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Farm-level efficiency and productivity measurement using panel data: wool production in south-west Victoria[†]

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In this article we explore some issues surrounding the use of farm-level efficiency and productivity estimates for benchmarking studies. Using an eight-year balanced panel of Victorian wool producers we analyse annual variation between estimates of farm-level technical efficiency derived using Data Envelopment Analysis and Malmquist estimates of Total Factor Productivity. We find that farms change their relative rank in terms of efficiency across years. Also, unlike aggregate studies of Total Factor Productivity, we find at best erratic and modest growth, a worrying result for this industry. However, caution is needed when interpreting these results, and for that matter, benchmarking analysis as currently practised when using frontier estimation techniques like Data Envelopment Analysis.

1. Introduction

The comparative analysis of individual farm performance measures (i.e. benchmarking) to identify scope for improvements in farm management at the individual farm level has a long history in farm management studies both in Australia and overseas. The basis for the comparison between individual management units varies from narrow-based partial measures such as labour productivity, land productivity and yields, to broader measures based on overall profitability, total factor productivity and economic efficiency (technical and allocative). Some recent examples in the agricultural economics literature are Fraser and Cordina (1999), and Jaforullah and Whiteman (1999).

While the concept of benchmarking seems to have been adopted and widely supported as a contemporary management tool in virtually all sectors

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of the economy,[1] there has been considerable debate about its value as a management tool in farming. For example, Ferris and Malcolm (1999) contended that benchmarking, as it is widely practised in agriculture, can be misleading because it concentrates on differences in average production measures between farms, rather than focusing on optimising firm-specific functions at the margin.

In this article we contribute to the debate by examining farm-level efficiency measures as benchmarking tools. Farm-level efficiency and productivity changes are estimated for a sample of south-west Victorian wool farms. The estimates of overall farm performance derived from the sample panel data set are assessed in terms of the information they provided for farm management decision-making. To facilitate this we employ Data Envelopment Analysis (DEA) to derive the efficiency estimates from a panel data set.

Unlike much of the existing literature that employs panel data to estimate farm-level efficiency and productivity change, as opposed to reporting point (average) estimates of farm-level efficiency for the entire data period, we focus on the annual estimates. The reason for focusing on annual estimates is because we wish to examine how technical efficiency varies through time at the farm level. The examination of the annual farm-level efficiency estimates provides important insights into the agricultural benchmarking literature. Furthermore, by estimating annual farm-level technical efficiency we can estimate and examine productivity change in our data set using Malmquist Total Factor Productivity (TFP) indices, another important benchmarking measure.

The specific objectives of this study are twofold. First, we assess the value of estimates of technical efficiency and productivity growth as benchmarking tools. We do this by estimating both changes in annual farm-level technical efficiency and the influence of these changes on estimates of productivity growth. In agriculture there is good reason to think that there may well be short-term random fluctuations in production that impact upon the estimation of technical efficiency and productivity change, but are not related to technical efficiency and productivity change as normally defined. Rather, these fluctuations are the product of the farm-specific activities and events. For example, there may be a disease or pest outbreak that can affect a single year's production and hence *ex-post* measures of efficiency. Alternatively, it may be necessary for a farm to re-seed, renovate or to establish a new paddock. The outcome will be such that there will be an increase in input use

[1] Benchmarking has become particularly popular in helping with the regulation of public utilities (e.g., Electricity Supply Association of Australia Limited, 1994, and ORG, 1998).

and a reduction in output, although in the longer run, the physical capacity of the farm increases and input use will decrease. The short-term fluctuation will reduce estimates of technical efficiency but is the farm any less efficient? By reporting year-to-year estimates we can provide insights into the limitations of employing cross-sectional or very short time-frame data sets to analyse technical efficiency and productivity change. Little or no attention is paid to the year-to-year variation in efficiency estimates.[2] In this article, by focusing on annual estimates of technical efficiency and productivity change, we raise questions about the necessary length of a panel data set.

Second, there are only a few studies of economic (technical and allocative) efficiency and productivity of the Australian wool industry. In terms of economic efficiency, Lawrence and Hone (1981) presented an econometric examination of relative technical and allocative efficiency for a sample of grazing properties in the high rainfall zone of New South Wales for 1975–76, using a restricted profit function. Employing an econometric specification based on Lau and Yotopoulos (1971), they tested to see if differences existed between large and small properties in terms of allocative and technical efficiency, and if operator's age influenced efficiency. They found larger farms to be more economically efficient than small but age did not affect efficiency. However, Lawrence and Hone could not reject absolute allocative efficiency based on size and therefore could not test for technical efficiency. Furthermore, they found that over the entire sample constant returns to scale prevailed. Lawrence and Hone acknowledged some of the limitations of the approach they used, in particular the cross-sectional data. Specifically, they noted that producers have long-term development plans or objectives that will take several years to come to fruition, so that evaluating efficiency from a single year's data may give rise to biased results.

The only study to address technical efficiency in the wool sector using DEA is by Chapman *et al.* (1999). Using data drawn from a specialist wool survey carried out by ABARE in 1997–98, they employ DEA to estimate technical efficiency. The focus of their study is the regional distribution of technical efficiency across the whole of Australia. Not surprisingly, Chapman *et al.* find that technical efficiency is strongly correlated with seasonal weather conditions within specified production regions. However, this study does not report any measures of technical efficiency or productivity change.

In terms of productivity estimation for the wool sector, there are a larger number of studies. A good example is Lawrence and McKay (1980) who

[2] In the stochastic frontier literature, time-varying technical efficiency estimates can be derived (Coelli *et al.* 1998 and Kalirajan and Shand 1999). Authors typically report average sample estimates or subsets of estimates for technical efficiency for the panel (e.g., Ahmad and Bravo-Ureta 1996).

employed Tornqvist quantity indexes to examine productivity change for the sheep industry between 1952–53 and 1976–77. Over this period they estimated that the industry had experienced productivity growth of 2.9 per cent per annum. Another study by Coelli and Kingwell (1991) examined western Australia's wheat and sheep industry. Using ABARE data, and employing Tornqvist indexes, they found that from 1952–53 through to 1987–88, annual productivity growth was 2.7 per cent. More recently, Mullen and Cox (1996) have measured productivity growth in broadacre agriculture, reporting annual estimates of between 2.4 and 2.6 per cent. Although this study does not focus on the sheep industry exclusively, it is an important component of the data set. Finally, Stoneham *et al.* (1999) estimated annual productivity growth using Fisher's Index for various agricultural sectors in Victoria, New South Wales, Western Australia, South Australian and Queensland. Using data collected by ABARE they found that for the Victorian sheep industry between 1977–78 and 1996–97 there was zero productivity growth, compared to 1.9 per cent in Queensland and 0.4 per cent for the Australian sheep industry as whole.[3]

A feature of virtually all the above studies is that they have been conducted at an agricultural zone or national level for sheep/wool producers. There is, therefore, an important gap in the agricultural economics literature that examines economic efficiency and productivity at the farm level. However, given that we wish to also examine the weakness of current benchmarking methods, the results we present in this article need to be treated cautiously.

The structure of this article is as follows. In the following section we review the meaning of technical efficiency and how to estimate technical efficiency using DEA and Malmquist TFP indices. The third section describes the data used in the analysis and important assumptions underpinning our analysis. Then the results of our analysis are presented. The results are divided into two sections, the technical efficiency estimates and the Malmquist TFP estimates. In the final section we discuss the results presented and provide conclusions.

2. Theory and estimation

The efficiency of a production system comprises two elements: technical efficiency and allocative efficiency. Technical efficiency measures the ability of a farm to produce maximal output from a given set of inputs, and allocative efficiency measures the ability of a farm to optimise on the use of

[3] Kingwell *et al.* (1999) provide a useful summary of wool productivity research in Australia.

inputs given their respective prices (Coelli 1995). In this article we focus exclusively on technical efficiency.

Farrell (1957) introduced a method to measure efficiency directly from observed data, for a single output (product) and multiple inputs. The basic approach is to estimate a frontier that envelops all the input–output data with observations lying on the frontier defined as technically efficient. Observations below the frontier are considered inefficient. That is, it is possible to reduce inputs while maintaining output or to use the same level of input use and increase output. This approach to measuring technical efficiency yields a relative measure — the efficiency of a farm relative to all others farms in a sample.

There are several techniques available, parametric and non-parametric, to estimate technical efficiency. The most widely used example of a non-parametric technique is DEA (Coelli, 1995; Seiford, 1996). Parametric techniques encompass stochastic frontier techniques and Bayesian methods (Kalirajan and Shand 1999). In this article we employ DEA to estimate both technical efficiency and Malmquist TFP indices. The reason for the choice of DEA as the method of estimation is that the methodology has been employed widely to conduct benchmarking analysis (for example, see Jaforullah and Whiteman 1999).

2.1 Data Envelopment Analysis

With DEA it is possible to measure technical efficiency using either output-oriented or input-oriented specifications. Assuming constant returns to scale (CRS) means that the input and output orientations provide equivalent measures of technical efficiency. In this article we employ an output-oriented measure of technical efficiency which considers by how much output can be increased, holding inputs constant. To estimate technical efficiency for the sample of sheep farms we employ the following CRS model.

$$Max_{\phi\lambda}\phi \tag{1}$$

subject to

$$-\phi y_i + Y\lambda \geq 0 \tag{2}$$

$$x_i - X\lambda \geq 0 \tag{3}$$

$$\lambda \geq 0 \tag{4}$$

where $1 \leq \phi \leq \infty$ and $\phi - 1$ measure the proportional increase in output that can be achieved by the i-th farm, with inputs held constant, and λ is a $N \times 1$ vector of constants. Hence, $1/\phi$ measures technical efficiency and estimates will lie between zero (inefficient) and one (efficient). The above model

(Equations (1)–(4)) is estimated over t time periods as we employ a panel data set and it is the annual estimates of technical efficiency that we focus on.[4]

A limitation of DEA is that measurement error is not accounted for. A stochastic frontier specification can be employed to deal with this aspect of the data-generating process. Although stochastic frontier techniques (i.e. Classical and Bayesian) may yield slightly different estimates of efficiency, Neff *et al.* (1993) and Sharma *et al.* (1997), found that estimates derived using DEA and other frontier estimation techniques are not statistically different from each other.[5]

2.2 Malmquist TFP index

The Malmquist TFP index provides an assessment of productivity growth by measuring the change between two data points, where a data point consists of inputs (x) and output (y). The Malmquist index is calculated by taking the ratio of the distance of each data point relative to a common technology. In practice the common technology is defined as the efficiency frontier derived from the DEA based on the sample data.

Following Fare *et al.* (1994), the Malmquist output-orientated TFP change index between periods 1 (the base period) and 2 (the subsequent period) is calculated as follows:

$$m_0(y_1, x_1, y_2, x_2) = \left[\frac{d_0^1(y_2, x_2)}{d_0^1(y_1, x_1)} \times \frac{d_0^2(y_2, x_2)}{d_0^2(y_1, x_1)}\right]^{0.5} \tag{5}$$

where $d_0^1(y_2, x_2)$, for example, is a distance function that measures the distance from period 2 data (input/output mix) to a period 1 technology (efficiency frontier). Similarly the other distance functions measure the distance between data points and a particular technology (i.e. year 1 or 2). Like the DEA specification, each of the distance functions is calculated as a linear program. To interpret the Malmquist index, when m_0 is greater than 1 this indicates that the TFP index has grown between periods 2 and 1 while m_0 less than 1 indicates that TFP has declined.

[4] In the DEA literature, Window Analysis introduced by Charnes *et al*. (1985) can be used to examine panel data. Given the limited use of Window Analysis in the literature to date we decided not to employ that methodology.

[5] A referee observed that DEA efficiency estimates are intransitive because each observation is based on a unique benchmark. This means that some farms can have lower efficiency simply because they are being compared against a tougher benchmark. However, we implicitly assume that all farms have access to a common technology and those farms on the frontier are using it most efficiently. This means that the benchmark is common to all farms in the sample. We are of the opinion that this is a reasonable assumption given the technically homogeneous nature of our sample.

An alternative way in which to represent the Malmquist index is as follows:

$$m_0(y_1, x_1, y_2, x_2) = \frac{d_0^2(y_2, x_2)}{d_0^1(y_1, x_1)}\left[\frac{d_0^1(y_2, x_2)}{d_0^2(y_2, x_2)} \times \frac{d_0^1(y_1, x_1)}{d_0^2(y_1, x_1)}\right]^{0.5} \tag{6}$$

By re-expressing the Malmquist index in this way we have derived the following components. The first term on the right-hand side of equation (6) measures the change in the output-oriented measure of technical efficiency between period 2 and 1. This is referred to as efficiency change. The second term on the right-hand side of equation (6) measures technical change and is measured as a geometric mean in the shift in the production technology between period 2 and 1 evaluated at the respective input levels, x_2 and x_1. Although it is not necessary, we follow Fare *et al.* (1994) for the purpose of consistency and impose CRS for the calculation of the Malmquist Index.

3. Data and estimation

The data used in the analysis are taken from the South West Victorian Monitor Farm Project (SWVMFP) survey (Patterson *et al.* 1998). The SWVMFP has been collecting farm level data for 28 years up to and including 1997–98. To conduct the analysis we constructed a balanced panel. Due to various changes in data collection and attrition amongst the sample of farms we were able to construct a data set from 1990–91 up to 1997–98 (8 years). Over this period 26 wool producers remained in the survey.

The survey predominantly focuses on wool-based farms although there is also beef and prime lamb production. Farm size varies between 120 and 3110 hectares, with numbers of sheep from zero to 16 846. Currently in the SWVMF there are 40 farms running sheep/wool enterprises with the average farm measuring 895 hectares with 5712 sheep. Although average enterprise mix in the SWVMF is 65 per cent wool, the importance of wool is significantly higher in our sample of farms. In 1998 for example, the average enterprise mix in our sample is 83 per cent wool, with a mode of 100 per cent. Similarly for 1991 the average enterprise mix is 90 per cent wool with a mode of 100 per cent.

An important feature therefore, of this study is that the data set controls for several factors that might influence production, but are not related to managerial ability. For example, all the farms are drawn from a relatively homogeneous geographical region and are subject to similar weather and agronomic conditions. By controlling for weather and location decisions we assume that these factors will not significantly influence the technical efficiency estimates obtained.

The reason why we focused on wool specifically is that had we also included other outputs then we would have had to aggregate inputs across all outputs to retain sufficient degrees of freedom during estimation. An important feature of the SWVMFP is that it provides farm-level, activity-specific input and output data. In this study we use the wool activity data. On the input side many variable inputs are reported such as contract labour, pasture costs, animal health, selling costs, and supplementary feed. All are reported in terms of dollar cost per dry sheep equivalent (dse) per hectare (deflated by the CPI). Average annual rainfall (mm per year) is also included as an input as a proxy for local weather variation. On the output side the wool cut (kilograms) is reported per dse per hectare. In order to accommodate the difference in wool quality (micron size) produced by the sample farms we employ the value of the wool cut in the DEA analysis. The value of wool cut is estimated at constant prices with a base of the average price for the period 1991–92 to 1997–98.

We acknowledge that there are limitations with the data set. Most obvious is that the data does not contain a measure of capital stock. It is common practice to include a measure of capital in an efficiency study. However, we effectively assume that all inputs (excluding rainfall) and output are normalised with respect to capital, where capital is proxied by number of dses. This means that we are assuming constant returns to the capital input on the farm, implying that we are estimating a conditional measure of farm-level efficiency. It may also be argued that we need to include a measure of information technology use on the farms. For example, the use of expert systems to help guide wool producers in drenching practices has been considered (Bishop-Hurley and Nuthall 1994). However, the data currently available preclude us from including any measure of the adoption and use of information technology.

Another limitation with the data set is that the number of farms in the panel data set we constructed means that it was necessary to aggregate some inputs to derive meaningful technical efficiency estimates. Chambers *et al.* (1998) suggest there should be at least three times as many firms as there are inputs in a DEA model. As a result of this we have aggregated pasture costs and supplementary feed to yield an overall measure of feed availability per dse per hectare, and we have also aggregated animal health expenditures and selling cost to yield a measure of other costs incurred per dse per hectare. Summary descriptive statistics of the data used in the analysis are given in table 1.

The summary statistics presented in table 1 indicate that there is quite a large degree of variation in the data. We therefore expect that there will be a significant degree of variation in the estimates of the technical efficiency and productivity.

Table 1 Output and input variables: summary statistics

	Output ($/dse/hec)	Contract labour ($/dse/hec)	Feed ($/dse/hec)	Other ($/dse/hec)	Rain (mm per annum)
Mean	160.4	23.6	37.9	29.2	615.4
Median	148.4	23.1	32.8	28.7	621
Standard Deviation	66.7	8.6	23.8	11.3	76.5
Minimum	32.9	3.1	0.18	6.2	425
Maximum	432	50.8	109	76.9	820

4. Results

4.1 DEA results

The results of estimating the DEA output-orientated CRS specification are presented in table 2. The first thing to note about the results in table 2, is that only one farm, farm 9, is fully technically efficient throughout the entire data period. Most farms appear on the frontier in one or more years but also lie well within the frontier in other years. For example, farm 17 was on the frontier in 1995 and 1996 but recorded a technical efficiency score of only 0.665 in 1994. So had 1994 been the cross-section of data that we had used to estimate technical efficiency, farm 17 would have been considered as being technically inefficient. However, had we picked either of the two following years in which to undertake the analysis, farm 17 would have been seen to be technically efficient.

There is no obvious pattern in the variation in efficiency scores. Farm 25 is on the frontier in the first four years of the study period and substantially within the frontier for the last four years. Conversely, farm 17 is well within the frontier in the first four years, but then best practice in the later years. This raises an interesting question: for those farms that are technically efficient some of the time, does the pattern of variation in technical efficiency mean that they are displaying varied managerial ability? In terms of the group of farms that are never fully technically efficient (like farm 11) does this mean that we have identified a group of farms that are truly inefficient or is there something in the current modelling specification that is inappropriate?

In terms of the level of technical efficiency exhibited by our sample of farms, there is a large variation in the estimates derived. The minimum estimate is 0.35 for farm 12 in 1996, while overall farm 1 recorded the lowest average at 0.529. The average efficiency score across the entire sample period for all farms is around 0.8 and this suggests that there is some room for improvement in terms of converting inputs into output. Four farms recorded

Table 2 Farm-level technical efficiency scores: DEA CRS output orientation

Farm	1991	1992	1993	1994	1995	1996	1997	1998	Average
1	0.41	0.60	0.55	0.53	0.50	0.67	0.46	0.51	0.53
2	1.00	1.00	0.77	0.93	1.00	0.83	1.00	1.00	0.94
3	0.68	1.00	1.00	0.92	0.81	1.00	0.87	0.79	0.88
4	0.62	0.71	0.86	0.77	0.69	0.84	0.70	0.63	0.73
5	0.75	0.81	0.89	1.00	0.98	0.77	0.79	0.71	0.84
6	0.64	0.54	0.59	0.65	0.78	1.00	0.71	0.77	0.71
7	0.91	0.80	0.79	0.98	1.00	0.99	0.93	0.82	0.90
8	0.90	0.80	0.92	0.80	0.86	0.71	0.82	0.78	0.82
9	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
10	0.69	0.50	0.74	0.57	0.68	0.82	0.63	0.57	0.65
11	0.76	0.83	0.79	0.81	0.79	0.86	0.81	0.86	0.81
12	0.54	0.62	0.59	0.74	0.51	0.35	0.49	0.50	0.54
13	0.89	0.82	1.00	1.00	1.00	1.00	1.00	1.00	0.96
14	0.99	0.94	0.69	0.84	0.84	0.89	0.71	0.77	0.83
15	0.89	0.90	1.00	0.77	0.85	0.58	0.74	0.58	0.79
16	0.72	0.71	1.00	0.95	0.78	0.95	0.90	0.77	0.84
17	0.64	0.81	0.79	0.67	1.00	1.00	0.90	1.00	0.85
18	0.51	0.73	0.48	0.68	0.83	0.59	0.79	0.61	0.65
19	0.95	1.00	0.94	0.91	0.93	0.90	0.88	0.84	0.92
20	0.62	0.73	0.75	1.00	0.87	0.86	0.61	0.54	0.75
21	0.96	0.78	1.00	0.87	0.84	0.96	0.71	0.64	0.85
22	0.75	0.69	0.88	0.66	0.67	1.00	0.69	0.61	0.74
23	1.00	0.93	0.94	1.00	0.96	1.00	0.72	0.97	0.94
24	1.00	0.82	1.00	1.00	0.76	0.99	0.70	1.00	0.91
25	1.00	1.00	1.00	1.00	0.77	0.78	0.87	0.63	0.88
26	0.75	0.74	0.70	0.76	0.85	1.00	1.00	0.76	0.82
Average	0.79	0.80	0.83	0.84	0.83	0.86	0.79	0.76	0.81
Median	0.75	0.80	0.87	0.85	0.84	0.89	0.79	0.77	0.84
Mode	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	N/A
Standard Deviation	0.18	0.14	0.16	0.15	0.14	0.17	0.15	0.17	0.12
Minimum	0.41	0.50	0.48	0.53	0.50	0.35	0.46	0.50	0.53
Maximum	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

average efficiency scores of less than 0.7. Finally, as would be expected, the standard deviation for the average estimates of technical efficiency is smaller than for any individual year. This is a reflection of the fact that variation in the estimates is reduced when we focus on average scores.

In terms of explaining the estimates of technical efficiency, Sale (1995) has suggested that for wool producers in south-west Victoria levels of phosphorous applications and enterprise mix are important explanatory factors. To see if this conjecture was supported by the estimates derived, the correlation between the estimates of technical efficiency, and phosphorus and enterprise mix were calculated. Reliable data on actual physical quantities of phosphorus used by the farms are only available from 1995. Over the four-year period the correlation coefficient estimate was 0.1487 while for the last two years it was 0.1579. For a measure of enterprise mix, based on wool as a percentage of overall farming activity, and technical efficiency the correlation coefficient over the 8 years was -0.027, from 1995–98 it was -0.086 and for the last two years -0.261.

These results provide some support for Sale (1995). The positive correlation coefficient for phosphorus implies that higher applications results in higher technical efficiency. The negative correlation coefficient for enterprise mix means that farms that are more diverse have higher technical efficiency. However, the statistical significance of these results is very weak. The only statistically significant correlation at the 5 per cent level of significance is for the last two years for enterprise mix and technical efficiency.

To assess if the technical efficiency estimates provide statistical evidence of a stochastic pattern and incidence of technical efficiency among the sample farms, we examine the statistical relationship between the annual estimates. To examine the relationship between the sets of efficiency scores we estimate Spearman Rank Correlation Coefficients (SRCC). The SRCC is used to measure the strength of the relationship between two variables, in our case technical efficiency estimates, that have been ranked ordinally from lowest to highest. The SRCC takes values between plus and minus one, with plus one indicating an exact positive relationship between the two variables. These results are presented in table 3.

The results in table 3 show that the correlation between ranks across years is positive and generally statistically significant, but not always high. In most years the SRCC is less than 0.6, with only three correlations between individual years higher than 0.7. The SRCC estimates suggest that 1996 was an abnormal year. The ordering of farms in 1996 was found to be statistically uncorrelated with the rankings in all of the earlier years, indicating that the ranking of technical efficiency estimates can change significantly through time. However, it is also found that the SRCC for 1991 and 1998 is positive and statistically significant, pointing to the likelihood that over the long run the relative performance of farms is stable.

We should not be surprised by these results, as farm-specific factors will mean that the position of farms in relation to the production frontier varies through time. However, the fact that the years furthest apart, 1991 and 1998, are not statistically different from each other, suggests that while variations as a result of farm-specific factors can alter the relative rank of farms on a year-to-year basis, farms maintain their relative rank in terms of technical efficiency over the long run.

Table 3 Spearman Rank Correlation coefficients estimates for efficiency ranks

Year	91	92	93	94	95	96	97	98
92	0.708* 0.000							
93	0.508* 0.002	0.540* 0.004						
94	0.610* 0.001	0.626* 0.001	0.632* 0.001					
95	0.413* 0.036	0.564* 0.003	0.219 0.282	0.513* 0.007				
96	0.262 0.196	0.167 0.414	0.288 0.154	0.205 0.314	0.298 0.139			
97	0.408* 0.038	0.578* 0.002	0.351** 0.078	0.392* 0.048	0.706* 0.000	0.388* 0.050		
98	0.579* 0.002	0.610* 0.001	0.411* 0.037	0.469* 0.016	0.621* 0.001	0.621* 0.001	0.702* 0.000	
Average	0.758* 0.000	0.785* 0.000	0.660* 0.000	0.765* 0.000	0.693* 0.000	0.516* 0.007	0.710* 0.000	0.835* 0.000

Notes: Top number is Test Statistic, bottom number is two-tailed level of significance.
* $-p < 0.05$ is statistically significant.
** $-p < 0.1$ is statistically significant.

Another interesting result presented in table 3 is the statistical relationship between the individual years and the pooled average of all years. It is common practice to report, when using panel data, average measures of technical efficiency. In all cases the SRCC is positive and statistically significant although the size of the SRCC ranges from 0.516 in 1996 to 0.835 in 1998. The average estimates derived from a panel data set will, to a certain extent, take account of measurement error and provide a more accurate measure of farm level efficiency. However, the average measures also factor out agronomic variability that might be important in explaining farm technical efficiency variation. Only by examining year-to-year estimates can this variation, which need not be measurement error, be observed.

4.2 Malmquist TFP results

Given the large variation in technical efficiency estimates it is important to see the impact that this has on Malmquist TFP estimates. The Malmquist TFP results for the whole sample of wool farms are reported in table 4 and depicted in figure 1.

Table 4 Malmquist TFP results: annual sample averages

Year	Efficiency change	Technical change	TFP change
1991	1	1	1
1992	1.230	0.932	0.953
1993	1.036	1.180	1.223
1994	1.011	0.705	0.712
1995	0.990	0.876	0.868
1996	1.027	1.344	1.381
1997	0.919	0.959	0.882
1998	0.958	0.988	0.947
Mean	0.994	0.980	0.974

The results presented in table 4 and figure 1 show that TFP growth has been volatile with little apparent trend. The changes in TFP growth closely follow changes in technical progress with changes in technical efficiency having had little impact on TFP. The years 1994 and 1995 appear to be outliers in the pattern of estimates derived. The variation in the estimates reported in table 4 and illustrated in figure 1 can also mean that we can alter significantly the way in which we could report upon efficiency change, technical change and TFP growth. For example, in 1996 TFP appears to have increased by 38 per cent when compared to the previous year. However, in 1997 measured TFP fell by 12 per cent. Over the whole of the sample period TFP fell at an average rate of nearly 2.5 per cent a year. This estimate of TFP is very different to the positive estimates reported for the industry

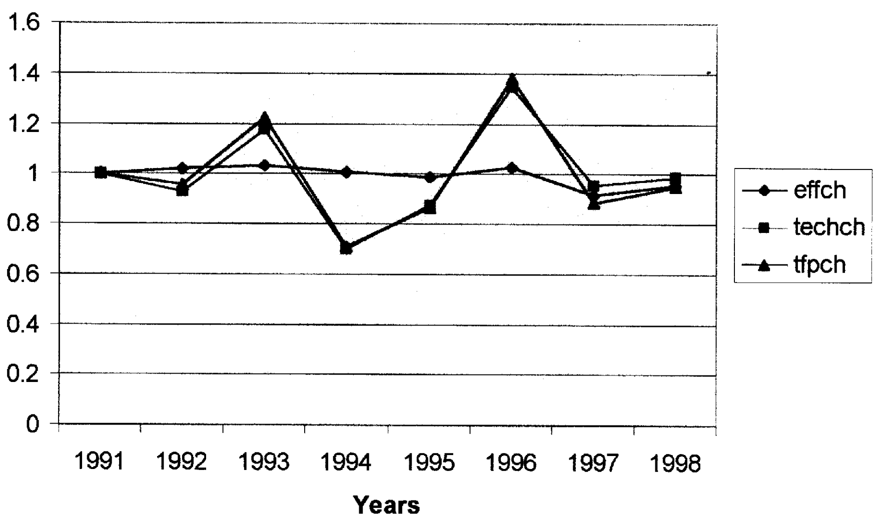

Figure 1 Malmquist TFP results

by Mullen and Cox (1996), but more in keeping with Stoneham *et al.* (1999).

The only comparable farm-level results to those presented here were reported by Te Kloot and Anderson (1977). They used farm-level data for a single grazing property in the semi-arid Queensland pastoral zone to estimate technical change between 1937 and 1970. Te Kloot and Anderson estimated that this property experienced negative technological change over this period, although they question the statistical validity of the results they obtained and the data used.

The variation of TFP within the sample for the individual farms is even more striking as can be seen in table 5. The results in table 5 again illustrate the within-sample variation that occurs. If we take farm 9 as an example, the variation in TFP is most marked in 1995–96. This extremely high estimate of TFP can be partly traced back to the technical efficiency estimate in the previous two years when TFP growth was substantially negative.

Table 5 Malmquist TFP results: farm level

Farm	91–92	92–93	93–94	94–95	95–96	96–97	97–98
1	1.353	1.065	0.809	0.877	1.506	0.637	1.083
2	0.892	0.862	0.797	1.018	0.807	1.232	1.045
3	2.331	0.819	0.505	0.792	2.049	0.702	0.870
4	1.014	1.383	0.741	0.816	1.604	0.792	0.854
5	0.955	1.285	0.892	0.906	0.982	1.045	0.879
6	0.768	1.272	0.905	1.104	2.191	0.556	1.016
7	0.843	1.137	0.998	1.015	1.163	0.939	0.859
8	0.867	1.279	0.740	0.912	1.122	1.104	0.981
9	0.964	1.181	0.810	0.851	1.727	0.955	0.944
10	0.704	1.866	0.579	1.060	1.294	0.740	0.959
11	1.050	1.222	0.593	0.891	1.140	0.896	1.027
12	1.092	1.112	1.025	0.616	1.044	1.315	0.946
13	0.949	1.382	0.793	0.892	1.290	1.054	0.957
14	0.918	0.873	1.027	0.870	1.434	0.747	1.037
15	1.013	1.685	0.445	0.978	0.923	1.301	0.736
16	0.967	1.776	0.515	0.747	1.846	0.945	0.933
17	1.258	1.124	0.687	1.388	1.037	0.821	1.202
18	1.323	0.904	0.739	0.968	1.163	1.305	0.688
19	0.936	1.032	0.924	0.824	1.358	1.016	0.826
20	1.150	1.163	0.910	0.720	1.304	0.719	0.787
21	0.806	2.048	0.296	0.864	1.294	0.715	0.875
22	0.855	1.597	0.454	0.842	3.014	0.642	0.974
23	0.780	1.103	1.073	0.771	1.383	0.721	1.159
24	0.732	1.514	0.717	0.662	1.946	0.625	1.919
25	0.454	0.993	0.538	0.591	1.557	1.110	0.808
26	0.877	1.061	0.815	0.952	1.344	0.993	0.775
Average	0.953	1.223	0.712	0.868	1.381	0.882	0.947

Other striking results are for farm 22 in 1995–96, and the within-sample variation provided by farm 21 in 1992–93 compared to 1993–94. These results serve to show that farm-level results can display a great deal of variation, making interpretation of the results in a conventional benchmarking context very difficult.

5. Conclusion

In this article we have analysed and estimated technical efficiency and TFP for a panel data set of wool producers. Our results indicate that there are significant statistical differences between the technical efficiency estimates across the years in the panel. This type of variation is generally ignored in technical efficiency studies. Most studies of efficiency that are based on panel data discuss technical efficiency in terms of overall sample estimates. However, we have seen that for a large proportion of the farms in the sample, estimated technical efficiency varies widely over the data period. For this reason we are cautious about the interpretation of our estimates of technical efficiency and productivity change. Hence, the results presented in this study lend support to the sceptical views expressed by Ferris and Malcolm (1999) about the role of benchmarking in agriculture.

Whether the year-by-year variation in technical efficiency observed is statistically significant needs to be assessed on a farm-by-farm basis. There already exist methods for assessing the statistical significance of DEA efficiency estimates within a year. Simar and Wilson (1998) use bootstrapping techniques to construct confidence intervals for DEA point estimates of technical efficiency. But for the between-year variation in efficiency estimates, no method currently exists to assess statistical significance.

The results from this study tentatively suggest that, over the data period, most farms operated at or near the frontier in at least some of the years studied. Moreover, the average technical efficiency score in most years is around 0.8. This reflects a reasonably high level of measured efficiency on the part of most farms in most years. However, there are substantial differences in overall performance between farms. The potential production differences between the highly efficient farms and the least efficient are generally consistent with the potential for an almost doubling of production on the less efficient farms without changing the level of their input use; for example, compare farms 1 and 12 with farms 9 and 13.

TFP growth on these farms has tended to be erratic and modest when measured over the whole of the time period. The Malmquist TFP results reflect a worrying picture for this industry. In the face of considerable downward pressures on profits from declining wool prices, farms in this region have not been able to identify areas for substantial sustained productivity growth. The continuation of this pattern means that economic recovery for these farms rests largely with a substantial recovery in wool prices. Importantly, this is beyond the control of individual farmers and probably beyond the influence of the industry as a whole. However, no inferences can be drawn from these results concerning the relative values of research and extension programs. That would require information on marginal research and extension returns rather than the average data revealed here.

The pattern of TFP change tends to be driven more by technical change (or technical progress) rather than improvements in technical efficiency. That is, the expansion and contraction of the underlying product frontier have had more to do with driving productivity growth than the success of farms in moving closer to the frontier. The Malmquist results show that the production frontier has contracted by around 2 per cent a year on average over the sample period. This result can largely be explained by substantial changes that occurred in both 1994 and 1995, a period of abnormal seasonal conditions in the study region. Therefore, the contraction in the production frontier over this two-year period reflects a constraint on production possibilities due to seasonal conditions rather than technical regress.

However, seasonal conditions are unlikely to explain the contractions in the production surface in 1992, 1997 and 1998. These contractions are consistent with a longer-term run-down in the productive potential of the study farms. This decline in productive potential could be explained by a general reduction in the quality of managerial decision-making among best practice farms, a deterioration in the natural resource base of the farms or possibly a decline in capital stocks not captured by our proxy measure for capital. Regardless of the reason for this decline, it has potentially serious implications for the longer-term financial viability of these farms.

Finally, the evidence we have presented of substantial variations in efficiency estimates between years points to the need for considerable caution in interpreting farm-level data based on an individual year's data or even averages across a number of years. Variations between years could reflect changes in managerial performance and may indicate the difficulty that is involved in sustaining a high level of efficiency in a complex production system. However, the variations could also reflect many other factors that are not associated with managerial inefficiency. For example, pasture renovation phases or production risks such as the chance outbreaks of disease can be consistent with both an optimal management strategy and a substantially reduced production level in any given year. In the dynamic market environment in which wool producers operate, efficiency needs to be measured in terms of a path of production decisions over time rather than as a ratio in any one particular year. The length of this time path will differ between production settings depending on factors such as investment planning cycles, and the nature and extent of production risk. For this reason we conclude that the necessary length of a panel data set must be at least as long as the economic cycles within a particular sector.

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