Parametric Estimation of Technical and Scale Efficiencies in Italian Citrus Farming

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Abstract

Ray (1998) has proposed a model for estimating scale efficiency using a parametric approach. Following this methodology, a scale efficiency measure is obtained from the estimated parameters of the production frontier function and from the estimated scale elasticities. This study aims to estimate technical and scale efficiencies achieved by the Italian citrus fruit-growing farms. A stochastic frontier production model is considered in order to estimate technical and scale efficiencies. The analysis is expected to estimate the role of both technical and scale efficiencies in conditioning productivity. Particular attention is put on determining the inefficiency effects associated with a set of structural and environmental variables and on the relationship between technical and scale efficiency scores. 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. Indeed, room for improving technical efficiency is, on average, larger (29%) than the margin due to scale inefficiency (18%). Results also indicate a weak relationship between the two efficiency measures.

Key words: *Technical efficiency, Scale efficiency, Stochastic Frontier Analysis, Citrus faming, Italy*

Introduction

According to Frisch's (1965) definition, optimal scale of production refers to an input bundle where scale elasticity equals unity and, as a consequence, a plant operates under constant returns to scale. It describes the maximally attainable output for that input mix. This definition substantially corresponds to Banker's (1984) concept of most productive scale size (MPSS) in the Data Envelopment Analysis (DEA) context.

Practically, plants rarely operate at an optimal scale for several reasons (e.g., constraints in the labour market or in capital disposability, land fragmentation, and existence of an inflexible land market). It means that a certain grade of inefficiency is observable.

Scale efficiency is a measure inherently relating to the returns to scale of a technology at any specific point of the production process. Traditionally, it measures how close an observed plant is to the optimal scale (Försund and Hjalmarsson, 1979). More precisely, scale efficiency reflects the ray average productivity at the observed input scale with respect to the efficient (optimal) scale (Försund, 1996).

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A great number of papers in the economic literature have estimated scale efficiency in agriculture. In most of these studies, scale efficiency is calculated using a non-parametric approach, specifically through DEA models (Bravo-Ureta *et al.*, 2007). In the DEA model, scale efficiency is measured by estimating two technical efficiency measures in a preliminary step, i.e., efficiency is calculated under different assumptions of constant and variable returns to scale. Thus, scale efficiency is obtained by dividing the first measure by the second one (Coelli, 1996a). Therefore, scale efficiency should measure the role of scale in determining technical efficiency.

On the other hand, a common task in parametric analysis is to estimate scale elasticity, without any reference to scale efficiency[1]. The most likely reason for measuring scale efficiency, which has not become widely held in the parametric approach, is that a closed form measure directly computable from the fitted model is not currently available for the more flexible functional forms, as translog specification. This is a significant analytical shortcoming, even though more than two decades ago, several scale efficiency measures were proposed in the context of the generalised Cobb-Douglas production frontier by Försund and Hjalmarsson (1979).

As emphasised by Orea (2002) and Karagiannis and Sarris (2005), the approach followed for the DEA is hardly transferable when a parametric methodology is used. Indeed, there is nothing to guarantee that the variable returns-to-scale technology is enveloped from the constant returns-to-scale technology in the parametric context.

A model for estimating scale efficiency within a parametric approach was proposed by Ray (1998). Following this methodology, a scale efficiency measure is obtained from the estimated parameters of the production frontier function–under the variable returns-to-scale hypothesis and from the estimated scale elasticity. Ray's (1998) model has the advantage of being easily tractable from the econometric point of view and being particularly suitable for a translog frontier function[2].

In spite of these operational advantages, the model proposed by Ray (1998) has been scarcely adopted for estimating scale efficiency in agricultural studies. Recently, Karagiannis and Sarris (2005) applied this model to investigate the Greek tobacco farms. They analysed a sample of tobacco growers during 1991–95 and calculated technical and scale efficiencies at the farm level. They found that, on average, the degree of technical efficiency (which varied from 64.7% to 76.2%) was lower than the degree of scale efficiency (from 90.1% to 95.9%). This would indicate that overall inefficiency may depend mainly on producing below the production frontier than on adopting an inefficient scale. Mo (2009) calculates scale efficiency of wheat farms in Kansas from parametric measures of technical efficiencies, but adopting the model illustrated by Featherstone *et al.* (1997) suitable for cost functions measures and applied by the authors to non-parametric efficiency measures.

On the other hand, other studies calculate technical efficiency using both parametric and non-parametric approach, but estimation of scale efficiency is carried out exclu-

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1 On the contrary, scale elasticity is scarcely measured using a non-parametric approach, even though this shortcoming has been resolved by Försund (1996).

2 On the basis of the methodological contribute of Ray (1998), Balk (2001) has proposed a model suitable for multi-output technologies using a translog output distance function.

sively adopting a non-parametric technique (Andreu and Grunewald, 2006; Vu, 2006; Bojnec and Latruffe, 2008). It is our opinion however that scale efficiency measures obtained from parametric models might give us relevant information as well as non-parametric measures about the role of scale in affecting productivity, especially when panel data are handled.

In the light of these considerations, the objective of the present study is to attempt an empirical evaluation of the technical and scale efficiencies exhibited by the Italian citrus farming. The paper is focused on understanding if great inefficiency exists in using technical inputs and in operational scale in order to assess how much some technical and structural constraints obstacle achievement of satisfactory performances by part of this sector.

Estimation of efficiency was done on a balanced panel data of 107 farms that participated in the official Farm Accountancy Data Network (FADN), which was investigated from 2003 to 2005 (a total of 321 observations).

A stochastic frontier analysis (SFA) model (parametric) is considered in order to estimate technical and scale efficiencies. Specifically, a non-neutral production function model and the Ray (1998) model were applied to estimate technical and scale efficiency, respectively. The joint estimation of these measures allowed us to evaluate the individual role of technical and scale efficiency in conditioning productivity. Particular attention was put on determining the (technical and scale) inefficiency effects associated with a set of structural and environmental variables that could affect efficiency and on assessing the relationship between technical and scale efficiency scores.

The article is organized as follows: the empirical model for the estimation of technical and scale efficiency is presented in the section 2; background information on the Italian citrus fruits sector is reported in the section 3; dataset and the applied model with the definition of the explanatory variables are described in the section 4; the empirical findings are discussed in the section 5; and, finally, concluding remarks are summarized in the section 6.

Methodological background

Stochastic Frontier Analysis (SFA)

Stochastic Frontier Analysis (SFA) was originally and independently proposed by Aigner *et al.* (1977) and Meeusen and van der Broeck (1977). In these models, the production frontier is specified which defines output as a stochastic function of a given set of inputs. The presence of stochastic elements makes the models less vulnerable to the influence of outliers than with deterministic frontier models. It concerns that the error term ε may be separated in two terms: a random error and a random variable explanatory of inefficiency effects:

(1a) $y_{it} = f(x_{it}, t; \beta) \bullet \exp \varepsilon$

(1b) $\varepsilon = (v_{it} - u_{it}) \qquad i = 1,2,\ldots N \qquad t = 1,2,\ldots T$

where y_{it} denotes the level of output for the i-th observation at year t; x_{it} is the row vector of inputs; t is the time index, β is the vector of parameters to be estimated; $f(\bullet)$ is a suitable functional form for the frontier (generally Translog or Cobb-Douglas); v_{it} is a symmetric random error assumed to account for measurement error and other factors not under the control of the firm; and u_{it} is an asymmetric non-negative error term assumed to account for technical inefficiency in production.

The v_i's are usually assumed to be independent and identically distributed $N(0, \sigma_v^2)$ random errors, independent of the u_{it}'s that are assumed to be independent and identically distributed and with truncation (at zero) of the normal distribution $|N(0, \sigma_u^2)|$. The Maximum Likelihood Estimation (MLE) of (1) allows us to estimate the vector β and the variance parameters $\sigma^2 = \sigma_u^2 + \sigma_v^2$ and $\gamma = \sigma_u / \sigma_v$; where $0 \leq \gamma \leq 1$. The TE measure is obtained by the ratio of y_{it} to the maximum achievable level of output:

$$(2) \quad TE = \frac{y_{it}}{y^*} = \exp(-u_{it})$$

where y* is the output that lies on the frontier. Furthermore, assuming a semi-normal distribution for u_{it} and according to Jondrow *et al.* (1982), the degree of technical efficiency of each firm could be estimated.

Most of the SFA function models proposed in literature are inappropriate to estimate the inefficiency effects caused by factors that affect efficiency. In order to estimate these effects, some authors proposed a *two-stage* method, in which the first stage consists in technical efficiency estimation using a SFA approach, and the second stage involves the specification of a regression model that relaxes technical efficiency with some explanatory variables (Pitt and Lee, 1981; Kalirajan, 1982; Parikh and Shah, 1994).

One-stage SFA models in which the inefficiency effects (u_i) are expressed as a function of a vector of observable explanatory variables were proposed by Kumbhakar *et al.* (1991), Reisfschneider and Stevenson (1991), Huang and Liu (1994). In this model, all parameters – frontier production and inefficiency effects – are estimated simultaneously. This approach was adapted by Battese and Coelli (1995) to account for panel data. They proposed an *one-stage* approach where the functional relationship between inefficiency effects and the firm-specific factors is directly incorporated into the MLE. The inefficiency term u_{it} has a truncated (at zero) normal distribution with mean m_{it}:

$$(3a) \quad u_{it} = m_{it} + W_{it}$$

where W_{it} is a random error term which is assumed to be independently distributed, with a truncated (at $-m_{it}$) normal distribution with mean zero and variance σ^2 (*i.e.* $W_{it} \geq -z_{it}$ such that u_{it} is non-negative).

The *mean* m_{it} is defined as:

$$(3b) \quad m_{it} = Z(z_{it}, \delta) \qquad i = 1,2,\ldots N \qquad t = 1,2,\ldots T$$

where Z is the vector (Mx1) of the z_{it} firm-specific inefficiency variables of inefficiency; and δ is the (1xM) vector of unknown coefficients associated with z_{it}. So we are able to estimate inefficiency effects arisen from the z_{it} explanatory variables[3].

Parametric estimation of scale efficiency

Orea (2002) argues that the *non-parametric* approach difficultly can be directly transferred into a parametric approach in order to calculate scale efficiency. Indeed when parametric approach is used, hypothesis that VRS technology is enveloped from CRS technology is weak by a theoretical point of view.

As mentioned above, Ray (1998) proposed a model in which scale efficiency can be calculated from the estimated parameters of the production frontier and from scale elasticity estimations. For a translog frontier function:

$$(4) \quad \ln y_{it} = \beta_0 + \sum_{j=1}^{n} \beta_j \ln x_{jit} + \frac{1}{2}\sum_{j=1}^{n} \sum_{k=1}^{l} \beta_{jk} \ln x_{jit} \cdot \ln x_{kit} + (v_{it} - u_{it})$$

and assuming an output-oriented approach for the technical efficiency estimation, scale elasticity at farm-specific input bundle is equal to:

$$(5) \quad \mathrm{E}_{it} = \sum_{j=1}^{n}\left(\beta_j + \sum_{k=1}^{l} \beta_{jk} x_{kit} + \beta_{ji} t \right)$$

Remanding to Ray (1998) for a more detailed description of the methodology, it follows that the output-oriented scale efficiency (SE^O) corresponds to:

$$(6) \quad \mathrm{SE}_{it}^{O} = \exp\left[\frac{(1 - \mathrm{E}_{it})^2}{2\beta} \right]$$

where:

$$(7) \quad \beta = \sum_{j=1}^{n} \sum_{k=1}^{l} \beta_{jk}$$

with β that is assumed to be negative definite as to guarantee that $0 < \mathrm{SE}_{it}^{O} \leq 1$[4].

This output-oriented scale efficiency measures the role of scale in conditioning technical efficiency. In case of an input bundle not operate in an optimal scale, the ray average productivity of its technical efficiency correspondence is lower than what is maximally attainable at the optimal scale. It means that scale efficiency reflects the relative output expansion by producing at optimal scale on the frontier for the observed factor proportions of a firm whose technical inefficiency has been eliminated (Karagiannis and

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[3] To facilitate estimation process and following the suggestion made by Battese and Corra (1977), Battese and Coelli (1995) suggest to replacing the parameter λ with $\gamma = \sigma_u^2 / \left(\sigma_u^2 + \sigma_v^2\right)$ because of it can be searched between zero and one and this property allows us to obtain a suitable starting value for an iterative maximisation process.

[4] Negative definiteness of β is a sufficient but not necessary condition (Ray, 1998).

Sarris, 2005). In other terms, following the Frisch's definition, scale efficiency measures the distance to full efficient scale after moving a production unit to the frontier in the vertical direction.

As reported by Ray (1998), scale efficiency (6) and scale elasticity (5) are both equal to one only at an MPSS, *i.e.* where constant returns to scale prevails. Elsewhere they differ and SE is < 1 irrespective of whether E_{it} is greater than or less than unity. It means that the magnitude of scale elasticity reveals nothing about the level of SE at the points different by the MPSS.

On the basis of the definition of scale efficiency measured by (6), the sub-optimal scale is associated with increasing returns to scale. When $E_{it} > 0$ (increasing returns to scale) then SE increases with an increase in output and the optimal scale should be reached expanding the observed output level. *Vice versa*, output should be contracted to reach the optimal scale when a plan operates in a decreasing returns to scale (supra-optimal) area ($E_{it} < 0$)[5].

In order to explain scale efficiency differentials among plans, Karagiannis and Sarris (2005) used a *two-stage* approach. At the first stage, SEs are estimated using the formula (6) and successively, at the second stage, the SE scores are regressed against a set of explanatory variables. Following the procedure proposed by Reinhard *et al.* (2002), these authors in the second stage used a MLE technique to estimate this stochastic frontier regression model:

(8a) $\ln \mathrm{SE}_{it}^{O} = m_{it} + \varepsilon_{it}$ with

(8b) $m_{it} = \mathrm{Z}\,(z_{it}, \rho)$ and

(8c) $\varepsilon_{it} = (v_{it}^{*} - u_{it}^{*})$ $\quad i = 1,2,\ldots.N \quad t = 1,2,\ldots.T$

where z_{it} represents the same set of variables used in the inefficiency model (5), ρ are the parameters to be estimated, ε_{it} is the error term composed by v_{it}^{*} that represents the statistical noise (independently and identically distributed with $N\,(0,\sigma_{v*}^{2})$ random variable truncated at $-m_{it}$) and by u_{it}^{*} that represents the conditional scale inefficiency remaining even after variation in the z_{it} has been accounted for ($u_{it}^{*} \sim N\,(-m_{it}, \sigma_{u*}^{2})$).

Regarding the technical efficiency estimation, the *two-stage* approach in the SFA models has been criticized by several authors because it is inconsistent in it's assumption regarding independence of the inefficiency effects (Battese and Coelli, 1995; Kumbhakar and Lovell, 2000). The rationale underlying is that the specification of the regression of the second stage - in which the estimated technical efficiency scores are assumed to have a functional relationship with the explanatory variables - conflicts with the assumption that u_i's are independently and identically distributed (TE is the dependent variable in the second stage procedure).

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5 Among the advantages of this measure, Ray (1998) argues that "*this (scale efficiency measure) should make findings from econometric models more directly comparable with the evidence from nonparametric DEA models, where scale efficiency measures are routinely reported* (p. 193)".

However, as underlined by Reinhard *et al.* (2002), a *two-stage* procedure can consistently be used as long as the efficiency scores are calculated from the first-stage parameter estimates, instead of being estimated econometrically at the first stage. In the case of the procedure illustrated above, no such assumption is made with respect to the dependent variable SE because SE scores are obtained from the parameter estimates and the estimated values of scale elasticity. Thus, Reinhard *et al*. (2002) recommended application of the *two-stage* procedure for estimating scale efficiency effects.

The Italian citrus fruit sector

Citrus fruit growing is one of the largest categories in the Italian vegetable and fruit sector. Since 2006, the value of production has amounted to more than 1 billion euro, accounting for about 10% of the total value of vegetables and fruits produced (Giuca, 2008). Oranges comprise about 54% of citrus fruit production, whereas the contribution of lemons and tangerines to overall production (in terms of value) is equal to 17% and 19%, respectively.

The land area cultivated to citrus fruits corresponds to about 122,000 ha, while the number of farms is about 85,000 (Ismea, 2008). Substantially, the farms are situated in the southern regions of Italy and, specifically, more than 70% of the farms and about 80% of cultivated land are located in only two regions: Sicily and Calabry. Since the early 1990s, however, land area covered by citrus fruits has decreased by about 30% (in 1990, it amounted to 184,000 ha) and the number of citrus farmers decreased by about 45% (about 170,000 in 1990). In this period, exports have slightly increased, while imports has grown sixfold (Giuca, 2008).

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 that historically characterised the Italian citrus fruit sector. Specifically, 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. The detection of technical and scale efficiencies can offer us more information about the nature of these problems. 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. An analysis of the relationship between technical and scale (in)efficiency would allow us to determine direction priorities - technical efficiency or scale efficiency oriented measures - in order to improve overall efficiency in the farms.

Data and the Empirical model

Data were collected on a balanced panel data 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 (more then 2/3 of farm gross revenue arises from citrus production). Farms with less than two European Size Units (ESU) were excluded from the sample[6]. Therefore, our analysis is based on a total of 321 observations (see Table 1 for summary statistics about farms).

Table 1 – Summary statistics for citrus farms in the sample (mean values)

Variable	2003	2004	2005
Gross revenue (*euro*)	54,508	53,861	56,542
Land area (*hectares*)	13.21	13.26	13.41
Expenditure for seeds, fertilizers, etc. (*euro*)	3,878	4,866	5,066
Machineries (*annual depreciation rate, euro*)	2,395	2,489	2,962
Capital (*annual depreciation rate, euro*)	5,050	5,182	5,052
Other expenditures (*euro*)	1,240	939	1,322
Labour (annual working *hours*)	2,785	2,814	2,772
Age of farm owner	59.1	59.7	60.7
Size (*ESU**)	4.7	4.7	4.7
Altitude (*metres*)	104	104	104
Number of plots of land	1.6	1.7	1.7

** ESU = European Size Units*

We assumed a Translog functional form as frontier technology specification for the citrus farms. The adopted 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)[7]. It means that the inefficiency term u_{it} explained by (1) is equal to:

$$(9) \qquad u_{it} = \delta_0 + \sum_{i=1}^{N} \delta_{it} z_i + \sum_{m=1}^{M} \delta_m \ln x_{mit} + W_{it} \qquad i = 1,2,\dots N \qquad t = 1,2,\dots T$$

The Translog stochastic function production model is specified as follows:

$$(10a) \qquad \ln Y_{it} = \beta_0 + \sum_{j=1}^{7} \beta_j \ln x_{jit} + \frac{1}{2} \sum_{j\leq}^{7} \sum_{k=1}^{7} \beta_{jk} \ln x_{jit} \cdot \ln x_{kit} + (v_{it} - u_{it})$$

6 In FADN, ESU indicates the farm economic size. ESU is defined on the basis of farm potential gross value added (Total Standard Gross Margin). More precisely, the Total Standard Gross Margin expressed in € is divided by an ESU coefficient (equal to 1,200 €) in order to obtain the economic size classification of farms. In FADN's methodology, farms are classified into 9 ESU classes (see www.inea.it for more information about Italian FADN and the relative analytical procedures).

7 Substantially, this model corresponds to the Battese and Coelli (1995) model with a non-neutral specification for the production frontier function.

The dependent variable (*Y*) represents the output and it is measured in terms of gross revenue from the *i*-th farm. The aggregate inputs, included as variables of the production function, are 1) X_1 the total *land* area (hectares) devoted to citrus fruit-growing by each farm; 2) X_2 the expenditure (euro) for seeds, fertilizers, water and other *variable inputs* used in the citrus fruits-growing; 3) X_3 the value (euro) of *machineries* used in the farm; 4) X_4 the value (euro) of *capital* (amount of fixed inputs such as buildings and irrigation plant, except for machineries); 5) X_5 the expenditure (euro) for *other inputs*, consisting in fuel, electric power, interest payments, taxes, etc.; 6) X_6 the total amount (annual working hours) of *labour* (including family and hired workers); 7) X_7 the *time* (year) that can assume value equal to 1 (2003), 2 (2004) or 3 (2005).

Regarding the machineries and capital variables, they were measured in terms of annual depreciation rate so to have a measure of annual utilization, on average, of the capital stock[8]. All variables measured in monetary terms were converted into 2003 constant euro value.

Taking into account the formula (3), the inefficiency model (9) has the follow form:

$$(10b)\quad u_{it} = \delta_0 + \delta_1 Age_{it} + \delta_2 Size_{it} + \delta_3 Altitude_{it} + \delta_4 Plots_{it} + \delta_5 Less\ favoured\ zones_{it} +$$

$$+\delta_6 R_{cam\ it} + \delta_7 R_{cal\ it} + \delta_8 R_{apu\ it} + \delta_9 R_{bas\ it} + \delta_{10} R_{sic\ it} + \delta_{11} R_{sar\ it} + \sum_{j=1}^{7} \beta_j \ln x_{jit} + W_{it}$$

Explanatory variables of the inefficiency effects were represented by 1) Z_1 the *age* of the farm owner; 2) 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[9]; 3) Z_3 the variable *altitude* that reflects the average altitude (in metres) by each farm; 4) 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 (0 = Less-Favoured zone; 1 = non Less-favoured zone); Z_6-Z_{11} that represent a set of *dummy* variables indicating the regional location of farms (R_{cam} = Campany; R_{cal} = Calabria; R_{apu} = Apulia; R_{bas} = Basilicata; R_{sic} = Sicily; R_{sar} = Sardinia); and finally – according to the non-neutral model proposed by Huang and Liu (1994) - the same pool of variables (included time) used to describe the frontier function production (x_{it}).

Variables such as age of farmers, farm size, and regional location have been widely used in the SFA applied to agriculture. The first is generally used as a proxy of farmer skills, experience, and learning-by-doing (the rationale is that the expected level of efficiency increases with experience). The second was implemented to evaluate the role of farm economic size in conditioning efficiency (the negative sign is expected: inefficiency tends to decrease in larger farms). The third serves to estimate the presence of territorial and geographic variability that may affect efficiency.

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8 As underlined by Madau (2008), value of capital goods is estimated in different ways into the efficiency analyses. Some authors have considered the total amount of value, whereas other authors have expressed capital in terms of annual capacity utilization. In this case, the capital measure depends on the adopted criteria for calculate capacity utilization.

9 Any observed farm exhibits an ESU Class 8 or 9.

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 has not been a variable generally employed in the efficiency analysis in agriculture. But, in our opinion and as highlighted above, it could be significant 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 (technical and scale) efficiency on the part of farmers. Applying the second-stage regression (8), 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.

Analytical findings and discussion

Parameters for the function and inefficiency model were estimated simultaneously. ML estimation was obtained using the computer program FRONTIER 4.1, created by Coelli (1996b). 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.

As testing procedure we adopted the *Generalised likelihood-ratio test*, which allows us to evaluate a restricted model with respect to the adopted model (Bohrnstedt and Knoke, 1994). The statistic associated with this test is defined as:

$$(11) \qquad \lambda = -2\ln \Lambda = -2\left[\ln \frac{L(H_0)}{L(H_1)}\right] = -2\,[\ln L(H_0) - \ln L(H_1)]$$

where $L(H_1)$ and $L(H_0)$ are the log-likelihood value of the adopted model and of the restricted model - specified by the formulated null-hypothesis - respectively. The statistic test λ has approximately a chi-square (or a mixed-square) distribution with a number of degrees of freedom equal to the number of parameters (restrictions), assumed to be zero in the null-hypothesis. When λ is lower than the correspondent critical value (for a given significance level), we cannot reject the null-hypothesis.

The first two tests are relative to the frontier model. The first one concerns the hypothesis of adopting a neutral frontier function ($H_0 : \delta_m = 0$). In case this null-hypothesis is not rejected, the preferable model should be described by the Battese and Coelli (1995) model illustrated by (1). The value of the likelihood ratio statistic for this restricted model is calculated to be 20.74 and it is significantly higher than 12.59, which is the critical value (at 5% significance level for 6 degrees of freedom) from the χ^2 distribution (Table 2). Hence, the null-hypothesis of neutral technology can be rejected and it suggest that the Huang and Liu (1994) non-neutral model is an adequate representation for the observed citrus farms. The second test hypothesis aims to assess if the Translog frontier is an adequate representation for the citrus fruits-growing or, vice versa, the Cobb-Douglas model is more suitable to the data ($H_0 : \beta_{ij} = 0$). The null-hypothesis was strongly rejected and it means that the Translog form is the preferable specification for the data.

Table 2 – Hypothesis testing for the adopted model

Restrictions	Model	L(H_0)	λ	*d.f.*	$\chi^2_{0.95}$	Decision
None	Translog, non neutral	-89.81				
$H_0 : \delta_m = 0$	Neutral	-100.18	20.74	6	12.59	Rejected
$H_0 : \beta_{ij} = 0$	Cobb-Douglas	-168.34	157.06	21	32.67	Rejected
$H_0 : \gamma = \delta_0; \delta_r;\delta_m = 0$	No inefficiency effects	-120.45	61.28	6	11.91*	Rejected
$H_0 : \gamma = \delta_0;\delta_m = 0$	No stochastic effects	-101.80	23.98	9	19.92*	Rejected
$H_0 : \delta_0 = 0$	No intercept	-90.44	1.26	1	3.84	Not rejected
$H_0 : \delta_r;\delta_m = 0$	No firm-specific factors	-118.76	57.90	11	19.68	Rejected
$H_0 : \delta_{6....}\delta_{11} = 0$	No *Regional* effects	-94.88	10.14	6	12.59	Not rejected
$H_0 : \delta_{1;}\ \delta_3 = 0$	No *Age* and *Altitude* effects	-92.65	5.68	2	5.99	Not rejected

* Critical values with asterisk are taken from Kodde and Palm (1986). For these variables the statistic λ is distributed following a mixed χ^2 distribution.

The other tests are associated with the inefficiency model. The third test is devoted to verify if inefficiency effects are absent from the model. Rejection of the null-hypothesis $H_0 : \gamma = \delta_{0;}\ \delta_1 \ldots \delta_4 = 0$ indicates that the specification of a model which incorporates an inefficiency model is an adequate representation of these data. The fourth test concerns the nature of the inefficiency effects (stochastic or not). If the inefficiency effects are not random, parameters γ and δ_0 will be zero because the model will be reduced to a traditional mean-response function, in which the explanatory variables are included in the function model[10]. In this case the null-hypothesis was rejected in favour of the stochastic. The fifth test regards the hypothesis $H_0 : \delta_0 = 0$, where inefficiency effects do not have an intercept. The null-hypothesis was not rejected. The sixth test aimed to evaluate significance of the regional areas in conditioning inefficiency. The null-hypothesis $H_0 : \delta_{6....}\delta_{11} = 0$ was not rejected and it indicates that inefficiency is not significantly dependent by regional placement of farms in Italy. In the seventh test, we assessed the influence of the selected variables on the degree of farm efficiency. Testing the null-hypothesis $H_0 : \delta_1; \delta_2; \ldots; \delta_4 = 0$, we can verify if the joint effect of the selected variables is significant, irrespective of the significance of each variables. The fact that this null-hypothesis was rejected would be taken as confirmation that the selected variables are actually illustrative of the efficiency if taken on the whole. The last test concerns the degree of suitability of the model without *age* and *altitude* effect. The estimated parameters showed an irrelevant magnitude in the adopted model, suggesting that these variables would be scarcely illustrative of efficiency. The null-hypothesis $H_0 : \delta_{1;}\ \delta_3 = 0$ was not rejected and it means that the null hypothesis can be confirmed.

The model was estimated in the light of the t-test results to obtain the preferred form. MLE for the more appropriate model are shown, as reported above, in the Table 3.

[10] δ_0 must be zero because the frontier model already involves an intercept

Table 3a – ML Estimates for SFA parameters and for TE (pref. model) - continue

Variables	Parameter	Coefficient	s.d.
	FRONTIER MODEL		
Constant	β_0	-0.608	*0.139*
Land Area	β_1	-1.827	*0.422*
Expenditure for seeds, fertilizers, etc.	β_2	1.515	*0.463*
Machineries	β_3	1.662	*0.378*
Capital	β_4	-0.526	*0.453*
Other expenditures	β_5	0.193	*0.287*
Labour	β_6	0.576	*0.569*
Year	β_T	-1.697	*0.696*
(Land Area) x (Land Area)	β_{11}	0.052	*0.037*
(Land Area) x (V. expenditure)	β_{12}	0.102	*0.038*
(Land Area) x (Machineries)	β_{13}	0.085	*0.028*
(Land Area) x (Capital)	β_{14}	0.021	*0.036*
(Land Area) x (O. expenditures)	β_{15}	0.010	*0.035*
(Land Area) x (Labour)	β_{16}	0.060	*0.060*
(Land Area) x (Year)	β_{1T}	-0.111	*0.053*
(V. expenditure) x (V. expenditure)	β_{22}	0.032	*0.031*
(V. expenditure) x (Machineries)	β_{23}	0.016	*0.026*
(V. expenditure) x (Capital)	β_{24}	-0.053	*0.037*
(V. expenditure) x (O. expenditures)	β_{25}	0.099	*0.033*
(V. expenditure) x (Labour)	β_{26}	-0.328	*0.069*
(V. expenditure) x (Year)	β_{2T}	-0.011	*0.055*
(Machineries) x (Machineries)	β_{33}	0.074	*0.017*
(Machineries) x (Capital)	β_{34}	-0.088	*0.033*
(Machineries) x (O. expenditures)	β_{35}	-0.125	*0.035*
(Machineries) x (Labour)	β_{36}	-0.198	*0.051*
(Machineries) x (Year)	β_{3T}	-0.020	*0.035*
(Capital) x (Capital)	β_{44}	0.030	*0.024*
(Capital) x (O. expenditures)	β_{45}	0.085	*0.024*
(Capital) x (Labour)	β_{46}	0.046	*0.058*
(Capital) x (Year)	β_{4T}	0.076	*0.051*
(O. expenditures) x (O. expenditures)	β_{55}	0.029	*0.021*
(O. expenditures) x (Labour)	β_{56}	-0.137	*0.072*
(O. expenditures) x (Year)	β_{5T}	0.089	*0.048*
(Labour) x (Labour)	β_{66}	0.228	*0.076*
(Labour) x (Year)	β_{6T}	0.141	*0.065*
(Year) x (Year)	β_{TT}	0.026	*0.076*
	INEFFICIENCY MODEL		
Age	δ_1	-	-
Size	δ_2	-0.495	*0.087*
Altitude	δ_3	-	-
Number of plots of land	δ_4	0.014	*0.031*
Less-favoured zones	δ_5	0.012	*0.010*
Campany	δ_6	-	-
Calabria	δ_7	-	-
Apulia	δ_8	-	-
Basilicata	δ_9	-	-
Sicily	δ_{10}	-	-
Sardinia	δ_{11}	-	-
Land Area	δ_{SUP}	-0.679	*0.147*
Expenditure for seeds, fertilizers, etc.	δ_{SV}	0.359	*0.105*
Machineries	δ_{QM}	-0.043	*0.062*
Capital	δ_{QC}	0.068	*0.110*
Other expenditures	δ_{AS}	0.319	*0.149*
Labour	δ_{LAV}	-0.740	*0.214*
Year	δ_T	0.091	*0.135*

Table 3b – ML Estimates for SFA parameters and for TE (preferred model)

Variables	Parameter	Coefficient	s.d.
	VARIANCE PARAMETERS		
σ^2	σ^2	0.127	*0.016*
γ	γ	0.333	*0.131*
γ^*	γ^*	0.579	
Log-likelihood function		-92.66	
	TECHNICAL EFFICIENCY		
Mean			**0.710**
s.d			*0.266*
Maximum			1.000
Minimum			0.060

Structure of production and technical efficiency

Since the Translog function takes into account also interaction among involved inputs, the production elasticities were computed using the traditional formula for the estimation of the elasticity of the mean output with respect to the *k*-th input (except for the time variable):

$$\frac{\partial \ln E(Y)}{\partial \ln(x_k)} = \beta_k + 2\beta_{kk}\, x_{ki} + \sum_{j\neq k} \beta_{kj}\, x_{ji} \tag{12}$$

Application of (12) indicates that, at the point of approximation, the estimated function satisfies the *monotonicity* (all parameters show a positive sign) and *diminishing marginal productivities* (magnitude is lower than unity for each parameter) properties (Table 4). The estimated production elasticities suggest that land is the foremost important input followed by expenditure for variable inputs, labour, and machineries. It means that enlargement of the land area would affect significantly farm productivity. Specifically holding all other inputs constant, an increase of 1% in land area would result in a 0.47% increase in output. According to other research findings, the high elasticity of the land area is not surprising in presence of small size farms because this factor could be considered a quasi-fixed input (Alvarez and Arias, 2004; Madau, 2007).

Except for land area, these findings suggest that production of Italian citrus farms is sensitively elastic with respect to these factors, which should allow farmers to easily vary their own use level in the short run - elasticity of variable inputs and labour is equal to 0.27 and 0.18, respectively - while the other quasi-fixed inputs (capital and machinery) affect productivity less (elasticity equal to 0.04 and 0.11, respectively). The time variable shows a negative sign, but the magnitude is not relevant, implying that time does not significantly affect production.

Returns to scale were found to be clearly 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, given their disposable resources.

As to the estimated technical efficiencies, the analysis reveals that, on average, citrus farms are 71% efficient in using their technology (Table 3). Since technical efficiency scores are calculated as an output-oriented measure, the results imply that farmers would be able to increase output by about 30% using their disposable resources more effectively (at the present state of technology).

Analysis of the ratio-parameter γ gives information on the technical efficiency weight into production. The estimated γ is significant (for $\alpha = 0.01$) and it indicates that differences in technical efficiency among farms is relevant in explaining output variability in citrus fruits-growing (1/3 of the variability on the whole). In the reality, the parameter value could not be taken as a measure of the relative contribution of the inefficiency term to the total output variance, but this measure can be obtained by estimating the parameter γ^* (calculated as described in Table 3).

Table 4 – Estimated elasticities and returns to scale

Input	Elasticity	s.d.
Land area	0.466	*0.219*
Expenditure for seeds, fertilizers, etc	0.265	*0.146*
Machineries	0.112	*0.101*
Capital	0.037	*0.050*
Other expenditures	0.080	*0.102*
Labour	0.182	*0.073*
Returns to scale	**1.144**	***0.372***
Time	-0.001	*0.145*

Estimation of this parameter suggests that about 58% of the general differential between observed and best-practice output is due to the existing difference in efficiency among farmers. Therefore, technical efficiency might play a crucial role into the factors affecting productivity in the citrus farming.

Empirical findings concerning the sources of efficiency differentials among farms are presented in Table 3. Farm size is positively related to efficiency level. The results indicate that improvement of technical efficiency strongly depends on citrus farms attaining an adequate size (magnitude is equal to 0.495). Specifically, farm size increase should affect positively both productivity (returns to scale more than unity) and efficiency (negative sign of *Size* variable). This 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).

As expected, the number of lots is negatively correlated to technical efficiency. The findings imply that technical efficiency tends to decrease in the case of partitioning farms in more plots.

On the other hand, the magnitude of this effect is low (0.014), indicating that the presence of a plurality of lots affect efficiency negatively but not sensitively from a technical point of view. Finally, as suggested by the positive sign of the associated parameter (magnitude is equal to 0.012), farms situated in less-favoured areas tend to be more inefficient than those located in normal zones[11].

Regarding the relationship between technical efficiency and technical inputs, ML estimation shows that all inputs have a significant part to play in determining efficiency (Table 3). Land area, labour, and machinery carry a negative sign, implying that an increase in each variable positively affects technical efficiency. The former two variables show a higher magnitude, specifically 0.679 and 0.740 for land area and labour, respectively. It implies that efficiency tends to increase sensitively with an increase of land area and number of hours devoted to labour. On the other hand, significant effects are also associated with expenditure for variable inputs, expenditure for other inputs, and capital. In these cases, however, the positive signs suggest an inverse relationship between increase in utilising these inputs and improvement of technical efficiency. In particular, on the basis of the estimated magnitudes, it seems that capital is weakly illustrative of inefficiency (0.068), while expenditures for variable (0.359) and other inputs (0.319) sensitively affect efficiency in the citrus farms.

Finally, the empirical findings suggest that farmers tend to become less efficient over time (the sign associated with the time variable is positive); also, if the magnitude is really low (0.091), it indicates a weak effect of time on efficiency level.

Scale efficiency

Scale elasticities and scale efficiencies were estimated applying formulas (5) and (6). Table 5 shows that the average scale efficiency is 81.8%. It implies that observed farms could have further increased their output by about 18% if they had adopted an optimal scale. Results also indicate that about 80% of the observations exhibit increasing returns to scale. They operate under a suboptimal scale, i.e., their output levels are lower than optimal levels and they should be expanded to reach the optimal 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).

On the other hand, only about 6% of the observations are characterised by operating under an optimal scale, while about 15% of the panel reveals decreasing returns to scale. However, in these latter scenarios, 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 (97.8%). Therefore, these results suggest that scale inefficiency is mainly due to the farms operating under a suboptimal scale and these suboptimal-scale farms must have adjusted their output levels to a greater extent than the supra-optimal-scale ones. 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 suboptimal-scale-efficient farms (Coelli *et al*., 2002; Karagiannis and Sarris, 2005; Latruffe *et al*., 2005; Cisilino and Madau, 2007).

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 mar-

[11] Similar results were found by Madau (2007)

ket and structural constraints are among the main factors that usually impede achievement of efficient scales by part of farmers. Regarding the Italian citrus farms, Idda (2006) and Carillo *et al*. (2008) found that, often, the input mix is unbalanced (with respect to the rational and efficient composition of the input bundle) 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.

Table 5 – Estimated scale efficiency and scale elasticity

	Observations		Scale efficiency	Scale elasticity
	n.	%		
Total sample (mean)	321	100	0.818	1.173
s.d			0.213	0.416
Maximum			1.000	1.588
Minimum			0.012	0.662
Supra-optimal scale	47	14.7	0.978	0.897
Optimal scale	19	5.9	1.000	1.000
Sub-optimal scale	225	79.4	0.775	1.237

The relationship between scale efficiency and farm size seems to be confirmed by analytical results on the scale efficiency effects (see Table 7 below). These were obtained from application of (10) to the estimated data. The original proposed model – the second-stage regression of the scale efficiency scores to the variables described in the paragraph 4 - was tested using the Generalised likelihood-ratio test procedure in order to evaluate if a restricted model is preferable. Specifically three tests were applied and results are reported in Table 6.

The first test aims to assess if the inefficiency effects have (or not) an intercept. As verified for the technical efficiency model, the null-hypothesis H_0 : $\delta_0 = 0$ was not rejected. The second test concerns evaluation of role of the regional areas in conditioning the farm scale inefficiency. The null-hypothesis H_0 : $\delta_{6....}\delta_{11} = 0$ was rejected and it indicates that – in contrast with the technical inefficiency effects – geographical location of the citrus farms affect significantly scale inefficiency. The last test was processed because of the scarce estimated significance of the coefficient associated to the Less-favoured area parameter. In this case, the null-hypothesis H_0 : $\delta_5 = 0$ was not rejected.

On the basis of the t-test results, we estimated the preferred model that is different from the proposed one for the absence of the intercept and the less-favoured area variable. Estimated findings of scale inefficiency effects are reported in Table 7.

As reported above, farm size might positively affect scale efficiency. It is the factor that contributes the most to conditioning scale efficiency (magnitude is equal to 0.040). This suggests that large-sized farms tend to have, as expected, higher scale efficiency than small-scale farms. Furthermore, the number of plots of land represents the second most important factor in the order of importance that affects scale efficiency (-0.030).

Table 6 – Hypothesis testing for the scale efficiency effects model

Restrictions	Model	L(H_0)	λ	*d.f.*	$\chi^2_{0.95}$	Decision
None	Translog, non neutral	123.92				
$H_0 : \delta_0 = 0$	No intercept	123.92	0.01	1	3.84	Not rejected
$H_0 : \delta_6 ... \delta_{11} = 0$	No *Regional* effects	114.71	18.42	6	12.59	Rejected
$H_0 : \delta_5 = 0$	No *Less-favoured area* effects	112.88	2.08	1	3.84	Not rejected

Table 7 – Scale efficiency effects (preferred model)

Variables	Parameter	Coefficent	e.s
Constant	δ_0	-	-
Age	δ_1	0.006	*0.001*
Size	δ_2	0.040	*0.017*
Altitude	δ_3	0.019	*0.024*
Number of plots of land	δ_4	-0.030	*0.014*
Less-favoured zones	δ_5	-	-
Campany	δ_6	0.044	*0.013*
Calabry	δ_7	0.002	*0.009*
Apulia	δ_8	-0.016	*0.050*
Basilicata	δ_9	-0.011	*0.057*
Sicily	δ_{10}	0.055	*0.061*
Sardinia	δ_{11}	0.051	*0.053*
Year	δ_T	-0.066	*0.099*

The consistent negative sign of the estimated coefficient indicates that in-farm land fragmentation might be a relevant structural constraint to achieving an adequate scale efficiency by part of citrus farmers. The low magnitude (0.006) of the farmers' age parameter suggests that this variable has little influence on the observed efficiency differentials. In other words, older and more experienced farmers tend to be more scale efficient than younger farmers, but even though significant, this is not a sensitive cause of inefficiency. Also, altitude has positive and significant effects on scale efficiency (0.019). Most likely, this is probably linked to citrus fruit varieties grown by many farmers in Sardinia, which are more suited for cultivation in hilly areas. Similar to technical efficiency effect estimation, the relationship between time and scale efficiency is negative (-0.066).

This lends support to the assertion that (technical and scale) efficiency tends to decrease over time. Finally, the findings show that there are statistically significant differences in scale efficiency between farms located in different geographical regions of Italy. Farms located in Apulia and Basilicata tend to be less scale-efficient than those located in the other southern regions. Specifically, farms situated in the two insular regions (Sicily and Sardinia) report a higher magnitude (0.055 and 0.051, respectively), implying that location in these regions positively and sensitively influences scale efficiency.

Relationship between technical and scale efficiencies

The empirical findings reported above show that the estimated degree of technical efficiency is significantly lower than the degree of scale efficiency (on average, the gap is more than 10 percentage points). According to the Ray (1998) definition and the measure of scale efficiency used in this work, it 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. In other words, it means that, to achieve the potential output, given their own structural conditions and input disposability, the priority of Italian citrus farmers should be to increase their ability in using their own technical inputs. Indeed, room for improving technical efficiency is, on average, larger (29%) than the margin due to scale inefficiency (18.2%).

On the other hand, significant variability was found in the farm-specific technical and scale efficiency scores, leading one to argue that priorities can differ among farmers. Furthermore, in contrast to other research findings (e.g., Karagiannis and Sarris, 2005), we found a weak relationship between scale and technical efficiencies (R^2 = 0.132). Determining the direction of causality in the interrelationship between the two efficiency measures (technical and scale) is difficult and more empirical research is needed to evaluate this (Karagiannis and Sarris, 2005). However, some considerations can be drawn from our empirical findings.

Table 8 illustrates the farm technical efficiency scores, on average, associated with different levels of estimated scale efficiencies.

Table 8 – Relationship between scale and technical efficiency

Scale efficiency	**Returns to scale**				**Technical efficiency (mean)**
	Sub-optimal	**Optimal**	**Supra-optimal**	**Total**	
< 0.200	3	-	-	3	0.758
0.201 - 0.300	9	-	-	9	0.807
0.301 - 0.400	9	-	-	9	0.683
0.401 - 0.500	17	-	-	17	0.652
0.501 - 0.600	18	-	-	18	0.682
0.601 - 0.700	18	-	-	18	0.732
0.701 - 0.800	33	-	1	34	0.594
0.801 - 0.900	50	-	2	52	0.516
0.901 - 0.999	99	-	44	143	0.794
1.000	-	19	-	19	0.833
Total	**255**	**19**	**47**	**321**	**0.710**

It can be argued that farms with very low scale efficiency scores (SE < 0.300) show higher technical efficiency than the estimated average level. The technical efficiency scores tend to be collocated around the average level in the case of scale efficiencies that vary from 0.300 to 0.700 and progressively technical efficiencies decrease under

0.600 in the case of scale efficiencies encompassing values between 0.700 and 0.900. Finally, farmers who report scale efficiency scores higher than 0.900 show, on average, a very high technical efficiency score.

These results suggest that, in the case of significant scale inefficiency (less than 0.300), citrus farmers are able to compensate for their hard structural disadvantages and their low scale efficiency with higher efficiency in input use. Probably, farmers who operate under large suboptimal returns to scale are more conscious of their disadvantages (e.g., difficulty in overcoming size farm constraints, high value of capital/land and labour/land ratios, wide presence of fixed and quasi-fixed inputs) and tend to be more cautious in their choice of technical inputs (kind and quantity) to be used.

In the case of scale efficiency scores varying from 0.300 to 0.700, farmers probably put less effort in optimising efficiency in their technical input use because they are more able to capitalise on more advantaged structural conditions with respect to the more scale-inefficient farmers. Empirical findings also suggest that this behaviour tend to be empathised for farms that operate under more favourable but not optimal scale efficiency ($0.700 \leq SE \leq 0.900$).

Vice versa, farms that operate under optimal or quasi-optimal scale might achieve a good level of technical efficiency. In these farms, the proportions among inputs are efficient or close to efficiency, and any (or few) adjustments are needed to attain full-scale efficiency. Since it is an output-oriented scale efficiency measure, it means that the observed average productivity - considering that technical inefficiency has been eliminated - corresponds or is close to the maximum average productivity. It should be logical that these farms, characterised by efficient and harmonic input-output combinations, are more able, compared with scale-inefficient farms, in using their own disposable inputs. Despite the results reported above, determining the nature and the direction of causality in the interrelationship between scale and technical efficiencies should be studied in more detail; indeed, an efficient use of inputs - oriented to maximise marginal and overall productivity - should positively influence the input proportions and, consequently, scale efficiency. This implies that in case of decreasing technical efficiency in these farms, scale efficiency would also tend to be lower than the actual level because input proportions might be mutated.

Conclusions

This paper aimed to evaluate technical and scale efficiencies on a sample of citrus farms located in Italy. Using a parametric approach, we found that some margins exist to increase efficiency, both using better disposable inputs and operating on a more appropriate scale. Empirical findings suggest that the overall inefficiency should depend on producing below the production frontier and on operating under a rational scale. The former reason might be more important since technical inefficiency appears greater than scale inefficiency. Most of the scale-inefficient farms operate under increasing returns to scale, i.e., under a suboptimal scale.

Regarding factors that affect inefficiency, the results indicate that, as expected, farm size and the number of plots significantly and sensitively influence both technical and scale efficiencies. More specifically, the larger and less fragmented farms tend to show higher technical and scale efficiencies. Furthermore, the findings suggest that farms managed by older farmers (who probably have more farming experience) appear more technical- and scale-efficient. On the other hand, the geographical location of the farms significantly affect only scale efficiency, while location in a less-favoured area and at a high altitude site exclusively affect scale and technical efficiency, respectively.

A weak relationship between technical and scale efficiencies was found, with technical efficiency tending to be higher in farms with very low scale efficiency score or that operate under an optimal or quasi-optimal scale. This information about the nature and the entity of interrelationship between the two measures could be useful to give technical and policy suggestions that aim to improve overall efficiency and productivity in the Italian citrus fruit sector.

In our opinion, however, more empirical research needs to be done to gather further information about the direction of causality of this interrelationship. Indeed, understanding the "cause-effect" relationship could allow us to improve the efficiency, efficacy, and effectiveness of measures that may be suggested to enhance the economic performance of the sector.

Generally speaking, understanding the specific role played by technical and scale efficiency in conditioning productivity and the degree of interrelationship between these two efficiency measures should give significant information to policy and decision makers relative to each farming practice where some technical and structural constraints exists. Policy implications that can drive from this sort of findings could be support policy decisions in order to improve productivity and competitiveness in a certain sector such as citrus farming in Italy.

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