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Comparing efficiency estimates from familiar stochastic frontier models

Beatrice Conradie

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About the author:

Beatrice Conradie is an associate professor in the School of Economics and a researcher in the Sustainable Societies Unit of the CSSR. She runs the Karoo Predator Project and is specialised in Total Factor Productivity Modelling.

Comparing efficiency estimates from familiar stochastic frontier models

Abstract

This paper compares the total factor productivity (TFP) scores generated from two panel datasets with two common stochastic frontier methods. Likelihood ratio tests determine model specification as usual. The first dataset (sheep) reveals that while there is sometimes little practical difference between the estimates obtained with the two methods, they can vary systematically and appear to be biased upwards by the more flexible error components method. There is even stronger evidence from the wine panel that this is in fact the case, and differences increase as time passes. It also seems as if the less flexible error components model emphasizes fixed factors (land, labour) over variable inputs (feed, chemicals, fuel). The two methods produced similar conclusions about the error structure. Model selection can therefore be a matter of convenience, but comparisons between studies should be handled with care.

1 Introduction

The different ways to determine total factor productivity include index number methods, non-parametric programming and stochastic frontier models. In datasets that cover long periods, the objective is often to determine technical change usually with index number methods (e.g. Conradie et al., 2009; Salim and Islam, 2010). For cross section data or short fat panels where technical change is unlikely, the emphasis is more commonly on measuring and understanding efficiency changes. In this case the literature prefers stochastic frontier methods in which estimates come with confidence intervals to data envelopment analysis which applies a linear programming algorithm to compute efficiency scores. Occasionally one comes across studies which compare parametric and non-parametric approaches (e.g. Andor and Hesse, 2011; Huynh-Truong, 2009; Bojnec and Latruffe, 2009) or Cobb Douglas and translog specifications of the same production frontier (e.g. Naqvi and Ashfaq, 2013; Conradie 2017), but different variants of the stochastic frontier method are not routinely compared.

Two of the most common stochastic frontier methods are the error components (Battese and Coelli, 1992) and technical efficiency effects models (Battese and Coelli, 1995). The latter is popular because it conveniently fits a frontier and explains deviations from it in a single step which generates noisy efficiency estimates. Consequently, efficiency trends from these models are often not reported (e.g. Piesse et al., 2018), or are smoothed by fitting secondary regressions (Conradie et al., 2009). The error components method which fits monotonically increasing or decreasing sets of scores generated from a mean divergence (η) trend and the dispersal of scores in the terminal period (u_{iT}) offers a shortcut. This method which was recently used to investigate the effects of weather conditions on farm productivity in the Karoo (Conradie et al., forthcoming) that could open a new direction of enquiry in climate change studies.

The purpose of this study is to learn how the choice of stochastic frontier method affects he efficiency scores generated. The literature does not contain any direct comparisons.

A brief description of the data and the model specifications appears in Sections 2 and 3. Section 4 reviews the statistical results for two small panel datasets (sheep, wine). Section 5 compares the efficiency output from the two methods for these two cases and the paper ends brief conclusions.

2 Datasets

Conradie et al. (forthcoming) fitted an error components model to an unbalanced panel of 75 sheep farms over three years (n = 199). The model explained sheep and wool income with the number of stock sheep in the flock, wages as a proxy for labour use, fuel as a proxy for machinery, and a composite variable of sheep consumables that include feed, veterinary costs and ram purchases. High collinearity of stock sheep and grazing land required that one or the other be left out and it was decided to go with sheep rather than land because some properties in the study area are lifestyle farms (Reed and Kleynhans, 2009). Flock size is measured as number of breeding ewes and wethers kept for wool. All other items including output are deflated with their appropriate deflators as published in the Abstract of Agricultural Statistics (DAFF, 2017). The summary data in Table 1 are in constant 2010 ZAR.

Table 1: Descriptive statistics for the datasets used to compare models

		Sheep panel n =199		*Wine panel n = 847*	
Variable	*Units*	*Mean*	*Std. dev.*	*Mean*	*Std. dev.*
Income	R thousands	627	666	3591	3036
Land	Hectares			106	90
Wages	R thousands	64	58		
Labour	FTE jobs			45	38
Crop chemicals	R thousands			359	345
Irrigation	R thousands			194	161
Fuel	R thousands	84	69	168	143
Electricity	R thousands			125	129
Stock sheep	Number	902	925		
Consumables	R thousands	70	85		

Piesse et al. (2018) fitted a technical efficiency effects model to a balanced panel dataset for 77 wine farms over 11 years (n = 847) to conduct a regional analysis of the wine industry. The model explained income from wine grapes with land (vineyard size), wages, pesticides, fertiliser, fuel and electricity, which were all statistically significant at the 95% confidence level. The inefficiency module contained eight variables of which half explained firm performance. For this study fertiliser and pesticides were combined as crop chemicals and labour was measured in fulltime equivalent jobs according to the assumptions in Conradie et al. (in press). Land is area planted to wine grapes, in hectares. Chemicals and fuel are in thousands of ZAR deflated with a crop protection and fuel price index. Irrigation, also in thousands of ZAR, combines the two main irrigation costs, water and electricity, and is deflated with an electricity price index. Output was made quality adjusted by deflating by CPI and the financial wine data in Table 1 represent constant 2010 values.

The sheep and wine datasets differ in two main ways. The eleven-year time span of the wine panel makes it more likely that it will pick up Hicks neutral technical change than the three-year sheep panel, especially since grape growing has made more technical progress over recent decades than extensive sheep rearing (Conradie et al., 2009). It is expected the wine efficiencies will all be relatively close to the frontier as the panel was compiled from study group data where technology transfer is assumed to be high. Most wine grapes are also irrigated. The sheep panel which derives from a community survey conducted under both good and average growing conditions is expected to yield a greater variety of efficiency estimates.

3 Model specifications

Consider a translog stochastic production frontier with an exogenous time trend (e.g. Hadley, 2006):

$$\ln Y_{it} = \alpha_0 + \sum_{k=1}^{K} \alpha_k \ln x_{kit} + \sum_{k=1}^{K}\sum_{j=1}^{J} \alpha_{jk} \ln x_{kit} \ln x_{jit} + \alpha_{t1} time + \alpha_{t2} time^2 + v_{it} - u_{it}$$

[1]

where all inputs and output are logged and mean-centred. Y_{it} is output produced by the i^{th} firm in period t, x_{kit} is the k^{th} input used by firm i in period t and v_{it} is an independently and identically distributed error term $N(0, \sigma_v^2)$. The second half of the term error term $-u_{it}$, captures firm i's deviation from the best practice frontier in period t. For the wine panel k = 5 and for the sheep dataset k = 4. The α_k and the α_{jk} are the parameters of the translog function to be estimated. The parameters α_{t1} and α_{t2} determine the rate of technical progress, if any.

In the error components version of the translog stochastic frontier, efficiencies are determined by a firm-level rate of convergence, η_{it}, and the firm's efficiency in period in the terminal period T, μ_i, as follows:

$$u_{it} = \eta_{it}\mu_i = e^{-\eta(t-T)}\mu_i; t \in \tau(i); i = 1,2,\ldots,N \qquad [2]$$

The amount of error variance explained by inefficiency is captured by the parameter $\gamma = \sigma_\mu^2/(\sigma_\mu^2 + \sigma_v^2)$ (Battese and Corra, 1977). If $\gamma = 0$ a mean response function is a sufficient representation of the data, and no systematic inefficiency effects can be claimed. If $\gamma > 0$, the inefficiency term μ_{it} can follow a truncated normal $N(\mu, \sigma_\mu^2)$ or half-normal distribution $N(0, \sigma_\mu^2)$ depending on the estimated value of the parameter μ. If μ =0 the distribution is half normal and otherwise it is truncated normal. Since fitting a frontier involves the estimation of three additional parameters μ, η and γ, the likelihood ratio test that compares this specification to the mean response function (OLS) has three restrictions. The test statistic, $LR = -2(LLH_r - LLH_u)$, is chi-square distributed with degrees of freedom equal to the number of restrictions. The subscripts stand for restricted and unrestricted. This test can determine model specifications in nested models fitted with maximum likelihood routines, in this case implemented with FRONT 4.1 because it can deal with unbalanced panels (Coelli, 1996).

Several likelihood ratio tests are performed to determine model specification. Test 1 hypothesises that $\alpha_{t2} = 0$, in other words that technical progress is a linear process in the error components model. Test 2 checks for evidence of growth by asking if $\alpha_{t1} = 0$ in the same model. In Test 3, which the translog functional form is compared to Cobb Douglas, proposes that $\alpha_{jk} = 0$ for all j and k. The time trend selected in tests 1 and 2 are included. Test 4 checks for a frontier by assuming that $\gamma = \mu_i = \eta_{it} = 0$ (Battese and Coelli, 1992). Since the test statistic for this test follows a mixed chi-square distribution critical values are taken from Kodde and Palm (1986).

In the technical efficiency effects version of the stochastic frontier model, the inefficiency module is a linear function of a set of firm and environmental characteristics, z_{mit}, which are often dummy variables or simple percentages as the coefficients δ_m are difficult to interpret due to the distribution of the inefficiency term. The $-u_{it}$ are the inefficiency effects obtained from the frontier, the δ_m are parameters to be estimated and w_{it} is an i.i.d. error term.

$$-u_{it} = \delta_0 + \sum_{m=1}^{M} \delta_m z_{mit} + w_{it} \quad [3]$$

For the wine panel eight z-variables were formulated from the available viticulture and accounting data (Piesse et al., 2018). The richer sheep dataset contains fourteen possible z-variables, of which ten worked in a Cobb Douglas specification and fewer in the translog. Nine of the ten z-variables remained significant in the translog specification, but the coefficients on the frontier variables became insignificant (Conradie, 2017).

To make the specifications as similar as possible the inefficiency module was restricted to time and time-squared in this study. These two variables plus a constant term let the inefficiencies vary across firms and years in the technical efficiency effects method. The source of the variation over time could be weather or market conditions and depending on the combination of time parameters fitted, it could increase or decrease at an increasing or decreasing rate. In the error components model the set of predicted inefficiencies is restricted to either increase at a decreasing rate or decrease at an increasing rate

(Battese and Coelli, 1992). If $\eta < 0$, inefficiencies increase monotonically over time, which is consistent with $\delta_1 > 0$. In the technical efficiency effects method spatial variation is captured by the constant term which responds to firm and operator differences. By moving time and time-squared into the frontier, the error components method allows for the possibility of Hicks neutral technical progress, which is not investigated in the technical efficiency effects model.

To specify the technical efficiency effects model three more likelihood ratio tests are run. The first of these (test 5) comes with the final maximum likelihood estimates in FRONT 4.1. The existence of the frontier requires that $\delta_m = 0 = \gamma$, is rejected. The mean response function (OLS) carries four restrictions in the model used here (3 x δ, γ). Test 6 asks if $\delta_{t2} = 0$, and if so, test 7 checks if $\delta_{t1} = 0$. These are worthwhile questions in models that try to understand the effects of climate change on regional production, although it unlikely that evidence of it will be found given the Karoo's 20-25 weather cycles (Du Toit and O'Conner, 2014). With the inefficiency module finalised, test 8 compares translog to Cobb Douglas by checking if $\alpha_{jk} = 0$ for all j and k.

In well-behaved production functions inputs should contribute positively and significantly to output. In Cobb Douglas models, significant (and positive) coefficients add up to mean returns to scale. The same applies to translog models fitted with mean-centred data. The coefficients on the squares and cross products vary, depending on whether a pair is substitutes (negative) or complements (positive). Only meaningful substitutability or complementarity will produce significance. There are examples in the literature where squares and cross products are included selectively (e.g. Theodoridis et al., 2014), but it is more common to include all (translog specification) or nothing (Cobb Douglas), which is why tests 3 and 8 are an important part of model selection.

4 Results

4.2 The sheep panel

Model specification for the sheep panel is decided based on the data presented in Table 2. The first version of the error components model to be fitted assumed a truncated normal distribution on the inefficiency term which could vary over time. The model included four basic inputs, their squares and cross products and a linear time trend and its square. In test 1 the parameter on time-squared was restricted to zero, which produced a likelihood ratio statistic of LR = 2.40 which is less than the critical value of 2.706 for one restriction at the 95% confidence level. The squared term was dropped. In test 2 the model was rerun with and without time to check for linear technical progress. With LR = 1.77 still less than the critical value of 2.706 for one restriction, it was concluded that sheep farming made no technical progress over the study period, an unsurprising result given that there was no technical progress in the sector over the previous fifty years (Conradie et al., 2009). To conduct test 3 time was dropped from the Cobb Douglas and translog specifications. It produced a value of LR = 54.09 which was greater than the critical value of 17.67 for ten restrictions, which indicated that translog was preferred. In test 4 that asked if $\gamma = \mu_i = \eta = 0$ produced a value of LR = 57.89 which confirmed that the translog function was a frontier.

Only three tests were needed to determine the specification of the technical efficiency effects model for this dataset. Test 5 checked for the joint significance of the inefficiency module and γ. The test statistic of LR = 75.20 rejected these four restrictions at the highest confidence level while test 6 indicated that both time trends are needed. This made test 7 obsolete. In test 8 a value of LR = 61.36 was greater than the critical value of 17.67 for the ten restrictions imposed by a Cobb Douglas specification.

Table 2 Model specification tests for the sheep panel (n = 199)

Test	*Restricted*	*Unrestricted*	*LR stat*	*Restrictions*	*Critical*
Translog Error Components Method					
$\alpha_{t2} = 0$	-116.11	-114.91	2.40	1	2.706
$\alpha_{t1} = 0$	-116.99	-116.11	1.77	1	2.706
$\alpha_{jk} = 0$ all j,k	-144.04	-116.99	54.09	10	17.67
$\gamma = \mu_i = \eta = 0$	-145.94	-116.99	57.89	3	7.045
Translog Technical Efficiency Effects Method					
$\gamma = \delta_m = 0$	-145.94	-108.34	75.20	4	8.761
$\delta_{t2} = 0$	-110.30	-108.34	3.92	1	2.706
$\alpha_{jk} = 0$ all j,k	-129.02	-108.34	61.36	10	17.67

Table 3 Estimation results for the sheep panel (n = 199). All variables in mean centred natural logarithms, explaining output.

	Error components method			*Technical efficiency effects method*		
	MLE	*SE*	*t-ratio*	*MLE*	*SE*	*t-ratio*
Constant	0.262	0.060	4.41*	0.350	0.039	8.89*
Stock sheep	0.743	0.080	9.25*	0.568	0.053	10.80*
Consumables	0.098	0.035	2.84*	0.080	0.028	2.81*
Labour	0.209	0.060	3.47*	0.205	0.048	4.26*
Fuel	0.055	0.068	0.80	0.181	0.050	3.62*
Sheep^2	0.190	0.079	2.39*	-0.012	0.060	-0.20
Sheep x consumables	0.079	0.059	1.34	0.011	0.046	0.23
Sheep x labour	0.191	0.051	3.78*	0.104	0.043	2.43*
Sheep x fuel	-0.474	0.133	-3.56*	0.018	0.100	0.18
Consumables^2	0.010	0.006	1.61	0.008	0.006	1.40
Consumables x labour	-0.086	0.043	-2.03*	-0.050	0.034	-1.48
Consumables x fuel	-0.010	0.056	-0.18	0.024	0.044	0.55
Labour x labour	0.014	0.007	2.06*	0.012	0.005	2.27*
Labour x fuel	-0.078	0.026	-3.05*	0.024	0.017	1.36
Fuel x fuel	0.315	0.058	5.42*	-0.012	0.037	-0.33
Constant				-45.741	22.597	-2.02*
Time				31.701	15.038	2.11*
Time^2				-7.376	3.498	-2.11*
σ^2	2.800	0.668	4.19*	6.838	3.258	2.10*
γ	0.963	0.010	91.85*	0.993	0.004	249.42*
μ	-3.284	0.642	-5.12*			
η	-0.178	0.054	-3.30*			
Log likelihood	-116.99			-108.34		
Mean returns to scale	1.10			1.03		
Mean efficiency	70%			72%		

* $p \leq 0.05$

The two sets of coefficients are presented side by side in Table 3 to make clear how the choice of method affects signs and magnitudes of the parameters fitted. The number of stock sheep in the flock is the dominant factor of production in both cases, followed by labour (wages), sheep consumables (feed, animal remedies and rams) and fuel. Both methods produced significant coefficients on sheep, consumables and labour. Fuel’s coefficient is as expected in the technical efficiency effects method but insignificant in the error components model.

The models differ substantially on stock sheep's output elasticity. Flock size accounts for 74% of the variation in output in the error components model, which it is explains only 57% of the variation in output in the technical efficiency effects model. The coefficients on labour and consumables are stable in both models at just less than 0.20 and 0.10 respectively. In the error components model where fuel is not significant, its output elasticity is 0.055 and it increases to 0.181 in the technical efficiency effects model, where it is significant. The error components method finds stronger evidence of increasing returns to scale (RTS = 1.10) if the fuel coefficient is included that if it is excluded and more evidence of increasing returns to scale the technical efficiency effects model (RTS = 1.03). This is possibly due to a greater degree of attrition amongst small firms.

Modelling seasonal variation explicitly in the technical efficiency effects model, results in fewer significant interaction effects than the simplified assumptions of decreasing and diverging performances indicated by η = -0.178 in the error components model. In the latter seven of the ten interaction terms are significant and all the squared terms point to increasing returns to scale. There is complementarity between sheep and labour and sheep and consumables, which makes sense. It more difficult to explain why sheep and fuel might be substitutions other than to blame it on the decision to apportion overheads to enterprises according to share of turnover. This was done in about 10% of cases. Consumables and labour and labour and fuel are substitutes, which is reasonable. Fuel and consumables are unrelated. In the technical efficiency effects model the only substitution effect that matters is the complementarity between sheep and labour, which is the only input that shows evidence increasing returns to scale consistent with the mean returns to scale estimate for this method. It shows that it is important to formally test for the inclusion of interaction terms and not just rely on the t-ratios on individual coefficients when deciding on model specification.

4.2 The wine panel

As before, the error components model specification begins with an evaluation of the time variables. The hypothesis that time squared is unnecessary is soundly rejected (LR = 32.48), which makes test 2 unnecessary. In test 3 the test statistic LR = 64.46 is greater than the critical value of 24.384 for the fifteen restrictions imposed by Cobb Douglas, which settles on translog as the preferred functional form. Test 4 confirms that this translog model is a frontier. The specification of the technical efficiency effects model begins with a translog frontier that includes a constant term and time and time-squared in the inefficiency module. Since the test statistic in test 5 of LR = 37.63 exceeds the critical value of 8.761 for four restrictions, a frontier is confirmed. Test 6 investigates if time-squared is zero and finds that it is not, which makes test 7 on the desirability of including a linear time trend, unnecessary. With the inefficiency module finalised, Test 8 compares Cobb Douglas to the translog and as in the case of the error components model, opts for translog.

Table 4 Model specification tests for the wine panel (n = 847)

Test	*Restricted*	*Unrestricted*	*LR stat*	*Restrictions*	*Critical*
Translog Error Components Method					
$\alpha_{t2} = 0$	174.65	190.89	32.48	1	2.706
$\alpha_{jk} = 0$ all j,k	158.66	190.89	64.46	15	24.384
$\gamma = \mu_i = \eta = 0$	-42.60	174.65	343.51	3	7.045
Translog Technical Efficiency Effects Method					
$\gamma = \delta_m = 0$	-51.13	-32.31	37.63	4	8.761
$\delta_{t2} = 0$	-36.92	-32.31	9.22	1	2.706
$\alpha_{jk} = 0$ all j,k	-109.81	-32.31	141.01	15	24.384

The estimation results from the two methods are compared in Table 5. The models agree on the relative importance of inputs which is area planted, followed by fuel, chemicals and irrigation and labour in a distant fourth place. In the error components model land accounts for more than three quarters of the variation in grape income, fuel for about 11% and irrigation and crop chemicals for about 5% each, while wages explain less than 2% of the variation in output. As discovered during the analysis of the sheep dataset, the technical efficiency effects method tends to downplay the effects of land compared to the variable factors. In this set of results the coefficient on area planted falls by 50%. The importance of fuel rises by almost 20% while the contributions of chemicals and irrigation increase three-fold. With mean RTS = 0.96 and RTS = 0.97 both models agree than there are no economies of scale in grape production over this range of firm sizes (100-12000 tons).

Table 5 Estimation results for the wine panel (n = 847). All variables in mean centred natural logarithms, explaining output.

	Error components method			*Technical efficiency effects method*		
	MLE	*SE*	*t-ratio*	*MLE*	*SE*	*t-ratio*
Constant	0.281	0.058	4.82*	0.111	0.056	2.00*
Land	0.754	0.059	12.84*	0.552	0.051	10.83*
Chemicals	0.044	0.031	1.41	0.126	0.029	4.29*
Irrigation	0.046	0.030	1.54	0.143	0.025	5.68*
Labour	0.014	0.040	0.36	0.018	0.032	0.58
Fuel	0.106	0.038	2.82*	0.126	0.041	3.10*
Land x land	-0.074	0.075	-0.99	-0.039	0.077	-0.50
Land x chemicals	-0.119	0.065	-1.82	-0.145	0.075	-1.93
Land x irrigation	0.119	0.030	3.94*	0.112	0.036	3.07*
Land x labour	-0.103	0.076	-1.34	0.007	0.074	0.10
Land x fuel	0.081	0.073	1.11	-0.037	0.087	-0.43
Chem. x chem.	0.057	0.025	2.25*	0.107	0.030	3.53*
Chem. x irrigation	0.013	0.019	0.69	-0.045	0.023	-1.93
Chem. x labour	0.083	0.045	1.84	0.004	0.050	0.08
Chem. x fuel	-0.041	0.048	-0.85	0.061	0.058	1.04
Irrigation x irrigation	0.007	0.002	4.24*	0.008	0.002	4.80*
Irrigation x labour	-0.055	0.026	-2.09*	-0.060	0.029	-2.05*
Irrigation x fuel	-0.056	0.021	-2.67*	-0.018	0.024	-0.73
Labour x labour	0.068	0.037	1.83	0.137	0.033	4.11*
Labour x fuel	0.022	0.053	0.41	-0.112	0.058	-1.93
Fuel x fuel	0.011	0.006	1.85	0.018	0.007	2.49*
Time	-0.031	0.009	-3.53*			
Time squared	0.004	0.001	5.83*			
Constant				-0.029	0.280	-0.10
Time				0.074	0.046	1.62
Time squared				-0.008	0.004	-1.85
σ^2	0.113	0.028	4.00*	0.122	0.037	3.31*
γ	0.746	0.063	11.85*	0.797	0.055	14.56*
μ	0.392	0.120	3.28*			
η	-0.032	0.009	-3.55*			
Log likelihood	190.89			-32.31		
Mean returns to scale	0.96			0.97		
Mean efficiency	0.70			0.77		

* $p \leq 0.05$

Land and irrigation are complements since the cross product of these inputs are significant in both methods. Their combined output elasticity is 0.80 in the error components model and 0.695 in the technical efficiency effects model, which is even more important than the land proxy was in the sheep panel. Irrigation is only marginally significant on its own in the error components model, but is a significant substitute for most other inputs, while land is not. According to the error components method, irrigation is a significant substitute for labour and fuel, but not for chemicals, to which is it unrelated. The technical efficiency effects method finds irrigation to be a substitute for labour and chemicals but not for fuel.

Labour and fuel are classic substitutes and should be in the wine industry which was rapidly mechanising in the period covered by the panel due to sharply rising farm wages. The error components method whose basic labour coefficient is not significant and very small, fails to establish that labour and fuel are substitutes, but the technical efficiency effects model, where labour has a bigger coefficient, comes closer to finding significant substitutability between labour and fuel. The other classic substitution is of labour saving chemicals for labour, for example by applying herbicide rather than digging over a field or thinning chemically rather than by hand. In this case, probably because the crop chemicals variable includes fertiliser and compost there is no evidence of this substitution. Instead in the error components model there is some indication of a degree of complementarity between these inputs.

The error components method places mean efficiency at 70%. The Hicks neutral time trend indicates a reversal of technical progress which slows down over the study period while $\eta < 0$ indicates the fastest decline amongst the weakest firms. The technical efficiency effects method predicts a mean efficiency of 77% which also decreases at an increasing rate. While there is no formal measure of convergence, the bottom panel of Figure 2 reveals that the greatest divergence occurred around period 5-6 after which performances might be converging again.

5 Discussion of efficiency results

The effect of method choice on predicted scores is shown in Figures 1 and 2 where each firm's scores are plotted in a different colour. Correlations and t-tests of means are given in Table 6.

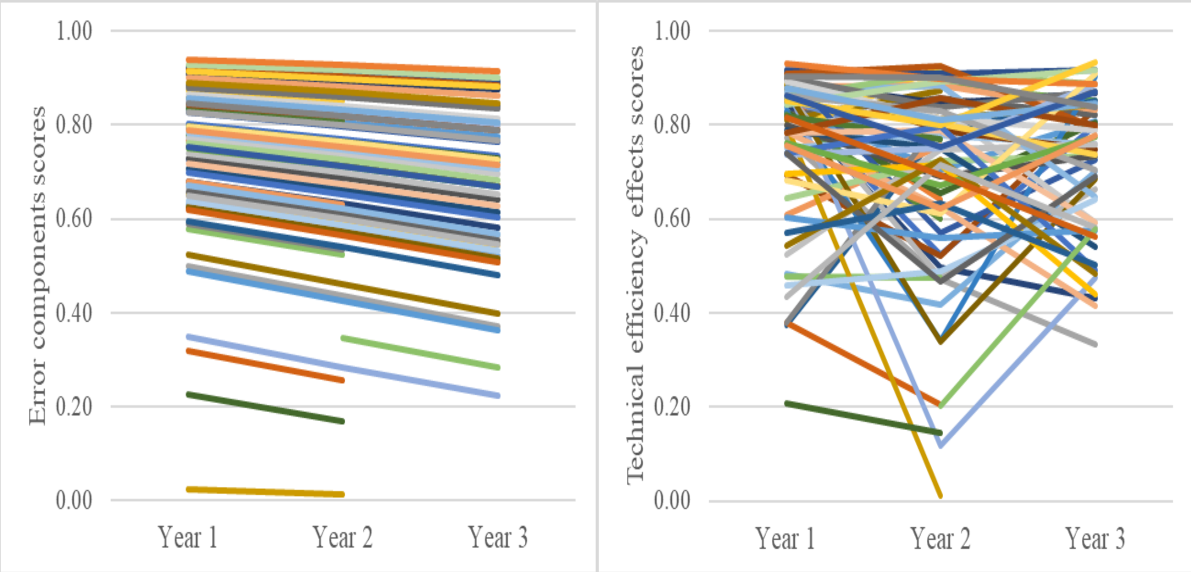

Figure 1 Efficiency scores for the sheep panel

Figure 1 shows that by imposing monotonicity on the efficiency scores the error components model disregards the outliers in period 2, which was a better season for some sheep farmers than period 1 and substantially worse for others. Pooling the years produces a high level of correlation (Pearson's r = 0.73) between the two sets of estimates. The main discrepancy is in year 1 where the error correction model imposes a greater spread than the technical efficiency effects method. Several bottom outliers drop out of the sample in period 3, because they can live off crop income (Conradie et al., forthcoming). With period 2 as their terminal period, these farms end up with much lower scores in period 1 than when predicted with the technical efficiency effects method. In years 1 and 2 means of the predicted efficiencies do not differ significantly and the direction of bias switches; year 1 the technical efficiency effects model predicts higher scores and in year two it predicts lower scores than the error components model. In year 3, when the difference is systematic, the technical efficiency effects method indicates a 2.5% better performance than the error components model. This difference is hardly material which leads to the preliminary conclusion that model choice is not important when conditions are normal.

The wine dataset contains less dramatic seasonal variation than the sheep data. While the sheep efficiency scores vary from zero to 97%, with 7% of observations below 0.40, the minimum wine score is 36% and the number of observations with scores below 0.40 just 0.35%. These outliers occur in periods 5 and 6 which results in relatively flat error components efficiency curves.

Table 6 Summary statistics of efficiency output by dataset and method

Period	*Method*	*Mean*	*Std. Dev.*	*Correlation*	*t-statistic*	*Prob.*
Sheep panel						
1	EC	0.732	0.029			
	TEE	0.757	0.026	0.581	-1.398	0.166
2	EC	0.693	0.035			
	TEE	0.680	0.045	0.812	0.924	0.359
3	EC	0.669	0.030			
	TEE	0.715	0.026	0.808	-3.293	0.002
Pooled	EC	0.700	0.032			
	TEE	0.718	0.033	0.734	-1.852	0.033
Wine panel						
1	EC	0.737	0.016	0.413	-2.741	0.0076
	TEE	0.777	0.012			
2	EC	0.730	0.016	0.624	-3.861	0.0002
	TEE	0.774	0.008			
3	EC	0.723	0.017	0.758	-3.687	0.0004
	TEE	0.759	0.010			
4	EC	0.716	0.018	0.732	-2.615	0.0108
	TEE	0.743	0.011			
5	EC	0.708	0.018	0.764	-3.697	0.0004
	TEE	0.746	0.013			
6	EC	0.701	0.019	0.754	-2.640	0.0101
	TEE	0.730	0.019			
7	EC	0.693	0.020	0.755	-5.878	0.0000
	TEE	0.756	0.014			
8	EC	0.685	0.021	0.782	-9.318	0.0000
	TEE	0.783	0.018			
9	EC	0.677	0.022	0.836	-13.168	0.0000
	TEE	0.801	0.012			
10	EC	0.669	0.022	0.570	-10.281	0.0000
	TEE	0.815	0.011			
11	EC	0.661	0.023	0.690	-11.497	0.0000
	TEE	0.806	0.012			
Pooled	EC	0.700	0.020	0.648	-19.031	0.0000
	TEE	0.772	0.013			

EC is error components, TEE is technical efficiency effects. Correlation is a Pearson's r. The t-statistic tests for equality of means across methods assumes equal variances.

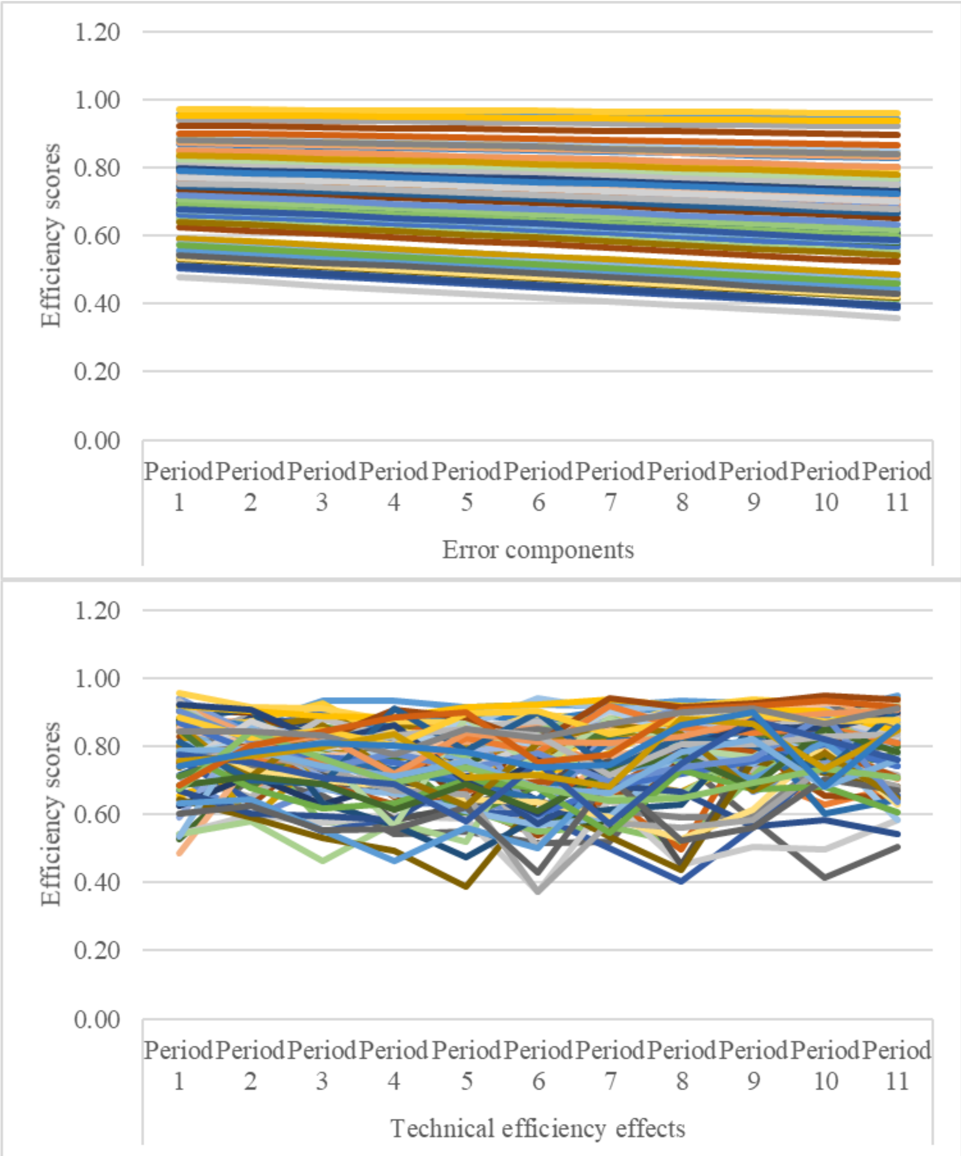

Figure 2 Efficiency scores for the wine panel

With the flat error components efficiency curves, it was surprising to find how much the mean scores varied. The difference in the means of the pooled scores was significant at the highest level and the means differed by 10%, but Table 6 reveals that there is a definite time dimension to the differences. In periods 1-6 the means differed by 4-6%, but after that the discrepancy systematically increases to an alarming 22% in periods 10 and 11. All annual differences were significant and the technical efficiency effects model produced higher estimates every time. The worst years for wine were periods 4, 5 and 6, coinciding with the 2008 global financial crisis when growing conditions were average to good in the winelands.

This leads to several observations. Firstly, irrigated agriculture seems less vulnerable to weather variation than extensive livestock production, but as a predominantly export product which a high imported content, wine grapes are vulnerable to macro-economic conditions. Secondly, the choice of stochastic frontier method is of more concern over longer than shorter periods and thirdly, the error components method will overstate the degree of collapse under worsening conditions. The data is not available to know if the opposite is also true, namely that the error components estimates be inflated related to the technical efficiency effects conditions when scores are improving and converging. More work is needed to understand how efficiency scores vary with size and fit of the inefficiency module in the technical efficiency effects method.

6 Conclusion

This study re-analysed two previously published datasets to investigate the degree of similarity between the efficiency scores produced with different stochastic frontier methods. Results show that Battese and Coelli's (1992) error components model rarely produces the same efficiency estimates as Battese and Coelli's (1995) technical efficiency effects model and where differences are significant, that the technical efficiency effects method tend to bias scores upwards. Therefore, there is a price to pay for the convenience of an intuitively simple set of monotonically increasing performance scores, which recommends the use of the model with the best explanatory power, even if it is more difficult to communicate its results to interdisciplinary and lay audiences. As compromise the analysis might begin with fitting a technical efficiency effects model, which can then be followed up with an error components analysis or a second stage regression of scores on a time trend.

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