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Efficiency in wine grape production: comparing long-established and newly developed regions of South Africa

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Abstract

Efficiency, partly based on technology, is central to international competitiveness. This article applies a stochastic frontier inefficiency model to a panel of 77 wine grape farms in South Africa between 2005 and 2015 and allows the comparison of efficiency levels for the old established wine regions with those of newer entrants. Thus, we investigate whether experience plus first choice of location matters more than the follower's advantage of newer technology.

In all regions, a greater share of permanent labor and increased supervision raised efficiency, while more inorganic fertilizer and less irrigation has the opposite effect. Innovations in trellising had insignificant effects (except in the old regions) but not replacing old vines reduced efficiency. However, a higher proportion of red varietals also lowered efficiency in the old regions due to a fall in the price of red wine as these farmers continued to concentrate on quality reds. The new regions compensated for falling prices by increasing crop size with irrigation and fertilizer and extending the area planted, but with less concern for quality. This appears to be more successful in efficiency terms, but as international demand for quality wine increases it may be a poor long-term strategy.

JEL classifications: Q12, Q16

Keywords: South Africa wine grape production; Stochastic frontiers; Farm efficiency

1. Introduction

South Africa is the world's seventh largest wine producer by volume, and exports about half the total output, up from a quarter in 2000. The sector accounts for 275,000 jobs and has 95,000 hectares under wine grapes, so maintaining this performance is important. Efficiency in production, which depends partly on technology, is crucial to achieving this goal. Economists have long been fascinated by the question of technological leadership. Do established firms have a technological advantage, due to factors such as greater experience, or does this lead to the entrenchment of old-fashioned ideas and techniques? Alternatively, does the new entrants' advantage of being able to choose later and better techniques decide the issue? These factors are largely reflected in relative efficiency levels, which are the main subject of this article.

Data on South African wine grape production from Vinpro have information on six inputs, which explain 90% of the variance in output and allow these two groups to be compared at the farm level. Vineyards in Stellenbosch and Paarl have been producing wine grapes since the 17th century, whereas those in the Orange and Olifants River regions are post-World War II developments. The *ex ante* expectation is that producers in the older regions have the *terroir* and the experience, while those in the more recently established areas have the usual followers' advantage, especially the latest technologies, and are not tied into historical practices that may now be a barrier to productive efficiency. This is the first contribution of the article. The second is to estimate the impact on efficiency of several viticulture practices that use farm-level data that have not been previously available.

The data are a panel of 77 wine grape farms from nine regions of South Africa for the period 2005–2015, resulting in a sample of 847 observations. The majority of the farms produce wine grapes that are delivered to local producer cellars

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(formerly cooperatives) where the wine is made and mostly sold in bulk. This is either exported or sold to producer wholesalers or to private cellars, with some bottled and marketed under their own labels. This distinction is important as the sample largely excludes private cellars, that is, farms that make and package the wine themselves. This allows us to avoid many quality adjustment problems although at the cost of excluding most of South Africa's quality wine production. The sample is split between the oldest wine growing regions of Paarl and Stellenbosch, and the newer ones, which include Breedekloof, Klein Karoo, Malmesbury, Olifants River, Orange River, Robertson, and Worcester. Frontier production functions are estimated and the farm-level efficiencies compared between the old and new regions. One of the major differences is expected to be in the use of traditional viticulture, such as trellising and caring for the grapes by hand, versus more recent output enhancing techniques and greater precision in the timing of the harvest.

The article is structured as follows. Section 2 is a brief history of wine production in South Africa, followed by a review of the limited relevant literature. Section 4 presents the models, while Section 5 describes the data and summary statistics. Section 6 reports the results, beginning with tests to determine the statistically preferred models. This is followed by a discussion of the implications of the study and suggestions for future work.

2. History

The South African wine industry was established in 1659, but a recent study (Vink et al., 2017) shows that the industry has experienced only three periods of sustained prosperity throughout its history. These have all been associated with a boom in exports, most recently in the decade following the introduction of democracy in 1994 when South African wines reentered markets lost during the era of boycotts and sanctions. Domestic consumption, on the other hand, has been unchanged for many years.

For most of the 20th century, the South African wine industry was controlled by the KWV,[1] a cooperative that had statutory powers to intervene in the market. These powers remained until it was registered as a for-profit company in 1997. The Board of the KWV had the power to set a minimum price for wine and to set the quota at which it was prepared to buy wine at the minimum price. Production in excess of the quota had to be delivered to the KWV free of charge. It is clear that over time the minimum price was set too high, which resulted in consistent surpluses of inferior quality wine. This resulted in a stagnant domestic market for wine during the second half of the 20th century while beer consumption increased more than sixfold.

In 1994, there was an inflow of financial and intellectual capital into the industry. Viticulturists began playing a far more prominent role and producers became keenly aware of the need to focus on the noble cultivars and to use superior plant material for both the rootstocks and vines. This led to a more careful matching of varietals with *terroir* and resulted in the development of new winegrowing areas. Thus, there are now major differences between the old and new wine growing regions and a clear distinction between viticulture practices, the adoption of new techniques and innovations, and consequently the performance of wine grape producers across South Africa.

[1] Koperatiewe Wijnbouwers Vereeninging Beperkt van Zuid-Afrika (The Co-operative Wine Growers Association Limited of South Africa).

3. Literature review

There are a limited number of studies that are directly relevant to this research, although two papers do address these issues and use similar approaches to the current study. First, Townsend et al. (1998) analyze farm management data for 1992–1995, for 117, 96, 112, and 124 cooperative wine farms in the Stellenbosch, Robertson, Worcester, and Olifants River regions, respectively. The farms are divided into three groups according to size measured by area planted or total labor employed. The relationships between land, labor, and total factor productivity (TFP) are estimated in order to link farm size and efficiency in different ways. The basic test of the inverse relationship between farm area and yields holds for only three of four years in Olifants River and is elsewhere not significant. The inverse relationship between total labor and labor productivity fares better, which suggests there are higher labor management costs as employment levels increase. However, in neither case did farm size explain TFP and neither land nor labor productivity are associated with TFP. With respect to returns to scale (RTS), the conclusion that farms are too small is based on the negative signs of the coefficient on land when it is included in the inefficiency part of the Battese and Coelli (1995) model.

In the second paper, Conradie et al. (2006) also estimated the Battese and Coelli (1995) inefficiency model, using five small samples of grape producers in the Western Cape Province. The data are two panels of wine grape farms (34 in Robertson and 36 in Worcester) for 2003 and 2004, and 37 table grape farms in De Doorns for 2004 only. These regions are located close to each other, with similar climate, no unusual rainfall patterns, and irrigation is used in all cases. Again, these data include outputs, inputs, and farm-specific characteristics that can be used to explain efficiency at the farm level. In three of the five samples, the sum of the output elasticities was around 1.2, with another at 1.5, and only Robertson in 2003 at less than unity (0.812). So, this crude aggregate measure suggests that the farms are predominantly too small. To confirm this result, the farm-level efficiencies, which do appear to be a monotonically increasing function of farm size, were divided into quartiles according to farm size. The quartile of smallest farms had an average efficiency of 65%, the next quartile 71%, the next 75%, and the largest 76%, suggesting increasing RTS, but it is relatively unimportant in explaining efficiency levels.

Similar studies focus on other countries, for example, there are efficiency papers on wine production for Portugal, Spain, Chile, China, and Australia. Barros and Santos (2007) used data envelopment analysis (DEA) and found that Portuguese cooperative wineries were more efficient than private farms. Another DEA study by Aparicio et al. (2013) decomposes revenue efficiency into technical and allocative components for Spanish-protected designation of origin (PDO) wineries. Vidal et al. (2013) use DEA to measure the efficiency of a sample of Spanish PDOs between 2008 and 2010 and also constructed Malmquist indices. They find the efficiency of the subset of Spanish PDOs is uniform over these time periods and that productivity is subject to only minor changes. Fernandez and Morala (2009) studied the cost efficiency of wine firms in Spain and identified improvements in technical efficiency for this sample. Liu and Lv (2010) also use DEA with a sample of 463 Chinese wine grape growers from 2009 to 2013 and find a slight increase in productivity over time, but this starts from a low base. They also show that medium-sized farms are more efficient than smaller or larger ones.

Carvalho et al. (2008) is more relevant to this article and uses stochastic frontier analysis for a sample of wine grape producers in the Alentejo region of Portugal. The estimate of RTS at the mean was 0.95, indicating mildly decreasing RTS, while mean technical efficiency was found to decrease from 79.3% in 2000 to 52% in 2005. Technical efficiency increased with farm size, entrepreneurship, and farm profitability. Moreira et al. (2011) also use a Cobb-Douglas form of the stochastic frontier model with a sample of 38 Chilean quality wine grape producers. RTS are found to be close to constant (elasticities sum to 1.02) and mean technical efficiency is 77.8%. Coelli and Sanders (2013) estimate translog stochastic production frontiers for a sample of 238 producers in the Murray-Darling basin, and find a mean technical efficiency of 79%, although some farms achieve well below this level. They note that these farms may face significant pressure if grape prices remain static but there was significant potential for improvement. A mean scale economies estimate of 1.07 is obtained, suggesting farm amalgamations may occur. Technical change is also estimated at 2.7% per year but this may be biased by drought during the early survey period.

There seem to be only two attempts at broad international comparisons. Toth and Gal (2014) use a Cobb-Douglas frontier production function with aggregate data for 16 old and new world countries for a 13-year period. Wine production is explained by the area planted to vines, the total agricultural capital stock, and agricultural employment. The single wine-specific input, area planted to vines, has a positive and significant output elasticity. The other two inputs are negative, which is at odds with production theory that requires these elasticities to be between zero and unity. Clearly, proper data are required but not yet available. Alampi Sottini et al. (2016) compare Italian and Spanish wineries, using DEA to generate Malmquist TFP indices. Their sample of 622 Spanish and 609 Italian wineries is over half the total for both countries for the period 2005–2013. Revenue and profits are explained by three inputs, labor, capital, and debt, and positive technical change was found to have been offset by declining efficiency. Overall, Italy appears to be more efficient.

Other relevant studies cover a variety of crops in Africa and developments in methodology. Like Townsend et al. (1998), Larson et al. (2014) investigate the inverse relationship between farm size and yields for a large number of farms in several African countries, using a model of endogenous technology choice. They find good support for the relationship. Slavchevska (2015) considers plot-level output for a large number of Tanzanian producers, but is less relevant to the present study as it concentrates on the impact of gender differences. Similarly, Wendimu et al. (2017) estimate production functions to compare the efficiency of sugarcane production on plots operated by a milling company with those of out-growers. They find out-growers are more efficient (their output elasticities for both land and intermediate inputs are higher) and attribute this to the likelihood that smallholders have more incentive to work hard than wage-laborers on company plots.

The most recent and relevant contributions are Asekenye et al. (2016), who use a stochastic frontier model to estimate efficiencies for groundnut farmers in Kenya and Uganda, and Nchinda et al. (2016), who use a similar approach to estimate efficiencies for yam producers in Cameroon. However, the literature on wine production remains somewhat limited.

4. Stochastic frontier inefficiency model

The measurement of firm-level technical efficiency has become commonplace with the development of frontier production functions. The approach can be deterministic, where all deviations from the frontier are attributed to inefficiency, or stochastic, which is a considerable improvement, since it is possible to discriminate between random errors and firm-level differences in inefficiency. This article uses a stochastic frontier model, of the type originally proposed by Aigner et al. (1977),[2] extended to include the characteristics of the farms that may explain the inefficiencies, following Battese and Coelli (1995). We follow the only two previous South African applications, Townsend et al. (1998) and Conradie et al. (2006) discussed above. The general form of the production frontier is

$$Y_i = \alpha + \sum_{j}^{\beta} x_{ij} + \varepsilon_i \quad \text{where } \varepsilon_i = V_i - U_i$$
$$\text{with} \quad U \sim |N(0, \sigma_U^2)| \quad \text{and} \quad V \sim N(0, \sigma_V^2), \qquad (1)$$

where the two elements of the error term are independent. The V_i's are independently and identically distributed random error terms and uncorrelated with the regressors, and the U_i's are nonnegative random variables associated with the technical inefficiency of the farm.

[2] See Fried et al. (1993) for a survey of methods and applications.

Fig. 1. South African wine regions. https://upload.wikimedia.org/wikipedia/commons/2/22/South_African_wine_regions.jpg [Color figure can be viewed at wileyonlinelibrary.com]

The technical efficiency of each farm is defined as the ratio of the observed output to the corresponding frontier output, conditional on the levels of inputs used. Thus, the technical efficiency of farm i in the context of the stochastic frontier production function is defined

$$TE_i = \frac{Y_i}{Y_i^*} = \frac{f(x_i : \beta)\exp(v_i - u_1)}{f(x_i : \exp(v_i)} = \exp(U_i), \quad (2)$$

where β is a vector of unknown parameters to be estimated. This model includes specific technical inefficiency effects, as well as incorporating tests to identify the correct model that is appropriate for the current data. In the inefficiency effects model, the U_i's, in Eq. (1) are assumed to be nonnegative random variables that reflect the technical efficiency of production, expressed as

$$U_i = z_i\delta + W_i, \quad (3)$$

that are assumed to be independently distributed and obtained by truncating the normal distribution, with mean μ_i, and variance $\sigma_u{}^2$, at zero. Thus, z_i is a vector of explanatory values associated with farm-level technical inefficiencies in production, δ is a vector of unknown parameters to be estimated, and W_i's are random errors. The variance, $\sigma_u{}^2$, is also an unknown parameter to be estimated.

5. Data

The 77 wine grape farms are spread unevenly across nine regions, as follows: Breedekloof (14), Klein Karoo (2), Malmesbury (6), Olifants River (7), Orange River (6), Robertson (6), Worcester (10), Paarl (7), and Stellenbosch (19) (see Fig. 1). Eleven years of data from 2005 to 2015 is sufficient to smooth seasonal fluctuations. As noted above, all the farms sell some grapes to local wineries, which minimize quality adjustment problems, but even with 11 years of data several regions have too few farms to model individually, which is a good motivation for comparing the aggregated old and new regions. Stellenbosch (which includes Franschhoek) and Paarl are defined as old regions. This group includes 26 farms, giving a sample of 286 observations. The remaining seven regions are considered to be new and account for the remaining 51 farms in the sample with 561 observations. The two old regions have milder winters and more rainfall, which tends to mean more fungal infections and pests, but less irrigation. Further inland, the new regions have less rainfall, so irrigation is important, while they are also less prone to pests and plant diseases due to serious frosts in the winter.

For the frontier production function, the dependent variable can be either output in kilograms or value of output (the product of quantity and price) in ZAR.[3] The second gave consistently better results, probably because aggregation using prices amounts to quality adjustment, which in wine grape production is important. Similarly, the total cost of labor (the product of wages and number of employees) is used for the labor input as the old regions have better educated, more experienced workers

[3] ZAR6.40 = US$1 in 2005 weakened to ZAR12.40 = US$1 in 2015 (5.5% pa).

Table 1
Variable means (monetary variables in constant 2010 ZAR thousands)

	Old wine regions – Paarl and Stellenbosch										
	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Frontier variables											
Output (ZAR)	4,915	4,450	4,200	3,868	3,497	3,497	4,060	3,934	3,897	4,376	3,854
Area (ha)	125	121	120	121	122	122	123	125	122	125	123
Wages (ZAR)	1,427	1,489	1,441	1,342	1,413	1,413	1,483	1,539	1,532	1,611	1,620
Fertilizer (ZAR)	63	68	66	60	66	66	61	75	88	96	91
Pesticides ZAR)	265	238	236	199	247	247	226	213	217	254	259
Fuel (ZAR)	141	173	179	197	170	170	199	223	230	238	213
Electricity (ZAR)	98	98	97	85	119	119	148	157	166	151	157
Efficiency effect variables											
Supervisor wages	261	270	242	232	230	230	223	234	230	215	177
% perm labor	64	63	66	61	58	58	59	62	61	62	63
% inorganic fert	92	94	92	90	92	92	90	94	96	98	99
% modern trellis	68	69	68	68	67	67	68	72	72	75	76
% old trellis	13	9	10	10	10	10	9	9	8	8	7
% drip irrigation	59	60	63	66	69	69	70	72	73	75	76
% dry land	15	15	15	14	14	14	15	13	13	12	12
% old vines	8	8	9	12	14	14	15	15	14	15	14
% red varietals	66	65	64	61	61	61	61	61	59	61	59
New wine regions – all others											
	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Frontier variables											
Output (ZAR)	2,927	2,943	3,167	3,021	3,239	3,106	3,144	3,560	3,710	3,875	3,854
Area (ha)	88	91	95	95	95	97	99	100	103	104	105
Wages (ZAR)	617	618	673	617	663	678	728	707	785	845	915
Fertilizer (ZAR)	62	70	79	81	86	92	100	118	125	153	155
Pesticides ZAR)	145	132	139	127	150	166	163	156	159	187	184
Fuel (ZAR)	108	123	132	138	148	136	140	178	200	207	196
Electricity (ZAR)	83	84	88	76	87	116	144	171	175	163	183
Inefficiency effect variables											
Supervisor wages	84	92	98	92	106	107	110	111	115	133	136
% perm labor	75	78	78	78	77	75	76	75	74	74	72
% inorganic fert	79	76	75	80	79	78	79	79	82	84	85
% modern trellis	28	29	30	30	32	32	33	32	34	33	32
% old trellis	18	17	17	16	16	16	15	15	14	15	16
% drip irrigation	64	66	66	69	70	71	72	73	74	76	78
% dry land	12	12	12	11	10	10	10	10	10	9	9
% old vines	11	12	13	14	12	13	13	14	14	15	16
% red varietals	24	24	23	23	24	26	26	25	26	27	27

Note: At the time of writing, the exchange rate was approximately $1 = ZAR13.50.

who are paid twice as much as those in the newer areas. The data provided a wide choice of possible inputs and the six reported here are those that were consistently significant regardless of the model specification. These are land, which is farm size in hectares; labor, which is the wages of permanent and temporary workers rather than the number of workers; pesticide and herbicide costs rather than quantities; and fertilizer, fuel, and electricity, all of which are in constant value terms. Machinery was best captured by fuel costs, without running costs and repairs, and this performed less well, perhaps due to the somewhat random occurrence of repairs. Electricity is largely used for irrigation and is consistently significant. All the monetary variables are deflated using the CPI, with a base year of 2010.

To explain the efficiency of the farms nine additional variables were used. The first are labor supervision costs, in thousands of ZAR, and the proportion of permanent to total labor costs. The remaining seven describe viticulture practices and other factors, all of which are expressed as percentages. These are the share of inorganic fertilizers in total fertilizer costs; the ratio of modern to old trellising; the proportion of total area on which drip irrigation or no irrigation was in place; the share of total planting that is on old vines; and the proportion of total planting allocated to red varieties. The descriptive statistics for all the variables that define the production frontier and are in the inefficiency model are in Table 1, separated into the old and new regions as defined above.

Table 1 shows that value of output is higher and area planted is greater in the old regions compared with the new. The total wage bill is also much higher in the old regions. This is easily explained as Stellenbosch and Paarl are adjacent to the Cape

Table 2
Hypothesis tests – total sample

Null hypothesis	Log-likelihood	χ^2 statistic	*Critical $\chi^2_{v,\,0.95}$	Decision
Unrestricted (translog) frontier model with inefficiency effects tested against alternatives	−13.3720			
(1) H_0: $\beta_{ij} = 0$, i,j, = 1, … 6	−62.9331	76.3051	$\chi^2_{21,\,0.95} = 32.08$	Reject H_0
Translog vs. Cobb-Douglas				
(2) H_0: Mean response vs. frontier	−48.9000	124.544	$\chi^2_{8,\,0.95} = 16.93$	Reject H_0
(3) H_0: all $\delta_i = 0$	−30.0764	86.8968	$\chi^2_{8,\,0.95} = 16.93$	Reject H_0
Inefficiency effects in the model				

Note: *Mixed $\chi^2_{v,0.95}$ critical values taken from Table 1 (Kodde and Palm, 1986). The likelihood-ratio test statistic, $X = -2\{\log[\text{Likelihood}(H_0)] - \log[\text{Likelihood}(H_1)]\}$, is distributed approximately χ^2 with degrees of freedom the number of parameters assumed to be zero in the null hypothesis.

Town metropolitan area and have access to better educated workers with a higher level of training. Fertilizer application is very similar between the old and new in the early years of the sample, although the new regions overtake the old from 2007. One cause is that as wine prices fell, the new regions were more inclined to compensate by raising yields, which tended to be at the expense of quality. Pesticide use is higher in the old regions, which is explained by the different climatic conditions discussed earlier, but whereas levels are steady in the old regions, there is an increasing trend in the new. Supervisor wages are much higher in the old regions for most of the period although these fall to only slightly more than the new regions by the final year of the data. New systems of trellising dominate in the old rather than the new regions and, not surprisingly, the new regions have lower levels of dry land because irrigation is more common, again reflecting different climatic conditions. Finally, more red varieties are grown in the old regions, where the red wine premium was higher, perhaps also as a result of established practice and reputation with the need to preserve existing labels.

6. Model selection, hypothesis tests, and results

Regardless of the approach taken, these data appear to give unusually consistent results. The pooled Cobb-Douglas mean response function is not reported, but the six inputs are all significant at the highest confidence levels and that they explain 87% of the variance in value of output. The output elasticities sum to 0.90, which suggests decreasing RTS, so on average the farms are too big to be scale efficient. Land is by far the most important input, followed by labor and pesticides, while fuel, electricity, and fertilizer make smaller contributions.

The method of maximum likelihood is used to estimate the unknown parameters, with the stochastic frontier and the inefficiency effects modeled simultaneously. A number of related models can be compared following estimation. First, the functional form of the production frontier is determined by testing the adequacy of the Cobb-Douglas against the flexible functional form of the translog. Second, the stochastic frontier should be tested against the mean response function, to confirm that the ordinary least squares (OLS) estimator is inadequate. Third, the significance of the inefficiency effects should be tested to ensure that they do improve the specification.

All the statistical tests to determine the preferred model suggest that this simple model is an inadequate representation of these data when compared with more advanced models, which is common in this literature (see, for example, Dong et al. (2016) and Seymour (2017). First, including the additional labor and viticulture variables in the OLS regression improved the F-statistic and increased the R^2 to 0.90, as four of the nine coefficients were significantly different from zero. The first test reported in Table 2 shows that the Cobb-Douglas production function is too restrictive compared to the translog, which allows for interactions between the variables and for nonlinearity. The frontier production function, with inefficiency effects was used, since the next test shows that the mean response function is inadequate and the third shows that the inefficiency effects do improve the model. Thus, the additional labor and viticulture practices are used to explain deviations from the frontier in the preferred model, which also exploits the panel nature of the data to use all the information fully.

The results in Table 2 are consistent regardless of the exact formulation of the model. The remaining important test statistic for the frontier is $\gamma = \sigma_u{}^2/(\sigma_u{}^2 + \sigma_v{}^2)$, which is the ratio of the errors in Eq. (1). So, γ is defined between zero and one, where if $\gamma = 0$, technical inefficiency is not present, and if $\gamma = 1$, there is no random noise. The null hypothesis is thus that $\gamma = 0$, indicating that the mean response function is an adequate representation of the data, whereas the closer γ is to unity, the more likely it is that the frontier model is appropriate. If γ is not significantly different from zero, the variance of the inefficiency effects (W_i in Eq. (3)) is zero and the model reduces to a mean response function in which the inefficiency variables enter directly (Battese and Coelli, 1995). In the preferred model, the value of $\gamma = 0.7959$ with a standard error of 0.051 for the full sample, which is a clear confirmation of the frontier model.

6.1. Results

The final translog model using the total sample has six inputs and eight additional terms to explain the inefficiencies, five of which are significantly different from zero. The first two columns of Table 3 shows that in the total sample and with six inputs there are 27 regressors, but with mean

Table 3
Maximum likelihood estimates – translog function (mean centered data)

Dependent variable: output	All regions		Old regions		New regions	
Frontier Determinants						
	Elasticity	Std Err	Elasticity	Std Err	Elasticity	Std Err
Constant	0.2749**	0.036	0.0988**	0.046	0.2256**	0.038
Land (Area)	0.5532**	0.035	0.4812**	0.084	0.6395	0.042
Labor (Wages)	0.1105**	0.030	0.1404**	0.072	0.0412**	0.038
Fertilizer	0.0428**	0.010	0.0101	0.019	0.0310**	0.013
Pesticides	0.1173**	0.021	0.1090**	0.042	0.1072**	0.025
Machinery (Fuel)	0.0473**	0.027	0.1923**	0.053	0.0943**	0.032
Electricity	0.0361**	0.017	−0.0963**	0.026	0.0345*	0.022
$Area^2$	0.0489	0.081	0.2199	0.188	0.1334	0.097
$Wages^2$	−0.0305	0.053	0.0244	0.100	−0.0060	0.079
$Fertilizer^2$	0.004**	0.001	0.0005**	0.002	0.0044**	0.001
$Pesticides^2$	0.1092**	0.025	0.5131**	0.083	0.1127**	0.030
$Fuel^2$	0.0106	0.010	0.1168	0.074	−0.0084	0.012
$Electricity^2$	0.0009	0.002	−0.0069**	0.003	0.0269**	0.007
Area*Wages	0.21**	0.098	0.1453	0.206	0.0201	0.133
Area*Fertilizer	0.0176*	0.013	0.0086	0.026	−0.0197	0.019
Area*Pesticide	−0.2867**	0.070	−0.1879*	0.180	−0.3108**	0.085
Area*Fuel	−0.0168	0.089	−0.2775	0.176	0.2961**	0.111
Area*Electricity	−0.0068	0.030	−0.0623	0.048	−0.0924**	0.042
Wages*Fertilizer	−0.0016	0.011	0.0223**	0.023	−0.0041	0.017
Wages*Pesticide	−0.0446	0.054	−0.5507**	0.155	0.0420	0.063
Wages*Fuel	−0.1169*	0.065	0.3538**	0.166	−0.2399**	0.084
Wages*Electricity	−0.0274	0.025	0.0709*	0.043	−0.0194	0.048
Fertilizer*Pesticide	−0.0138*	0.008	−0.0690**	0.027	0.0062	0.010
Fertilizer*Fuel	0.0197*	0.011	0.0044*	0.021	0.0258*	0.015
Fertilizer*Elect	−0.0047	0.004	−0.0008**	0.008	−0.0061	0.007
Pesticide*Fuel	0.101*	0.055	−0.2406	0.143	0.0627	0.060
Pesticide*Electricity	0.0149	0.011	0.0548	0.020	0.0036	0.018
Fuel*Electricity	0.0335**	0.015	−0.0050	0.024	−0.0159	0.035
Inefficiency effects						
Constant	0.5342**	0.117	0.300	1.611	0.5463**	0.140
% supervisors of total labor	−0.0095**	0.004	0.010	–1.984	–0.0172**	0.005
% permanent labor of total	−0.0023**	0.001	0.002	–4.079	0.0013	0.001
% inorganic fertilizer	0.0021**	0.001	0.002	2.050	0.0014	0.001
% modern trellising of total	−0.0008	0.001	0.001	–4.667	0.0020**	0.001
% drip irrigation of total	−0.0033**	0.001	0.002	0.122	–0.0070**	0.001
% dry land of total	0.0014*	0.001	0.003	0.133	0.0000	0.000
% old vines of total (>20 years)	−0.0017	0.002	0.003	0.113	0.0022**	0.001
% red varietals of total	0.0007	0.001	0.003	4.758	–0.0030	0.016
Gamma	0.7959**	0.051	0.157	1.768	0.7128**	0.079
log likelihood	–13.74		53.332		55.932	
LR test of the one-sided error	148.37		75.34		201.036	

Note: **Statistically significant at 95% confidence, *statistically significant at 90% confidence.

centered data, the direct effects shown at the top are the output elasticities for the six inputs and all are positive and significant. Land is the dominant input, accounting for over half the variation in value of output, followed by labor and pesticides, while machinery, fertilizer, and electricity account for smaller shares. These output elasticities sum to between 0.91 and 0.92 for all three samples, so there is decreasing RTS. The coefficients on the squared terms and cross-products are of less interest, but note that 11 of the 21 are significantly different from zero at the 90% confidence level. If the Cobb-Douglas is an adequate representation of the data, these need to be insignificant, so this is consistent with the test result in Table 2.

6.2. *Inefficiency effects*

The variables that explain deviations from the frontier begin with supervision costs. The coefficients cannot be interpreted as elasticities but their signs, relative magnitudes, and statistical significance matter. The coefficient on supervision is negative and significant at the 99% confidence level and it has a greater impact than the other inefficiency variables. This means that more supervision decreases inefficiency, which is very reasonable although it is costly, and the same is true for a greater share of permanent labor. This could have had either sign as the permanent labor is better trained, but could be too costly at periods when the demand for labor on the farm is reduced. The opposite is true of the share of inorganic fertilizer, which increases inefficiency. This suggests that natural fertilizer, such as chicken manure, is preferable to chemical fertilizers in the light sandy soils of the Western Cape. Modern trellising has no significant impact in this model, but is left in the table as it did reduce inefficiency in some specifications of the model. Drip irrigation is modern and efficient so the negative coefficient agrees with expectations of increased efficiency. Similarly, higher proportions of nonirrigated land increases inefficiency. Indeed, all these results seem to be in keeping with expectations.

6.3. Differences between old and new regions

The third and fourth columns of Table 3 report the estimation results for the old regions, Paarl and Stellenbosch. The last two columns do the same for the new regions, that is, the remaining seven. There are clear differences between the two samples. Land is far more important in the new regions, where the output elasticity of 0.64 means that land accounts for 70% of the variance in output (elasticity divided by the sum of the elasticities, so 0.64/0.92). For the old regions, the figures are 0.48 and 52%. For labor, the position is reversed, with an elasticity of 0.04 in the new regions and 0.14 in the old. Since it is not possible to produce with no labor at all, the insignificance of this small elasticity is ignored. Together, the two results suggest that extensification is the norm in the new areas, whereas this is not possible in Paarl and Stellenbosch due to lack of available land. Here, intensification is the norm. Fertilizer makes an insignificant contribution in old areas where the focus is on smaller, high-quality harvests, while it is of some importance in the new areas where due to weaker market access high yields are more important. It also explains the coefficient on electricity as this is mainly used for irrigation pumps, which are more important in the new regions. Pesticide matters in both groups, accounting for about 12% of the variation in value of output. The results for machinery are less sensible, as it is twice as important in the old regions. Since labor was not important in the new regions and while area expansion does seem to be, our expectation was the reverse of this result.

The results for the inefficiency effects that explain deviations from the frontier also vary considerably between the two regions. Supervision of labor is about equally important in both and the negative signs mean it reduces inefficiency. The percentage of permanent labor has no effect in the new regions, but increases efficiency in the old. More inorganic fertilizer reduces efficiency in both, which suggests that natural manure is more cost effective. More modern trellising reduces inefficiency in the old regions substantially, while it has the opposite effect in the new. This maybe that the recent investment in new trellising is not yet working effectively or it is too soon to have any impact. Drip irrigation is statistically significant and increases efficiency throughout the sample, but has twice as much impact in the old regions. The percentage of dry land was less than 15% in all cases and this is reflected in a lack of statistical significance. However, the percentage of old vines seems to not matter in the old regions, but reduces efficiency in the new ones. Lastly, the percentage of red wine reduces efficiency in the old regions, but is not significant in the new, which grow lower levels of red wine grapes. Table 1 shows that the share of red wine in the old regions is about 60%, while in the new it is only 25%. Thus, with the red wine prices depressed, the old regions are penalized far more.

Table 4
Regional effects in inefficiency model relative to Stellenbosch

Region	MLE coefficient	Standard error
Breedekloof	−0.009	0.0044
Klein Karoo	−0.002	0.0013
Malmesbury	0.002	0.0008
Olifants River	−0.001	0.0006
Orange River	−0.003	0.0009
Paarl	0.001	0.0009
Robertson	−0.001	0.0010
Worcester	0.001	0.0011

A less detailed overview of the regional differences can be generated by replacing the inefficiency variables with regional dummies, as in Table 4. Stellenbosch is excluded to avoid collinearity, so the regional coefficients are all relative to that district. The negative sign on Breedekloof means it is more efficient than Stellenbosch and the same is true of Klein Karoo, Olifants River, and Orange River. Malmesbury is less efficient and Paarl, Robertson, and Worcester are not significantly different.

6.4. Relative efficiency levels for all the regions

The Battese and Coelli (1995) model produced all the econometric estimates reported above. It also estimates efficiencies for each farm for each year as deviations from the best practice frontier. As this amounts to 847 efficiencies, some aggregation is required to make the results comprehensible. The more useful aggregations analyzed are reported in Table 5. For the full sample of 77 farms in each of the 11 years, the efficiencies are reported three lines from the bottom. The mean efficiencies are steady in the mid 1970s until 2010, which was a notably bad year. There was a partial recovery in 2011 and the figure stabilized at around 73%, until 2015, which was also a bad year.

In the penultimate line, it is clear that the performance in the old regions is on a downward trend, from an average of 80% efficiency, down to 70% and although this is exacerbated by the two bad years, some action is required to prevent this gradual decline continuing. For the new regions, there is no obvious decline, just downturns in the bad years of 2010 and 2011, largely due to poor climatic conditions. Maybe, they are better insulated against natural changes than the old regions, largely as a result of irrigation.

The results for the nine regions are not so different as it is the aggregates of these that produced the old and new regions

Table 5
Mean efficiency levels – translog stochastic frontier – all regions

District	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	Total
Breedekloof	0.769	0.802	0.831	0.771	0.755	0.746	0.748	0.842	0.786	0.745	0.777	0.779
Klein Karoo	0.856	0.792	0.912	0.822	0.884	0.752	0.875	0.863	0.862	0.863	0.829	0.846
Malmesbury	0.592	0.547	0.493	0.541	0.581	0.527	0.489	0.436	0.514	0.601	0.571	0.536
Olifants	0.726	0.806	0.784	0.817	0.795	0.751	0.816	0.798	0.794	0.736	0.698	0.775
Orange	0.556	0.651	0.545	0.552	0.458	0.583	0.528	0.531	0.696	0.695	0.731	0.593
Paarl	0.873	0.843	0.809	0.788	0.779	0.669	0.712	0.745	0.701	0.745	0.708	0.761
Robertson	0.822	0.734	0.760	0.724	0.765	0.700	0.731	0.789	0.749	0.706	0.675	0.741
Stellenbosch	0.779	0.757	0.735	0.709	0.745	0.640	0.726	0.695	0.700	0.743	0.664	0.718
Worcester	0.775	0.821	0.836	0.808	0.813	0.775	0.724	0.812	0.837	0.780	0.771	0.796
Total	0.754	0.760	0.750	0.729	0.733	0.684	0.707	0.730	0.735	0.733	0.709	0.730
Old regions	0.804	0.780	0.755	0.730	0.754	0.648	0.722	0.709	0.700	0.743	0.676	0.729
New regions	0.728	0.750	0.747	0.728	0.723	0.702	0.699	0.740	0.753	0.728	0.725	0.729

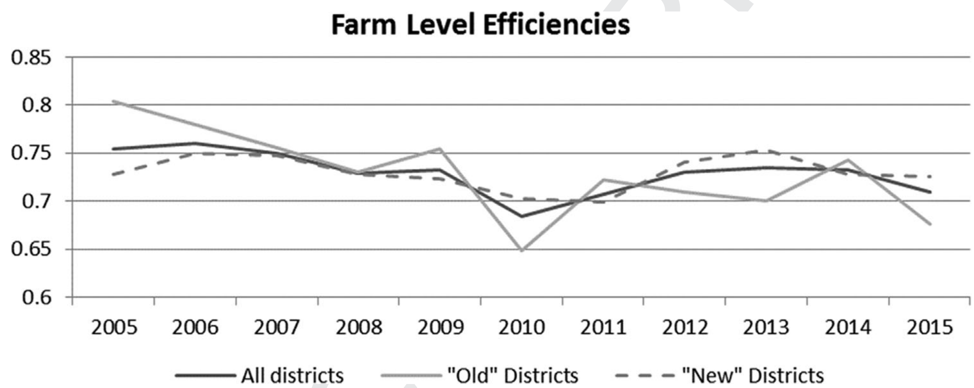

Fig. 2. Efficiency levels for the full sample and old and new regions.

data. However, the ranking of the regions is odd. The most efficient over the full period is the Klein Karoo, at 85%, but this must be discounted as being too unreliable with a sample of only two farms. In efficiency order, it is then Worcester, Breedekloof, Olifants, and Paarl, all over 75%, with Robertson just below that and Stellenbosch last of the over 70% group. That leaves two outliers, Orange River and Malmesbury, each based on a sample of six farms. The approach here is totally different from the regional dummies used for Table 4, so the exact same results are unlikely to be found. The Klein Karoo and Breedekloof should rank highly and do so. Olifants River was ranked fairly highly and is here too, as is Paarl, which does better than Stellenbosch. The Robertson and Stellenbosch results are not exceptional either, and the other two regions are quite different from the expectations based on Table 3. There, Worcester did very poorly, but here ranks second only to the dubious Klein Karoo result. At the opposite extreme, Orange River looked like the second best region on the basis of the dummy variables, but here it ranks second last, ahead of only Malmesbury, which ranks last in both approaches. These contradictory results require further investigation, but for seven of the nine regions the two approaches give similar results.

The means for all, old and new regions, in the last three rows of Table 5 serve as a warning on how averages hide differences in the data. By coincidence, the old and new averages are the same up to the fourth decimal place. The coefficients of variation, which reflect dispersion around the mean, are not the same. For the full sample, the coefficient of variation is 0.029, for the old regions 0.059, and for the new 0.023. Fig. 2 shows how different the series are but the means obscure this completely.

7. Conclusion

This article attempts to guide policy advice aimed at improving the efficiency of wine grape production in South Africa. It exploits the long history of wine production in by splitting the sample into two groups to determine the efficiency effects of technology in old established regions as compared with those that follow far later.

The statistically preferred model fits a six input translog production frontier, with eight farm characteristics to explain efficiency differences, to panel data for 77 farms for 11 years. The full sample results are as expected. Land is the most important input, followed by labor and pesticide, while fertilizer, machinery, and electricity make smaller contributions to output. For the old regions, land area has a smaller impact on output than in the new and the reverse is true for labor. Inefficiency levels were reduced by labor supervision in both regions and by a higher ratio of permanent to casual labor and modern trellising in the old areas, but not in the new. More inorganic fertilizer increased inefficiency in both regions. Increased drip irrigation reduced inefficiency in the new regions, but not the old, while more dry land had a negative effect in the new areas but not the old. A higher proportion of red to white grapes reduced efficiency in the old regions but not the new. And finally, more old vines as a share of the total, suggesting low levels of replacement of the vine stock, only had a negative effect in the new regions.

The regional differences can also be determined by using dummy variables. These are all relative to Stellenbosch and showed that Breedekloof, Klein Karoo, Olifants, and Orange Rivers were more efficient, Malmesbury less and Paarl, Robertson and Worcester not statistically different. An alternative approach compares the aggregate annual efficiency levels for the two regions and shows that these were fairly constant for the new areas, but for the old, there is a marked decline in efficiency over time. Thus, decreasing RTS and declining efficiencies over time matches the findings of Carvalho et al. (2008), but the cause is not easy to determine. There is evidence that the new regions have tended to go for higher yields at the expense of lower quality, whereas the old regions have tried to maintain their reputation for quality. It is possible that in efficiency terms, this was the wrong strategy, at least in the short run. The issue of scale efficiency is not pursued further here as summing the output elasticities is a very crude approach. Nonparametric methods do give scale efficiencies for every observation and will be used for this purpose in future research. However, information on viticulture practices at the farm level has provided a much richer data set with which to estimate productivity frontiers, particularly as these additional variables can be used to explain differences in efficiency between these wine grape growing regions and is an important extension to the existing literature.

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