Technical and Scale Efficiency in the Italian Citrus Farming: A Comparison between SFA and DEA Approaches

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Abstract

Several studies have compared technical efficiency estimates derived from parametric and non parametric approaches, whereas a very small number of studies have aimed to compare scale efficiency estimations. This paper aims to estimate technical and scale efficiency in the Italian citrus farming. Estimation was carried out using both Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA). Empirical findings suggest that the greater portion of overall inefficiency in the sample might depend on producing below the production frontier than on operating under an inefficient scale. Furthermore, we found that the estimated technical efficiency from the SFA model is substantially at the same level of this estimated from DEA model, whereas the scale efficiency arisen from SFA is larger than this obtained from DEA analysis.

Keywords: *Technical efficiency, Scale efficiency, Citrus farming; Comparison Analysis*
J.E.L.: *C13, Q12*

1. Introduction

Since the Farrell's (1957) seminal paper several procedures have been proposed in order to calculate efficiency and productivity. However two main approaches have been mainly proposed in literature: the Stochastic Frontier Analysis (SFA) and the Data Envelopment Analysis (DEA). Both approaches have their advantages and disadvantages and the suitability of method to the data depends on the industry to be examined (Ruggiero, 2007). Literature has shown several studies on comparing the two approaches (Gong and Sickles, 1992; Hjalmarsson *et al.* 1996; Sickles, 2005) and more papers have focused attention on agriculture (Kalaitzandonakes and Dunn 1995; Sharma *et al.* 1997; Wadud and White, 2000; Theodoridis and Psychoudakis, 2008; Minh and Long 2009). They have mostly investigated on differences between technical efficiency scores and their distribution on the observed sample even if discordant results have been found (Sharma *et al.*, 1997; Ruggiero, 2007; Minh and Long, 2009).

On the contrary, poor relevance has been given on comparison in scale efficiency scores[1]. Scale efficiency is a measure inherently related to the returns to scale of a tech-

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[1] Among the others, Banker *et al.* (1986); Ferrier and Lovell (1990), Bjurek *et al.* (1990) Førsund (1992) compared scale efficiencies and scale properties obtained from parametric and non parametric approaches in other sectors different from agriculture.

nology at any specific point of the production process (Førsund and Hjalmarsson 1979). It measures how close an observed plant is to the optimal scale, *i.e.* it describes the maximally attainable output for that input mix (Frisch, 1965). A great number of papers have estimated scale efficiency in agriculture, generally using a DEA model (Bravo-Ureta et al., 2007). However choice of the method is a crucial issue because differences in scale efficiencies interpretation and scale properties might derive from inherent differences between parametric and non parametric models. It is expected to obtain some differences according to the methodology applied for estimating scale efficiencies in terms of scores – *e.g.*, caused by divergences in properties of the technology itself or in evaluation of distance to the frontier - and their distribution on the sample (Banker *et al.*, 1986; Førsund. 1992; Orea, 2002). Therefore, the issue is determining the "true" efficiency of a firm (Andor and Hesse, 2011). Using empirical data, it is impossible to evaluate the performance of the methods or to demonstrate absolute advantages of a method over its competitors. However, comparison between the two methods allows us to put on evidence if an estimated differences in efficiency measures exists and eventually to estimate the influence factors that lead to these differences.

The aim of this paper is to contribute in the existing literature providing a comparison between SFA and DEA approaches for estimating efficiency in agriculture with particular attention on scale efficiency. Specifically, we estimated efficiencies in the Italian citrus farming. This sector has been historically characterized by presence of small scale farms and structural disadvantages. If significant technical and/or scale inefficiency were found, this would indicate that structural problems prevent farm expansion and the rational use of technical inputs. It is the first attempt of comparing SFA and DEA scores in the Italian agriculture.

2. The Italian citrus farming

Citrus fruit growing is one of the largest categories in the Italian vegetable and fruit sector (Giuca, 2008). The value of production amounts to about 1.5 billion of Euros that corresponds to about 3% of the total gross domestic product from Italian agriculture (Ismea, 2011). In terms of value, oranges contributes to more than 50% to Italian production and about a 40% is equally distributed by tangerines and lemons.

Citrus farming is performed by more than 80,000 farms, mostly located in the southern regions of Italy. Specifically, more than 70% of the farms operate in Sicily and Calabry, whereas the rest of the farms are sited in Apulia, Campany, Sardinia, and Basilicata. During the period 1985-2014, the number of farms and the land area covered by citrus fruits have decreased by about 35% and 45%, respectively (Istat, 2015). Several reasons for this deterioration can be explored. First, the increasing competition in the world citrus fruit market has penalised Italian farmers because of structural and organisational problems. Italian farms appear significantly small (on average, the area is 1.44 Ha) and most of the citrus farms are located in less favourable areas where economic and productive alternatives are limited. Furthermore, despite the small size, many farms are fragmented in more plots of land, with evident implications on the ability to operate under efficient conditions. These and other factors have contributed in the last few years to Italy's declining competitiveness and efficiency in the world citrus fruit market. Structural constraints seem to negatively affect the performance of the Italian sector and inhibit economic development of citrus farming.

3. Data and the empirical models

Data were collected on a sample of 107 Italian citrus farms. All the selected farms participated in the official Farm Accountancy Data Network (FADN) during the period 2003-2005 and they are specialized in citrus fruit-growing (Table 1)[2].

DEA was carried out using an *output-oriented* approach and performing separated analyses for each considered year. We calculated efficiency both under constant (CRS) and variable returns to scale (VRS) as to estimate scale efficiency by the ratio of the CRS to the VRS measure (Banker, 1984; Banker et al., 1984).

The adopted SFA model corresponds to the Huang and Liu (1994) non-neutral production function model applied on panel data, which assumes that technical efficiency depends on both the method of application of inputs and the intensity of input use (Karagiannis and Tzouvelekas 2005)[3]. A time-varying technical inefficiency dependent on the levels of inputs used is provided in the Huang and Liu (1994) model, implying

Table 1 – *Involved variables and summary statistics for citrus farms in the sample (mean values)*

Variable		**2003**	**2004**	**2005**
Output				
Gross revenue (*euro*)	Y	54,508	53,861	56,542
Technical inputs				
Land area (*hectares*)	X_1	13.21	13.26	13.41
Expenditure for seeds, fertilizers, etc. (*euro*)	X_2	3,878	4,866	5,066
Machineries (*annual depreciation rate, euro*)	X_3	2,395	2,489	2,962
Capital (*annual depreciation rate, euro*)	X_4	5,050	5,182	5,052
Other expenditures (*euro*)	X_5	1,240	939	1,322
Labour (annual working *hours*)	X_6	2,785	2,814	2,772
	X_7			
Inefficiency variables				
Age of farm owner	Z_1	59.1	59.7	60.7
Size (*ESU*)*	Z_2	4.7	4.7	4.7
Altitude (*metres*)	Z_3	104	104	104
Number of plots of land	Z_4	1.6	1.7	1.7
Less-favoured zones (*dummy*)	Z_5	-	-	-
Location in Campany (*dummy*)	Z_6	-	-	-
Location in Calabry (*dummy*)	Z_7	-	-	-
Location in Apulia (*dummy*)	Z_8	-	-	-
Location in Basilicata (*dummy*)	Z_9	-	-	-
Location in Sicily (*dummy*)	Z_{10}	-	-	-
Location in Sardinia (*dummy*)	Z_{11}	-	-	-

*ESU = European Size Units

2 Farms with less than two European Size Units (ESU) were excluded from the sample.

3 For more details on adopted SFA see Madau (2011).

that the frontier of each firm shifts differently over time (Karagiannis and Tzouvelekas 2009). We assumed a Translog functional form as frontier technology specification and we applied that to a balanced panel data (321 observations).

In the DEA, the dependent variable (Y) represents the output and it is measured in terms of gross revenue from the *i*-th farm. The aggregate inputs are X_1 the total *land* area (hectares) devoted to citrus fruit-growing by each farm; X_2 the expenditure (euro) for seeds, fertilizers, water and other *variable inputs* used in the citrus fruits-growing; X_3 the value (euro) of *machineries* used in the farm; X_4 the value (euro) of *capital* (amount of fixed inputs such as buildings and irrigation plant, except for machineries); X_5 the expenditure (euro) for *other inputs*, consisting in fuel, electric power, interest payments, taxes, etc.; X_6 the total amount (annual working hours) of *labour* (including family and hired workers). Machineries and capital variables were measured in terms of annual depreciation rate so measure the annual utilization, on average, of the capital stock.

Explanatory variables of the inefficiency effects were represented by Z_1 the *age* of the farm owner; Z_2 the *dummy* variable *size* of the farm measured in terms of European Size Units (ESU) that can assume a value involved from 3 to 7; Z_3 the variable *altitude* that reflects the average altitude (in metres) by each farm; Z_4 the *number of plots* of land in which farm is fragmentized; Z_5 a *dummy* variable that reflects the placement (or not) of each farm in a *Less-favoured area* such as defined by the EEC Directive 75/268; Z_6-Z_{11} that represent a set of *dummy* variables indicating the regional location of farms.

Variables such as age of farmers, farm size, and regional location have been widely used in the efficiency analysis applied to Mediterranean agriculture (Tzouvelekas *et al.*, 2001; Alvarez and Arias, 2004; Madau, 2007). The first is generally used as a *proxy* of farmer skills, experience, and learning-by-doing. The second was implemented to evaluate the role of farm economic size in conditioning efficiency. The third serves to estimate the presence of territorial and geographic variability that may affect efficiency.

Altitude and location in a less-favoured area are variables used in some efficiency analysis to account for geoclimatic and socioeconomic heterogeneities (Karagiannis and Sarris, 2005; Madau, 2007). On the other hand, the number of lots could be a significant factor in conditioning both farm technical and scale efficiencies in the Italian citrus farming. Indeed, the subdivision of the farm land area into more plots of land could be an obstacle toward achieving full efficiency.

The Translog function used in the SFA model involves the same bundle of inputs selected for the DEA model and a variable that represents the time (*year*). The inefficiency model involves the same set of explanatory variables used for the DEA model and in addition, according to the non-neutral model proposed by Huang and Liu (1994), also the inputs (x_{it}) used in the production.

Scale efficiency effects were calculated using the same bundle of variables used for the technical efficiency effects model, with the exception of inputs that describe the frontier production. Scale efficiency was estimated using the method proposed by Karagiannis and Sarris (2005) that basically derives from the Ray (1998) parametric model.

4. Analytical findings

Technical efficiency scores arisen by application of the DEA model were estimated using the DEAP 2.1 program created by Coelli (1996a) and the main results are reported in Table 2. The mean estimated technical (VRS measure) and scale efficiency are equal to 0.711 and 0.894, respectively[4]. Imposing the *non increasing returns to scale* (NIRS) condition, we found that the most of the farms exhibit an increasing returns to scale. This implies that scale inefficiency is mainly due to the farms operating under a sub-optimal scale, *i.e.* farms where their output levels are lower than optimal levels and they should be expanded to reach the optimal scale. In the most of sub-optimal scale farms, scale efficiency is sensitively lower than estimated for the supra-optimal scale farms.

To explain technical and scale efficiency variations among the farms, the efficiency scores were regressed on the farm-level characteristics. A Tobit regression model was used, since the efficiencies vary from zero to unity. Technical efficiency is significantly and positively affected by farm size, whereas is negatively related to number of lots and location in less-favoured areas (Table 2). On the other hand, scale efficiency is negatively related to scale efficiency as well as number of plots, whereas farm size positively affects scale efficiency. Farm location appears to be a significant factor in conditioning scale efficiency because three regions show significant coefficients.

Concerning the SFA application, all parameters were estimated simultaneously using the computer program FRONTIER 4.1, created by Coelli (1996b). Maximum Likelihood (ML) estimates for the preferred frontier model were obtained after testing various null hypotheses in order to evaluate suitability and significance of the adopted model. The *Generalised likelihood-ratio test* was applied in order to estimate the more suitable functional form of the frontier (Transolg or Cobb-Douglas specification; non-neutral or neutral specification), presence of inefficiency effects, nature of inefficiency effects, presence of an intercept in the inefficiency model, presence of a time-variant or invariant effect, presence of farm-specific factors, presence of regional effects and, finally, presence of Age and Altitude effects. Table 2 reports the results arisen by the preferred model.

The analysis reveals that, on average, citrus farmers would be able to increase output by about 30% using their disposable resources more rationally (TE = 0.711). Returns to scale were found to be increasing (1.144). Therefore, the hypothesis of constant returns to scale is rejected. It means that citrus farmers should enlarge the production scale by about 14%, on average, in order to adequately expand productivity.

Empirical findings concerning the sources of efficiency differentials show that farm size is positively related to efficiency level. As expected, the number of lots is negatively correlated to technical efficiency, even if the low magnitude. Farms situated in less-favoured areas tend to be more inefficient than those located in normal zones.

ML estimation shows that all inputs play a significant role in determining efficiency and that farmers tend to become less efficient over time, even if the magnitude is really low.

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4 We also calculated the Malmquist productivity index in order to assess if technical change exists over the observed period. Findings suggest that no total factor productivity change exists, implying that no appreciable change and efficiency effects were estimated. Furthermore, not significant differences between the estimated annual technical efficiency scores were found, therefore the triennial average score was only reported in Table 2.

***Tab. 2** – Estimated technical efficiency and scale efficiency for DEA and SFA models*

	DEA			SFA	
	EFFICIENCY				
	TE^{CRS}	**TE^{VRS}**	**SE**	**TE**	**SE**
Mean*	**0.623**	**0.711**	**0.894**	**0.710**	**0.818**
s.d.	*0.242*	*0.256*	*0.163*	*0.266*	0.213
Min	0.226	0.257	0.287	1.000	1.000
Max	1.000	1.000	1.000	0.060	0.012
	RETURNS TO SCALE				
		% farms	SE	% farms	SE
Supra-optimal scale		13.1	0.934	14.7	0.978
Optimal scale		20.6	1.000	5.9	1.000
Sub-optimal scale		66.3	0.692	79.4	0.775
Total sample		**100.0**	**0.894**	**100.0**	**0.818**
	INEFFICIENCY EFFECTS				
		TE^{VRS}	**SE**	**TE**	**SE**
Constant		0.607 ***	0.756 ***	-	-
Age		-0.001	-0.003 **	-	0.006
Size		0.036 *	0.042 **	-0.495	0.040
Altitude		-0.001	-0.001	-	0.019
Number of plots of land		-0.056 *	-0.040 **	0.014	-0.030
Less-favoured zones		-0.018 *	0.005	0.012	-
Campany		0.110	0.269 *		0.044
Calabria		0.082	-0.002		0.002
Apulia		0.225	-0.045		-0.016
Basilicata		0.049	-0.093 *		-0.011
Sicily		0.090	-0.179 **		0.055
Sardinia		redundant	redundant		0.051
Land Area				-0.679	
Expenditure for seeds, fertilizers, etc.				0.359	
Machineries				-0.043	
Capital				0.068	
Other expenditures				0.319	
Labour				-0.740	
Year				0.091	-0.066

Scale efficiency amounts, on average, to 0.818. We found that about 80% of the observations exhibit increasing returns to scale. In these farms, scale efficiency is sensitively lower than the average (77.5%) and the average scale elasticity is abundantly upper than unity (1.237). Only about 6% of the observations operate under an optimal scale, whereas about 15% of the panel reveals decreasing returns to scale.

The original proposed inefficiency model was tested using the *Generalised likelihood-ratio test*. Concerning the preferred model, farm size is the factor that contributes the most to conditioning positively scale efficiency. The number of plots of land represents the second most important factor in the order of importance that affects scale efficiency. The low magnitude of the farmers' age parameter suggests that this variable has little influence on the observed efficiency differentials, whereas altitude has positive and significant effects on scale efficiency. Similarly to technical efficiency effect estimation, the relationship between time and scale efficiency is negative. The findings show that there are statistically significant differences in scale efficiency between farms located in different geographical regions of Italy.

5. A comparison between SFA and DEA estimates and discussion

We found that technical efficiency estimated from DEA model under variable returns to scale hypothesis and from SFA show not significant differences. Vice versa, significant difference (for $\alpha = 0.05$) is revealed between DEA CRS and SFA model.

DEA VRS score was expected to be less than that obtained under the specifications of stochastic frontier because the DEA approach attributes any deviation of the data from the frontier to inefficiency, while SFA deviation can be determined also by random shocks beyond the control of the farmers (Theodoridis and Psychoudakis, 2008). According to Bravo-Ureta *et al.* (2007) difference between the two scores can result not significant in case of presence, as we found, of several DEA scores equal 1.000.

Distribution of scores on the sample should give us more information about differences between estimated technical efficiencies calculated from SFA and DEA. As reported in Table 3, findings arisen by DEA (under variable returns to scale) suggest that the main share of farms reveals an optimal degree of efficiency (more than 20%), whereas a full efficiency is achieved by less than 2% of the sample in case of estimation trough SFA model. On the contrary, the share of farms that report an efficiency score close to the frontier ($0.900 < TE < 1.000$) amounts to 34.9% and 14.9% for SFA and DEA models, respectively. It might depend on the DEA method of constructing the frontier and its inherent difficulty under variable returns to scale hypothesis to detect the real efficiency due to possibility of overestimating number of full efficient units (Førsund, 1992; Kumbhakar and Tsionas, 2008).

In the light of differences in distribution of the scores on the sample, we computed the Spearman rank correlations between efficiency ranking of the observed sample (Table 4). All the correlations coefficients are positive and highly significant. The strongest correlation is obtained between the rankings from the SFA and the DEA VRS model. It confirms that hypothesis of constant returns to scale should be rejected, as reported above, in the SFA model implying that under the same set of data and assuming variable returns to scale for the DEA frontier, the SFA model holds no real advantage over DEA in estimating technical efficiency scores and efficiency variability.

Concerning scale efficiency scores, as found by other authors we estimated that in both cases it is higher than the related technical efficiency score (Karagiannis and Sarris, 2005; Theodoridis and Psychoudakis, 2008). The mean scale efficiency relative to SFA model (0.818) is lower than that estimated from the DEA model (0.894) and we found significant differences from the two scores (for $\alpha = 0.05$). It suggests that the choice of model sensitively affect estimation of scale efficiency and difference between SFA and DEA mean scale efficiency is significantly greater than difference in terms of technical efficiency. A possible reason at the basis of the higher scale efficiency arisen by DEA derives from the fact that it is a technology invariant measure. It means that DEA scale efficiency might result closer than SFA score to the frontier because the former model attributes any deviation of each observation from the frontier to inefficiency, whereas the latter model permits to separate noise from inefficiency term and to make statistical inferences about estimated scale efficiency.

As a consequence, some differences might be found in the efficiency scores distribution. Table 3 shows that distribution of scale efficiency scores on the sample is similar between DEA and SFA measures, except to share of farms that reveal full efficiency. Using SFA model, 5.9% of the sample reports an optimal degree of scale efficiency, whereas this percentage amounts to 18.7% in case of application of DEA model. According to Førsund (1992), it could depend on identification problem of full efficient

Table 3 – *Frequency distributions of technical and scale efficiency from the SFA and the DEA^{VRS} models*

Efficiency score	**TECHNICAL EFFICIENCY**			
	SFA		**DEA ^{VRS}**	
	Observations	**%**	**Observations**	**%**
< 0.200	13	4.0%	-	-
0.201 – 0.300	27	8.4%	12	3.7%
0.301 – 0.400	17	5.3%	27	8.5%
0.401 – 0.500	26	8.1%	51	15.9%
0.501 – 0.600	22	6.9%	42	13.1%
0.601 – 0.700	23	7.1%	39	12.1%
0.701 – 0.800	19	5.9%	18	5.6%
0.801 – 0.900	57	17.8%	18	5.6%
0.901 – 0.999	112	34.9%	48	14.9%
1.000	5	1.6%	66	20.6%
Total	321	100.0%	321	100.0%
Efficiency score	**SCALE EFFICIENCY**			
	SFA		**DEA ^{VRS}**	
	Observations	**%**	**Observations**	**%**
< 0.200	3	0.9%	-	-
0.201 – 0.300	8	2.5%	3	0.9%
0.301 – 0.400	9	2.8%	9	2.8%
0.401 – 0.500	17	5.4%	6	1.9%
0.501 – 0.600	18	5.6%	9	2.8%
0.601 – 0.700	18	5.6%	6	1.9%
0.701 – 0.800	34	10.6%	24	7.4%
0.801 – 0.900	54	16.8%	57	17.8%
0.901 – 0.999	141	43.9%	147	45.8%
1.000	19	5.9%	60	18.7%
Total	321	100.0%	321	100.0%

observations by part of DEA model because units located at the end of size distribution may be identified as efficient simply for lack of other comparable units. *Vice versa*, since the mean DEA scale efficiency score is higher than the correspondent SFA measure, a larger number of full efficient farms computed trough DEA might be attributed to real differences due to the methodologies adopted to estimate the frontier.

Computation of the Spearman rank correlations suggests that correlation between scale efficiency ranking from the SFA and the DEA models is positive and significant but magnitude is not sensitively high (Table 4). It implies that choice of the method might influence estimation of scale efficiency. This is a relevant point arisen by this study and it confirms how scale efficiency can vary depending on the model adopted for estimating frontier function on a given sample of farms, as found by several authors (Banker *et al.*, 1986; Førsund, 1992; Sharma *et al.*, 1997; Wadud and White, 2000; Ruggiero, 2007; Andor and Hesse, 2011).

Table 4 *– Spearman rank correlation matrix of TE and SE rankings obtained from different models*

TE	Estimated average	Spearman rank correlation (p)		
		TE^{CRS}	TE^{VRS}	TE^{SFA}
TE^{CRS}	0.623	1.000		
TE^{VRS}	0.711	0.715	1.000	
TE^{SFA}	0.710	0.610	0.922	1.000
SE	Estimated average	Spearman rank correlation (p)		
		TE^{DEA}	TE^{SFA}	
TE^{DEA}	0.894	1.000		
TE^{SFA}	0.818	0.547	1.000	

However, scale efficiency is found to be high, on average, from application of both methods. Since the technical efficiency score is, on average, lower than the scale efficiency score this implies that the greater portion of overall inefficiency in the sample might depend on producing below the production frontier than on operating under an inefficient scale. It means that the search for an optimal scale would not become a priority for citrus farmers, whereas it would be a priority increasing ability in using disposable technical.

Furthermore, both DEA and SFA analyses suggest that scale inefficiency is mainly due to the farms operating under a sub-optimal scale. Indeed, we found that the most of the observed farms operate under increasing returns to scale for both methods also if the incidence of sub-optimal scale farms on the total citrus farms is higher if scale efficiency is measured trough SFA (66.3% vs. 79.4% for DEA and SFA, respectively). In addition, both analyses suggest that these sub-optimal-scale farms must have adjusted their output levels to a greater extent than the supra-optimal-scale ones. In these latter farms, the margin that separate them from the optimal scale seem to be really narrow, as suggested by the estimated scale efficiency that is, on average, close to unity (SE equal to 0.934 and 0.978 for DEA and SFA, respectively), whereas in the sub-optimal scale farms this margin is large (scale efficiency equal to 0.692 and 0.775 for DEA and SFA, respectively). Therefore it implies that scale inefficiency is mainly due to the farms operating under a suboptimal scale.

These findings are not surprising, considering that recent studies have focused on realities characterised by the presence of small-sized farms and have found similar results about diffusion of sub-optimal scale efficient farms (Coelli *et al.* 2002; Karagiannis and Sarris 2005; Latruffe *et al.* 2005). The underlying rationale is that these realities are often characterised by a large number of small-sized farms that generally face capital, structural, and infrastructural constraints (*e.g.*, vast land fragmentation, huge number of single-household farms, insignificant presence of land market). They usually do not have adequate farming implements or up-to-date technologies or they are not allowed to reach their optimum size under their particular circumstances. Thiele and Brodersen (1999) argue that these market and structural constraints are among the main factors that usually impede achievement of efficient scales by part of farmers. Carillo *et al*. (2008) found that the input mix is unbalanced in the Italian citrus farms in favour of a high ratio of capital to land area and labour to land area. This should be mainly caused by a scarce flexibility in the land market, which forces farmers to expand the use of other inputs (except for land), especially labour and capital, with practical implications on the scale efficiency. Therefore, the presence of a quasi-fixed factor such as land should negatively affect scale efficiency and should favour exhibition of increasing returns to scale.

Estimation of the inefficiency effects show that it is slightly sensitive to the method used. Both computations of DEA and SFA reveal that technical efficiency should significant depend on farm size (positive effect), on number of plots of land and (negative effect) and on location in a less-favoured area (negative effect).

It must be underlined that the fact that farm size affect technical efficiency is an empirical finding that is often found in the literature, even if studies show controversial results about the relationship between technical efficiency and farm size (Sen 1962; Kalaitzandonakes *et al.* 1992; Ahmad and Bravo-Ureta 1995; Alvarez and Arias 2004).

Also estimation of scale efficiency effects show similar results in DEA and SFA application. In both analysis farm size (positive effect), number of plots of land (negative effect) and geographical location of farm should be the main factors that affect scale efficiency in the Italian citrus farming.

6. Concluding remarks

This paper is a first attempt in Italian agriculture to investigate differences in technical and scale efficiencies between parametric and not parametric approach. Findings arisen by SFA and DEA applications on a sample of citrus farms suggest that structural problems prevent farm expansion and the rational use of technical inputs. Therefore some margins exist to increase efficiency. Furthermore, we found that estimation of scale efficiency in the Italian citrus farming is not neutral to methodological approach used because the scale efficiency arisen by SFA is larger than this obtained from DEA analysis. Vice versa, both methods estimate similar technical efficiency scores.

There is no *a priori* reason to expect differences in estimated efficiencies using different methods. Estimated differences might depend on specific data used and each model shows advantages as well as certain shortcomings relative to the other. In this study, comparison between the two methods allowed us to differently interpreter efficiency in the Italian citrus fruit-growing farms according to the inherent nature of the applied model. In other terms, comparison cannot permit to individuate the best performer method - since there is no *a priori* reason for choosing any of the alternative models – but applications of more models allows us to differently interpreter capacity in efficiently producing citrus.

However, evaluation of the effective role of technical and scale efficiency in conditioning the Italian citrus fruit sector's performances is a crucial issue. Choice of method for estimating (technical and scale) efficiency and related measures should depend on perspectives trough researchers would analyse a given reality. This is particularly relevant when policy implications can derive from efficiency analysis.

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