Efficiency Measurement in Greek Dairy Farms: Stochastic Frontier vs. Data Envelopment Analysis

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Abstract
Parametric Stochastic Frontier Analysis (SFA) and non-parametric Data Envelopment Analysis (DEA) have become very popular in the analysis of productive efficiency. This paper undertakes a comparison of the SFA and the constant returns to scale (CRS) and variable returns to scale (VRS) output-oriented DEA models, based on a sample of 165 dairy farms in Greece. However, the aim of this paper is not only to compare estimates of technical efficiency obtained from two approaches, but also to produce efficiency data about the farms studied, which have implications for agricultural policy to improve dairy production. The results indicate that there is a potential for increasing production in the dairy farms through improved efficiency.

Keywords: Data Envelopment Analysis, Stochastic Frontier Analysis, Dairy Farms

JEL classification: Q18, D24, Q12

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1. Introduction

Efficiency measurement has been the concern of researchers with an aim to investigate the efficiency levels of farmers engaged in agricultural activities. Based on Farrell's (1957) pioneering article, several approaches to efficiency measurement have been developed. Among these, Stochastic Frontier analysis (SFA) models and Data Envelopment Analysis (DEA) models have proved an extremely useful tool in measurement of the technical efficiency of production units. The stochastic frontier approach was initiated by Aigner *et al.* (1977) and Meeusen and van der Broek (1977), while DEA approach was proposed by Charnes *et al.* (1978). Many authors in economic literature have dealt with the two approaches. Comprehensive reviews can be found in Kumbhakar and Lovell (2000), Seiford and Thrall (1990), Fried *et al.* (1993), Coelli, Rao and Battese (1998), Bravo-Ureta and Pinheiro (1993), Coelli, (1995), Cooper *et al.* (2000).

The main advantage of non-parametric DEA is that it does not require specification of the functional form of the production function. Furthermore, DEA simultaneously utilizes multiple outputs and multiple inputs with each being stated in different units of measurement. DEA focuses on revealed best practice frontiers rather than on central-tendency properties or frontiers and it generates a set of "peer" units with which a unit is compared. However, several properties that represent strengths in one capacity may act as limitations in another. DEA is deterministic and attributes all the deviations from the frontier to inefficiencies, i.e. at first sight, the method does not have any statistical foundation; it is not possible to make inference about estimated DEA parameters, sensitivity, asymptotic properties, etc. Recently, bootstrap techniques have been applied in order to obtain measures of statistical precision in the DEA estimates (Simar and Wilson, 2000a, 2000b, Löthgren and Tambour, 1999).

In contrast, the parametric stochastic frontier approach treats deviations from best-practice as comprising both random error (white "noise") and inefficiency. SFA also assumes a structure for the best-practice frontier and then fits a curve. An advantage of the econometric approach is that it allows for formal statistical testing of hypotheses and the construction of confidence intervals (Hjalmarsson *et al.*, 1996). The main drawback of the approach is that it requires a pre-specification of the functional form and an explicit distributional assumption for the technical inefficiency term.

The main purpose of this study is to compare technical efficiency measures from SFA and DEA models and to test if there are significant differences in the estimates of efficiency. A few studies (Hjalmarsson *et al.*, 1996; Kalitzandonakes and Dunn, 1995; Bjurek *et al.*, 1990; Wadud and White, 2000; and Sharma *et al.*, 1997) have compared empirical performance of the two techniques. As it concerns the dairy sector, there exist many studies which apply one of the two methods (Kumbhakar and Hjalmarsson, 1993; Tauer and Mishra, 2003; Cuesta, 2000; Bravo-Ureta and Rieger, 1991; Kumbhakar and Hesmati, 1995; Weersink et al., 1990; Manos and Psychoudakis, 1997; Hallam and Machado, 1996 and Luijt and Hillebrand, 1991), but there is only one (Reinhard, 1999), at least to our knowledge, comparative study of SFA and DEA approach concerning the dairy sector. Furthermore, this study contributes to the existing literature with the use of data from Greek dairy farms.

For the purpose of this paper, the analysis is limited to technical efficiency. A Cobb-Douglas stochastic frontier production function and constant returns to scale (CRS) and variable returns to scale (VRS) output-oriented DEA models are estimated. The analysis is based on farm accounting data from Greek dairy farms, which have not been studied before.

The paper is organized as follows: Section 2 describes the Stochastic Frontier Analysis and Data Envelopment Analysis models. Section 3 describes the dairy data. Section 4 contains the empirical results and their implications. Section 5 concludes the paper.

2. Theoretical Models

2.1 Stochastic Frontier Model

The stochastic frontier production function can be expressed as:

$$y_i = f(x_i;\beta)\cdot \exp\{v_i - u_i\} \qquad i = 1,2,3,...,n \tag{1}$$

where y_i is scalar output, x_i is a vector of inputs, and β is a vector of parameters to be estimated. The first error component, v_i, is assumed to be independently and identically distributed (iid) and symmetric, distributed independently of the u_i and captures the effects of statistical noise. The second error component, $u_i \geq 0$, is intended to capture the effects of technical efficiency component and it is assumed to be independently and identically distributed truncations (at zero) with mean, μ, and variance, σ_u^2. The technical efficiency of the *i*th farm, denoted by TE_i, can be estimated as:

$$TE_i = \exp(-u_i) \tag{2}$$

The prediction of technical efficiencies is based on the conditional expectation of e^{-u_i} given the values of $v_i - u_i$ (see Jondrow *et al*. (1982) and Battese and Coelli (1988)). This method allows a direct comparison between the results from the stochastic frontier approach and DEA.

Coelli (1995) suggests that the stochastic frontier method is recommended for use in agricultural applications, because measurement error, missing variables and weather, are likely to play a significant role in agriculture. More details and further approaches can be obtained from books edited by Fried, Lovell and Schmidt (1993), Coelli, Rao and Battese (1998) and Kumbhakar and Lovell (2000).

2.2 Data Envelopment Analysis

The non-parametric approach to efficiency measurement obtains technical efficiency estimators as optimal solutions to mathematical programming problems. Charnes *et al.* (1978, 1979, 1981) formulated the Data Envelopment Analysis (DEA) methodology, which defines a non-parametric frontier and measures the efficiency of each unit relative to that frontier. Assuming that there are n decision making units (DMUs), each producing single output by using m different inputs and the ith DMU produces y_i units of output using x_{ki} units of the kth inputs, the variable returns to scale (VRS) output-oriented DEA model for the ith DMU is expressed as follows:

$$\underset{\theta_i,\lambda_j}{Max}\,\theta_i \tag{3}$$

subject to:

$$\begin{aligned} &\sum_{j=1}^{n}\lambda_j y_j - \theta_i y_i - s = 0 \\ &\sum_{j=1}^{n}\lambda_j x_{kj} + e_k = x_{ki} \\ &\sum_{j=1}^{n}\lambda_j = 1 \\ &\lambda_j \geq 0; s \geq 0, e_k \geq 0; \end{aligned} \tag{4}$$

k = 1, …, m inputs; j = 1, …, n DMUs;

where θ_i is the proportional increase in output possible for the ith DMU; s is the output slack; e_k is the kth input slack; and λ_j is the weight of the jth DMU.

When the restriction $\sum_{j=1}^{n}\lambda_j = 1$ is removed the constant returns to scale (CRS) is obtained.

The output-oriented DEA model maximizes the proportional increase in output while remaining within the production possibility set. The proportional increase in output is obtained when output slack is zero. The ith farm is efficient, which means that the unit lies on the frontier when $\theta_i = 1, \lambda_i = 1$, and $\lambda_j = 0$ for $j \neq i$. The frontier level of production for the ith farm, denoted by y_i^*, is given by

$$y_i^* = \sum_{j=1}^{n}\lambda_j y_j = \theta_i y_i\,. \tag{5}$$

The output-oriented measure of technical efficiency of the ith farm unit, denoted by TE_i, can be estimated by

$$TE_i = \frac{y_i}{y_i^*} = \frac{1}{\theta}. \tag{6}$$

This measure can be compared directly with the measure of technical efficiency obtained under the stochastic production frontier. Both techniques consider the observed production relative to the corresponding potential production, given the quantities of the inputs used. Hence, the technical efficiency scores from the output-oriented DEA model are comparable with those obtained from the stochastic frontier model.

The scale efficiency measure for the *i*th farm, denoted by SE_i, can be calculated from the relationship of the estimate of technical efficiency of the ith farm in the VRS DEA (TE_i^{VRS}) and that in the CRS DEA (TE_i^{CRS}) as:

$$SE_i = \frac{TE_i^{CRS}}{TE_i^{VRS}} \tag{7}$$

where $SE_i = 1$ indicates constant returns to scale and $SE_i < 1$ indicates scale inefficiency. The nature of scale inefficiency can be of two types. First, a farm is too small and belongs to the section of the frontier where increasing returns to scale prevail; second a farm is too large and belongs to the section of the frontier where decreasing returns to scale prevail. In order to determine the type of scale inefficiency the sum of the weights is inspected. According to Banker and Thrall (1992) if the sum of the weights is greater than 1.0 we have decreasing returns to scale and if the sum of the weights is less than 1.0 we have increasing returns to scale. Constant returns to scale occur when the sum of weights equals one. (See also Banker *et al*., 1984; Löthgren and Tambour, 1996; Ali and Seiford, 1993; and Favero and Papi, 1995).

Table 1. Summary statistics for variables

Variable	Sample mean	Standard Deviation	Minimum	Maximum
Gross Output (€)	129030.98	142462.81	3363.90	743681.10
Labor (hours)	5315.72	3267.90	386.50	20650.00
Fixed Cost (€)	220705.60	206048.47	6001.00	989030.50
Variable Cost (€)	65294.55	71255.48	2803.00	359243.70

3. Data

The farm accounting data for this empirical application was collected from 12 prefectures in the regions of Macedonia and Thessaly through a farm management survey carried out during the period of 2003-2004. A sample of 165 dairy farms, which are located mainly in Macedonia, Greece, was surveyed for the application of this analysis.

All farms have the required characteristics for the empirical application of both DEA and SFA. The summary statistics of the variables gathered from the farms are reported in Table 1. In the specification chosen in this study, the conventional inputs have been aggregated into three categories (labor, fixed capital and variable capital). The labor input consists of total labor, measured in hours. Fixed capital is composed of buildings, machinery and livestock for breeding and utilisation, measured in Euros. The variable capital contains fertilisers, fuel, hired labour, purchased feed, rent of land and other variable inputs, all expressed in Euros. The rent of the land is included in the variable capital since the crop production has been used as feedstuff in the farms. Gross output, measured in Euros, is selected as the dependent variable in this study. The standard deviation of the average Gross output indicates the large variability of output among the farms.

4. Empirical Results

4.1 Stochastic Frontier Results

The maximum likelihood estimates of the Cobb-Douglas stochastic frontier are reported in Table 2. Specifically, in this table the coefficients of the estimated variables, their t-ratios and the variance of the parameters are presented. Maximum likelihood estimates of the parameters of the stochastic frontier model are obtained using the program FRONTIER 4.1 (Coelli, 1996). All coefficients are significant at the 1 percent level. As expected, the signs of the slope coefficients of the stochastic frontier are positive. The estimated value for the variance parameter, γ, in the stochastic production is significant, suggesting that inefficiency was present in production and that the traditional "average" production function is not an adequate representation of the data. Hence, technical inefficiency effects have significant impact on output (Wadud and White, 2000; Sharma *et al*. 1997; Hjalmarsson *et al*. 1996). The estimate of γ indicates that the portion of the one-sided error component in the total variance is as high as 61.6 percent. Thus, 61.6 percent of variation in the data between farms can be attributed to inefficiency and the remaining 38.4 percent is pure "noise". The estimated parameter σ_{ε}^2 is also found to be statistically significant at the 1 percent level. This result, which is consistent with Wadud and White (2000), Sharma *et al*. (1997) and Hjalmarsson *et al*. (1996), suggests that a conventional production function is not an adequate representation of the data. The mean technical efficiency estimated for the SFA approach is 0.812.

A more flexible translog production function was also applied. A Generalized Likelihood Ratio test (LR) was performed to test whether or not Cobb-Douglas production function could be used as an appropriate form of the production function estimated in this study. The result of the LR test suggested that translog stochastic production function is an inadequate representation of the data and it is rejected confidently in favor of the Cobb-Douglas. The test statistic was equal to 8.3, which is less than 12.6, the 95 percent critical value for the Chi-squared distribution with six degrees of freedom. The results presented here refer solely to the Cobb-Douglas production function. Another LR test was conducted to test the distribution of the inefficiency effects. The null hypothesis, which states that the half-normal distribution is an adequate representation for the distribution of the inefficiency effects could not be rejected.

Table 2. Maximum-likelihood estimates of the Cobb-Douglas stochastic production frontier model

Name of Variables	Parameters	Coefficients	t-ratios
Stochastic frontier			
Constant	β_0	0.0417 (0.2885)	0.1447
Labor	β_1	0.1928 (0.0603)	3.1964***
Fixed Cost	β_2	0.1281 (0.0459)	2.7913***
Variable Cost	β_3	0.7830 (0.0429)	18.2360***
Variance Parameters			
Sigma-squared	$\sigma_\varepsilon^2 = \sigma_u^2 + \sigma_v^2$	0.1257 (0.0317)	3.9626***
Gamma	$\gamma = (\sigma_u^2 / \sigma_\varepsilon^2)$	0.6159 (0.1985)	3.1034***
Sigma-squared of u	σ_u^2	0.0774	
Sigma-squared of v	σ_v^2	0.0482	
Log-likelihood		-21.2643	

Note: *** indicate the variables are significant at the 1% level of significance, respectively.
Figures in parentheses indicate standard errors.

The value of the elasticity of scale, which is found to be statistically significantly different from unity, is 1.1, implying that dairy farms operate under mildly increasing returns to scale, a finding, which is similar to that of Reinhard (1999).

4.2 DEA Frontier Results

The constant returns to scale (CRS) and variable returns to scale (VRS) output-oriented DEA models are estimated. The method has been applied to the same sample (same number of farms) and the same output and input variables as for the stochastic frontier model. As it has been already mentioned in the previous section, the output orientation has been selected because the technical efficiency scores obtained from the DEA method are comparable with those of the stochastic frontier production function.

Table 3. Frequency distribution of technical efficiency estimates from both the stochastic frontier and technical and scale efficiency from the DEA models

Efficiency Score	Stochastic frontier		Data Envelopment Analysis					
			CRS		VRS		SE	
	No. of farms	% of farms	No. of farms	% of farms	No. of farms	% of farms	No. of farms	% of farms
< 0.3	0	0.00	7	4.24	3	1.82	1	0.61
0.3-0.4	0	0.00	8	4.84	6	3.64	0	0.00
0.4-0.5	0	0.00	32	19.39	17	10.30	0	0.00
0.5-0.6	5	3.00	33	20.00	41	24.84	2	1.21
0.6-0.7	10	6.10	26	15.75	29	17.58	2	1.21
0.7-0.8	41	24.84	24	14.54	19	11.52	9	5.45
0.8-0.9	93	56.36	16	9.69	20	12.12	23	13.94
0.9-1.0	16	9.69	10	6.10	13	7.88	97	58.79
1.0	0	0.00	9	5.45	17	10.30	31	18.79
Total	165	100.00	165	100.00	165	100.00	165	100.00

The mean technical efficiencies estimated for the CRS and VRS DEA approaches are 0.634 and 0.685; a result which is consistent with the theory that the VRS frontier is more flexible and envelops the data in a tighter way than the CRS frontier. The mean technical efficiencies of the DEA models indicate that there is substantial inefficiency for the dairy farms in the sample, which confirms the expectations. Seventeen farms are fully technically efficient in terms of the VRS model and 9 farms are fully technically efficient under the CRS model. The technical efficiency scores estimated under the CRS DEA frontier are equal to, or less than those calculated under the VRS DEA model. This relationship, as stated above, is used to obtain the measure of scale efficiency SE. The scale efficiency index for the sample ranges from 0.298 to 1.000 with a sample mean and standard deviation of 0.927 and 0.098 respectively. Of the 165 farms, 27 show CRS, 61 show IRS and 77 show DRS.

The frequency distribution of the efficiency estimates obtained from the stochastic frontier and DEA model are presented in Table 3, while their summary statistics in Table 4.

Table 4. Summary statistics of efficiency estimates from both the stochastic frontier and DEA model

Efficiency score	SF	CRS	VRS	SE
Mean	0.8121	0.6340	0.6849	0.9270
Minimum	0.5195	0.2271	0.2540	0.2984
Maximum	0.9409	1.0000	1.0000	1.0000
Standard Deviation	0.0781	0.1902	0.1919	0.0985
Skewness	-1.2031	0.2137	0.1498	-2.9204
Kurtosis	1.7979	-0.6782	-0.8781	12.0185

4.3 Comparison of the Efficiency Results

Two different approaches have been applied to measure the technical efficiency of dairy farms. The mean efficiency for each of the methods is reported in table 4. Efficiency measure obtained from the stochastic frontier model is greater than that obtained from the VRS and CRS DEA model. DEA efficiency scores was expected to be less than those obtained under the specifications of stochastic frontier because the DEA approach attributes any deviation of the data from the frontier to inefficiency, while stochastic frontier analysis acknowledges the fact that random shocks beyond the control of the farmers can affect output. Both the CRS and VRS DEA measures exhibit greater variability than the stochastic frontier efficiency measure.

Spearman rank correlation coefficients between the technical efficiency rankings obtained from the stochastic frontier and the DEA are reported in Table 5. The general impression here is that all correlation coefficients are positive and highly significant at the 1 percent level. The strongest correlation is obtained between the efficiency rankings estimated from the VRS and CRS DEA model. The weakest correlation is achieved between the rankings from the stochastic production frontier and the VRS DEA model.

There are very few studies which have compared the technical efficiency estimates derived from the stochastic parametric frontier and deterministic nonparametric frontier. Sharma *et al.* (1997) reported similar results with ours, while Wadud and White (2000) reported a greater mean technical efficiency (0.858) obtained from the VRS DEA model than those of both CRS DEA and stochastic frontier model (0.789 and 0.791 respectively). However, Wadud and White (2000) did not find a greater variability of technical efficiencies from the DEA models than from the stochastic frontier efficiency measures. Hjalamarsson *et al.* (1996) reported both similar and dissimilar results obtained from the stochastic frontier analysis and, the DEA frontier analysis, depending upon the inclusion of the control variables in the stochastic frontier and the sequential or intertemporal specification in the DEA frontier. Kalaitzandonakes and Dunn (1995) found a significantly higher level of mean technical efficiency under CRS DEA (0.93) than under the stochastic production frontier model

(0.74), which is opposite from what we have found in this study. Finally, the results from Reinhard (1999), who applied the two frontier methods to a dairy sample using panel data, are very similar to ours. Reinhard (1999) found that SFA technical efficiency score (0.889) are higher (by about 10 percent) than CRS DEA efficiency score (0.783) and exhibits less variability.

Table 5. Spearman rank correlation matrix of technical efficiency rankings of sample dairy farmers obtained from different methods.

	TE_{SF}	TE_{VRS}	TE_{CRS}
TE_{SF}	1.000		
TE_{VRS}	0.7991	1.000	
TE_{CRS}	0.8384	0.9034	1.000

4.4 Implications

The dairy sector is one of the most heavily supported and is protected by the Common Agricultural Policy (CAP) mechanisms. The milk quota regime (introduced in 1984) has put a limit on the amount of milk that dairy farmers produce each year, in order to reduce the imbalance between supply and demand on milk and milk products market and the resulting structural surpluses, thereby achieving better market equilibrium. However, in Greece where the Mediterranean climatic conditions prevail, the country experiences a permanent deficit in its dairy production. Greece is a net importer of milk and milk products. The national reference quantity for Greece is 820,513 tones (Greece has "succeeded" an increase in its national quota by almost 100,000 tones, see EU Council Regulation No 1788/2003), whereas its milk production is only 721,261 tones. It is of particular interest to examine the potential of milk production in Greece, if dairy farms could operate efficiently.

Table 6 presents, according to farm size, the average levels of the actual outputs and frontier outputs relative to the stochastic and DEA frontiers. The farms were divided in this manner in order to get a close approximation as possible to the structure of Greek dairy sector and to include a satisfactory number of farms in each category. Based on the stochastic results, farms in the last category (>125 cows) could, on average, increase their output by 17.8 percent, farms in the third category (75-125 cows) by 16.3 percent, farms in the second category (25-75 cows) by 14.2 percent, and small farms (<25 cows) by 18.6 percent by producing their frontier outputs. The corresponding values for the VRS DEA frontier are 9.7 percent, 18.2 percent, 28.0 percent and 36.9 percent and those for the CRS DEA frontier are 20.5 percent, 21.8 percent, 30.9 percent and 40.4 percent, respectively. These results indicate that dairy production could have been increased substantially. This increased output could restore the equilibrium between supply and demand in the internal dairy products market in Greece. Furthermore, it would increase the profitability and the competitiveness of Greek dairy sector, since increased revenues would compensate for the high production costs.

Table 6. Average actual and frontier output for Greek dairy producers by farm size (in euros).
Note: Figures in parentheses are standard deviations.

Farm size	Number of Farms	Actual output	SF output	DEA frontier output	
				VRS	CRS
< 25 cows	60	28345 (16425)	33618 (19137)	38802 (22528)	39804 (22283)
25-75 cows	61	121350 (55207)	141472 (61602)	155376 (65686)	158895 (65661)
75-125 cows	27	302581 (117805)	351966 (123691)	357681 (106642)	368627 (116182)
> 125 cows	17	533417 (125838)	628319 (136221)	585183 (102370)	642564 (130874)
Total farms	165	129031 (142463)	150814 (164120)	157259 (156199)	163211 (166777)

5. Conclusion

In this paper two alternative approaches are applied for the estimation of technical efficiency, SFA and DEA. The econometric frontier model is estimated under the specification of the Cobb-Douglas stochastic frontier production model. A more flexible translog stochastic frontier is also applied but it is rejected in favor of the Cobb-Douglas model. In the DEA analysis, the output-oriented frontiers are estimated under the specifications of constant and variable returns to scale. Both approaches are used in order to estimate the technical efficiency of 165 Greek dairy farms. The objective of the paper is to compare the measures of technical efficiency obtained from the two approaches and to contribute to the existing relevant literature with the use of data from Greek dairy farms.

The estimated mean technical efficiency in the stochastic frontier model is larger than those obtained from the DEA analysis. According to the spearman rank coefficients the correlation between the two approaches is positive and highly significant. The highest correlation is observed between the stochastic frontier and the VRS DEA. The dairy farms appear to be characterized by mildly increasing returns to scale under the econometric specification, but by increasing and dominantly decreasing returns to scale under the DEA approach.

Results from both econometric and programming frontier indicate that there are substantial production inefficiencies among the sample dairy farmers. The sample dairy farmers, given the existing technology, could, on average, enhance their production by 17-26 percent and improve their competitive position if they could operate efficiently.

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