0.951
26	0.587	0.451	0.996	0.451	0.764	0.492	0.913
20	0.584	0.436	1.000	0.436	0.783	0.480	0.916
12	0.503	0.392	0.855	0.392	0.647	0.425	0.784
10	0.498	0.371	0.867	0.371	0.669	0.409	0.789
1	0.497	0.384	0.831	0.384	0.644	0.418	0.766
6	0.468	0.343	0.822	0.343	0.638	0.380	0.745
18	0.461	0.347	0.792	0.347	0.614	0.381	0.724
25	0.406	0.195	1.000	0.195	0.846	0.248	0.866

MCB = Multiple Comparisons with the Best Intervals.
MCC = Multiple Comparisons with a Control (sample best) Intervals.
MgCB = Marginal Comparisons with the Best Intervals.