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Article

A DEA Model toward Efficiency Assessment of Olive Oil Cultivation

Spyros Niavis, PhD[1], Nikos Tamvakis, BSc[2], Basil Manos, PhD[3], George Vlontzos PhD[2]*
[1]Dep. of Planning and Regional Development, University of Thessaly, Pedion Areos, Volos 38333, GREECE. Email: niavisspyros@gmail.com
[2]Dep. of Agirculture, Crop Production and Rural Development, University of Thessaly, Volos 38446, GREECE. Email: nitamvak@agr.uth.gr
[3]Dep. of Agriculture, Aristotle University of Thessaloniki, Thessaloniki, GREECE. Email: manosb@agro.auth.gr
*Correspondence: Email: gvlontzos@agr.uth.gr; Tel.: +302421093083

Abstract: The production of olives and olive oil in the Mediterranean region is one of the most important cultivation. The continuous changes of the European Common Agricultural Policy (CAP) towards strengthening the influence of market forces, has increased the necessity for assessing the efficiency of production protocols or patterns being implemented by the farmers. The case of olive trees cultivation, despite the fact that it is very important for both farmers and consumers, has not been in depth analyzed regarding the efficiency of inputs being used during the production process. This study evaluates the efficiency rates of 100 agricultural holding specialized on olive trees cultivation in Greece, by implementing a DEA input oriented model. The inputs being used are land, fertilizers, agrochemicals, labour, and energy. The output being used is the revenue of each holding. The results quantify the significant differentiation of efficiency scores, providing evidence that there is space for restructuring the production process, in order to improve efficiency and decrease by this way the production cost of inefficient farmers.

Keywords: data envelopment analysis; olives; efficiency

Introduction

The Mediterranean region is the authentic place for olive trees cultivation and olive oil production since ancient years. The significance of the cultivation is proven via the influence of it on every tradition and religion being developed, exceeding its importance from the strict limits of dietary purposes. There is a series of studies verifying the positive impact of olive oil consumption on human health, being this recognition the motive for the considerable increase of consumption globally. This excessive demand is the driving force for cultivating olive trees and producing olive oil beyond the Mediterranean region, where the climate and soil conditions permit this expansion. There are many such successful cases in America, Asia and Australia. This global recognition of the product can be either an opportunity or a threat. Perhaps the most obvious is the opportunity being created because of the increase of demand, but there is also the threat aspect due to the excessive increase of producing quantities worldwide, suppressing mainly producers' price towards such levels capable of jeopardizing the sustainability of the production process. According to Food and Agriculture Organization (FAO) of the United Nations (UN) the overall olive oil production for 2014 exceeds the 3 million tones, with Spain to be the leader country, holding 59% of global production. Important key players, regarding production, globally are Italy with 10%, Greece with 7%, Tunisia with 6%, Morocco with 4.5%, Turkey with 2.5%, Syria with 3.5%, Algeria with 1.8%, and Portugal with 2.2%. Outside the Mediterranean the most important countries are Argentina and the USA, with their production though to be still below 1% [1](FAOSTAT, 2017). It is therefore quite important to introduce and apply methodology assessments capable and reliable for evaluating the efficiency level of cultivating and production practices.

The main target of the European Union (EU) Common Agricultural Policy (CAP), especially after the implementation of the AGENDA 2000 reform, is to improve both operational and environmental efficiency of primary sectors of member states, aiming by this way to increase their sustainability in an environment where protectionism is substantially reduced or eliminated. Perhaps AGENDA 2000 can be characterised as the most radical reform, because it established a totally new framework for subsidies management, decoupled from both crop and animal production[2,3](Manos *et al*, 2011; Manos *et al*, 2013). Additionally, the environmental quantification of this reform is being expressed by the 20-20-20 strategy which focuses on increasing the energy efficiency by 20%, reducing the CO_2 emissions by 20% and produce 20% of overall energy consumed by renewable energy resources [4](European Commission, 2011). This new era of CAP started in 2005, providing by this way the ability to the EU to fully comply with the last World Trade Organization (WTO) agreement of the Uruguay Round [5](European Commission, 2013).

This enforcement of influence of market forces on agricultural income formation increased the necessity for continuous and more detailed assessment of production costs in agriculture, being this approach one of the most feasible ways for increasing the efficiency of production processes. Up to now, not only for agriculture but for many economic sectors as well, the implementation of Data Envelopment Analysis (DEA) has contributed substantially towards this goal. This non-parametric approach, in accordance with the absence of a priori assumptions, formulates the essential framework where it is easily applicable. The ability being provided to the researcher to use multiple inputs and outputs for efficiency assessment increases the objectivity of the results being obtained when the objective of the study is real life tasks[6-9](Emrouznejad *et al*, 2008; Mulwa *et al*, 2009; Vlontzos and Pardalos, 2017; Vlontzos and Pardalos, 2017). The reliability and acceptability of DEA is not questionable due to the fact that is it implemented for various and quite important economic sectors, like banking, education, and health care. Agricultural production and food processing industries have been assessed also applying DEA models, trying to evaluate the efficiency rates of inputs used, as well as the outputs achieved. In this paper DEA is used to assess efficiency of holdings producing olive oil in operational terms, quantifying by this way their positive or negative impact, providing at the same time hints for counteractive actions.

The efficiency issue is not only important on a managerial level, but it is a main issue for policy assessments too. Policy makers are continuously in a need for new tools aiming in many cases to improve economic and environmental performance. Therefore, the problem of emission permits reallocation was reached by the implementation of DEA. The applicability of the methodology was based upon the fact that there is no need to have under consideration the prices of inputs and outputs, because the approach is non-parametric. The first implementation was applied for the paper industry in Sweden [10](Lozano *et al*, 2009). The same methodology was used for reallocation of emission permits for the 15 EU member states regarding agricultural GHGs. The results verified that the reduction and reallocation mechanism applied was fair, benefiting by this way countries operating up or very close to the efficient frontier being obtained [11](Wu *et al*, 2013).

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Background

DEA has been introduced, when Farrell (1957) stated the problem of measurement of productive efficiency [12]. Based on these ideas Charnes et al (1978) developed further this methodological approach quantifying relative deficiencies of multi-input and multi-output production units [13]. The most important characteristics of DEA are the use of peer groups, the identification of efficient operational practices, the setting of targets, the development of efficient strategies, the ability to monitor efficiency changes over time, and resource allocation [14](Boussofiane *et al*, 1991).The great acceptance and usefulness of DEA is proved by the use of it for efficiency assessment of very important production sectors of the economy, even nowadays [15](Cook and Seiford, 2008). One of the first implementations of this was for the banking sector [13,16](Charnes *et al*, 1978; Thanassoulis, 1999). Quite important sector for economies is the energy one. Special research focus has been given on the electric power plants efficiency on both operational and environmental terms, with DEA being implemented for this purpose [17,18](Sozen *et al*, 2010; Arabi *et al*, 2014). Additionally, DEA has been used for evaluation of logistics, and more specifically for ports efficiency evaluation, presenting by this way best management practices in a highly competitive sector of international economy [19] (Cullinane *et al*, 2006).Under the same rational there were efficiency evaluation for school units and educational systems [20,21](Smith and Mayston, 1987; Thanassoulis and Dunstan, 1994) with satisfactory and widely acceptable results.

Agricultural production efficiency in various cases has been assessed with DEA models, proving the profound impact of the methodology on primary sectors evaluation. A series of different inputs and outputs have been used in various combinations, covering by this way the natural, economic and environmental aspects of agricultural production. The results being obtained have created a specific know-how on efficiency assessment, by identifying the best mixture of both inputs and outputs, leading to efficiency measurements, as well as the impact and significance of these aspects on efficiency scores. DEA has been used for both animal and crop production assessments. Application of DEA on citrus production lead to specific alternatives on efficiency improvement especially in areas where small size of agricultural holdings is a major issue, which is the case in many Mediterranean countries [22](Martinez and Picazo-Tadeo, 2003). The most competitive animal production sector is the dairy one. In this case two different DEA models have been applied focusing on natural and economic inputs and outputs. The results obtained verified that it is more important to combine in efficient way both natural and economic resources than focusing on output maximization and more specifically milk maximisation [23](Stokes, 2007). On the same trend, a similar study identified efficiency scores of different combinations of management practices and feeding [24,25](Heinrichs *et al*, 2013; Hansson and Ohlmer, 2008). A holistic approach in the same sector included in the analysis external operational parameters as well as internal operational characteristics and micro-social issues used to assess efficiency. The results obtained focused on farm size and management, which can be either a constraint or a driving force [26] (Hansson, 2007).

The increasing significance of the environmental aspect of agricultural production has driven researches towards assessing the impact of inputs being used in agriculture on eco-efficiency too. It has been proved that DEA methodology autonomously implemented to assess environmental efficiency is a widely accepted approach. This acceptance is based upon the accuracy of results for small data sets and the ability to include undesirable outputs and inputs [27] (Song *et al*, 2012). For this reason a combination of Life Cycle Assessment (LCA) and DEA has been used regarding

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evaluating agricultural production on both operational and environmental terms. LCA is a tool for estimating the possible environmental degradation when a process is being implemented or when a product is being produced. DEA implementation by using LCA results can lead to super efficiency analysis to simplify the selection process of reference performers, which is essential in a benchmarking process [28](Iribarren *et al*, 2010). The application of LCA and DEA for the dairy sector provided very useful and applicable results, focusing on reducing the operational cost of dairy farms, as well as improving their environmental footprint [29,30](Silva and Stefanou, 2003; Iribarren *et al*, 2011).Quite vital issue for farming is the efficiency assessment of labour management too. Application of DEA on citrus cultivation lead to specific alternatives focusing on efficiency improvement in areas where small size of agricultural holdings is a major issue, which is the case in many Mediterranean countries [22](Martinez and Picazo-Tadeo, 2003). Applications of DEA can be found also for mussel production, where the targets being obtained can be utilised as virtual cultivation sites with considerably less input use, achieving simultaneously more output production [31](Lozano *et al*, 2008). The fisheries sector is expanding quite fast, due to the continuous increase of demand for fishes and fish products. At the same time the sector is being characterised by intense competitiveness and rivalry among firms, increasing the significance of efficiency. Interesting findings were found when DEA methodology was used to assess both operational and environmental efficiency. This combination was appropriate for these cases where multiple input/output data should be used, providing at the same time the ability of not using standard deviations which is usually the case when working with average inventories [32](Vazquez- Rowe *et al*, 2010). The suitability of this methodology was verified for arable crops cultivation too. Iranian holdings producing soybeans found to be efficient up to 46% of the sample. The most important input contributors to global warming were irrigation and fertilization by 63% and 34% respectively, providing a road map for both efficiency improvement and mitigation of environmental degradation [33](Mohammadi *et al*, 2013). Following the same methodological approach, DEA was used to assess energy efficiency of wheat farms, aiming to separate efficient from inefficient farmers on the basis of inputs being used in a wasteful way and quantify the gap among them. The most important findings, being at the same time quite impressive, originated that only 18% of growers were technically efficient, with the overall technical efficiency to be 0.82[34]. It has been observed also that by implementing energy optimisation the total Greenhouse Gas (GHG) emissions can be reduced substantially [35](Khoshnevisan *et al*, 2013). The same methodology was applied for alfalfa production. In this, 46% of growers were found technically efficient, with the average technical efficiency to be 0.84. Optimisation of energy use improved the energy use efficiency by 10.6% [36](Mobtaker *et al*, 2012). DEA implementation for grape production and vinification verified quantified inefficiencies in both operational and environmental terms. In NW Spain a necessity for 30%, on average, on inputs reduction was identified, leading to an increase of 28%-39% of environmental gains, depending on the impact category [37](Vazquez- Rowe *et al*, 2012). The same methodology was implemented for the assessment of energy efficiency of grape production. The main differences between efficient and inefficient farms were focused on the use of chemicals, diesel fuel and water for irrigation. Education level is positively related with high efficiency scores [38](Khoshroo *et al*, 2013)

Another quite important sector is the greenhouse production, which at the same time is quite competitive too. It is widely accepted that energy costs of greenhouse vegetable production are the

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most important ones, affecting directly feasibility and competitiveness of agricultural holdings. An input-output analysis quantified the energy efficiency of greenhouses producing vegetables, and more specifically, tomatoes and cucumbers. The results showed that inputs substantially affecting energy costs are diesel fuel and fertilizers. Quite important is also the energy ratio for the two cultivations, which is 0.69 and 1.48 respectively. In pure economic terms it is indicated that tomato cultivation is more profitable, compared with the cucumber one [39](Heidari and Omid, 2010). In a similar study, energy use efficiency in greenhouse was assessed comparing again tomato and cucumber production, the results showed that there is a difference between them, with technical efficiency scores to be on average 0.94, signifying the increased competitiveness of the sector. Regarding energy efficiency, about 25.15% of the total input energy could be saved without reducing tomato yield [40](Pahlavan *et al*, 2011). Implementation of DEA for the determination of energy efficiency in greenhouse cucumber production having included in this analysis the GHG emissions as an undesirable output, the technical efficiency was calculated, with 27% of the sample being efficient. In this study CO_2 emissions were included as the major GHG undesirable output [41](Khoshnevisan *et al*, 2013). The most intensive cultivation though in greenhouses is floriculture. Rose production in greenhouses is a typical case of it, being at the same time absolutely necessary to keep efficiency rates quite high due to the high intensity of rivalry characterising the sector. Possible inefficiencies have a direct impact on competitiveness. Such an assessment demonstrated average technical efficiency up to 0.83 and input energy savings of about 43.59% on average can be achieved without reducing rose yield. This percentage can be considered as very important [42](Pahlavan *et al*, 2012).

The impact of CAP on farming efficiency, as it was mentioned above, is a continuous issue for both farmers and EU policy makers. DEA use to olive-growing farms proposed an allocation system for subsidies, having in mind the new subsidy administrative scheme. Farm efficiencies were calculated by decomposing DEA scores by means of internalising both positive and negative externalities of agricultural activity [43] (Amores and Contreras, 2009). The DEA model when it was applied for policy efficiency measurement has proved to be a quite appropriate tool. When the issue was the assessment of regional inefficiencies for industry sectors, the calculation of efficiency scores of lead sectors, as an evaluation perspective of their future competeveness, proved to be a reliable methodology [44](Dinc and Haynes, 1999). The same trend can be followed regarding development policies. It is accepted that public investments, mainly in infrastructure, aim to attract private investments. Efficiency assessment of such public policy was calculated by the use of DEA, identifying investment mixtures attracting successfully private investments [45-48](Karkazis and Thanassoulis, 1998; Abello *et al*, 2002; Papajorgji and Pardalos, 2005; Zopounidis and Pardalos, 2010). Finally, assessing rural development policies with DEA quantified the impact of them on employment generation in rural areas, being at the same time a useful tool for reallocation of resources among different areas maximising by this way policy efficiency [49](Vennesland, 2005). The same approach when applied for the evaluation of local actions for LEADER+ project in Greece identified inefficiencies regarding inputs use and proposed corrective alternatives aiming to increase the total efficiency of this project [50](Vlontzos *et al*, 2014).

There are several studies on olive oil efficiency assessment. Special focus was given on eco-efficiency and presented the linkages between eco-inefficiency and input management. The use of DEA for olive trees cultivation provided the ability to measure inefficiencies related with resources

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management like land and water, in Andalusia were especially water availability is a crucial issue for both inhabitants and cultivations [51](Gomez-Limon *et al*, 2011). Spanish olive growers were proven to be quite eco-efficient with inefficiencies to be closely related with technical inefficiencies. Eco-efficiency was boosted via implementation of agri-environmental projects like university education [52,53](Picazo-Tadeo *et al*, 2010; Picazo-Tadeo *et al*, 2012). Eco-efficiency is closely related with land use management too[54] (Kuosmanen and Kortelainen, 2005).

Material and methods

The scope of this study was the assessment of efficiency levels of olive trees cultivation. This field research took place at Pilio Mountain of the Region of Thessaly, in Central Greece.

Figure 1: Field research placement

During the 2016 cultivation period 100 farms participated in this research, by reporting inputs usage, as well as the outputs being obtained. More specifically, the inputs being monitored were the acreage in Ha of each farm, and the annual costs of energy, agrochemicals, fertilizers, and labour. As outputs were considered the olive oil quantities produced from each farm and the revenue being achieved. The majority of farmers were male, up to 82% and the average age level was 56.4 years old. The classification of education level of the sample consists of 19% primary school, 14% high school, 32% secondary school, and 35% university graduates. The following table presents the descriptive statistics of both inputs and outputs being used for this research.

Table 1: Descriptive statistics of inputs and outputs

	Mean	Standard Dev.	Min.	Max
Acreage	28.17	47.53	5	400
Fertilizers	270.20	271.12	120	4,000
Fungicides	41.90	133.33	110	2,500
Pesticides	139.88	102.19	150	4,500
Labour	2418	687.58	1,200	120,000
Energy	574.25	344.81	60	11,000
Yield	1,058.95	442.91	150	15,000
Revenue	3,455.01	2,410.34	1,000	60,000

Source: Own calculations

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In this paper the input-oriented envelopment model is applied assuming Variable Returns to Scale (VRS). The VRS model allows for variations in returns to scale. Input oriented models aim to maximize the proportional decrease in input variables. The choice of one model or the other is based on the characteristics of the dataset analyzed. Taking the circumstance into account of imperfect competition, constraints, finance, etc., Banker, Charnes and Cooper(1984)have extended DEA to the case of variable returns to scale (VRS). This model distinguishes between pure technical efficiency and scale efficiency (SE), identifying if increasing, decreasing or constant returns to scale are present. The following DEA model is estimated in order to measure the technical efficiency of the olive oil producing farms sample:

CRS Model

$$\min \theta - \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right)$$

Subject to

$$\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = \theta x_{io} \quad \text{i=1,2,…,m}$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{ro} \qquad \text{r=1,2,…,s}$$

$$\lambda_j \geq 0 \qquad \text{j=1,2,…,n} \tag{1.1}$$

VRS Add $\sum_{j-1}^{n} \lambda_j = 1$ (1.2)

where j is the number of observations of the Decision Making Unit (DMU)s. Each observed DMU$_j$ (j=1,2,…,n), uses m inputs x_{ij}(i=1,2,…,m) to produce s outputs y_{rj}(r=1,2,…,s). The efficient frontier is determined by these n observations. There are two properties to ensure that a piecewise linear approximation has been developed to the efficient frontier and the area dominated by the frontier.

$\sum_{j=1}^{n} \lambda_j x_{ij}$ (i=1,2,…,m) and $\sum_{j=1}^{n} \lambda_j y_{rj}$ (r=1,2,…,s) are possible inputs and outputs achievable by the DMU$_j$, where λ_j (j=1,2,…,n) are nonnegative scalars that $\sum_{j=1}^{n} \lambda_j = 1$. The same y_{rj} can be obtained by using $\hat{x}_{ij}$, where $\hat{x}_{ij} \geq x_{ij}$ and the same x_{ij} can be used to obtain $\hat{y}_{ij}$, where $\hat{y}_{ij} \geq y_{ij}$.

s_i^- and s_j^+ represent input and output slacks respectively. The efficient target is

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Peer-reviewed version available at Agriculture 2018, 8, 25; doi:10.3390/agriculture8020025

$$\hat{x}_{ij} = \theta^* x_{io} - s_i^{-*} \quad i=1,2,\ldots,m$$

$$\hat{y}_{ij} = y_{io} + s_r^{+*} \quad r=1,2,\ldots,s$$

If $\theta^* = 1$ then the DMU under evaluation is a frontier point. If $\theta^* < 1$ then the DMU under evaluation is inefficient and has to decrease its input levels. The non-zero optimal λ_j^* represents the benchmarks for a specific DMU under evaluation.

Results

The findings of the implementation of the above model are being presented in the following tables.

Table 2: DEA VRS efficiency scores

Average	0.860
Standard Deviation	0.092
Min	0.576
Max	1.000

Table 3: Efficiency classification of DMUs

0.50<Score<0.59	1 DMU
0.60<Score<0.69	4 DMUs
0.70<Score<0.79	18 DMUs
0.80<Score<0.89	34 DMUs
0.90<Score	43 DMUs

The above findings provide useful information about the quantitative and qualitative characteristics of olive orchards farms. Despite the fact that the variance of the structural characteristics of farms is quite high, the efficiency results do not follow the same trend. Only 23% of the sample succeeded efficiency scores below 0.80, while the 43% of the sample achieved efficiency score between 0.9 and 1. This classification can be considered as satisfactory, providing at the same time space for substantial improvements regarding cultivating practices.

Given the common production technology among the farmers, the efficiency variations could be attributed to several characteristics exogenous to the production function [55](Battese and Coelli, 1995). In order to define the effect of the exogenous factors on the efficiency of farmers, the scores obtained by the model 1.2 are regressed on selected demographic and socioeconomic characteristics of the farmers under consideration.

This variation of efficiency scores is quite important to be justified. One critical issue to be defined before conducting the regression analysis is the selection of its functional form. More precisely, given the fact that efficiency scores obtained by DEA modelsare point estimates without statistical distribution renders the estimations of a parametric regression such as this of Ordinary Least Squares is biased. To overcome this difficulty, [55]Simar and Wilson (2007) proposed a truncated regression

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with parametric bootstrapping which leads to more accurate and consistent results. Under the truncated regression, the distribution of the error term $\varepsilon_j \sim N\left(0, \sigma_\varepsilon^2\right)$ is assumed to be uniformly truncated with zero mean (before truncation) and unknown variance σ_ε^2. We specify the truncation limit at the maximum DEA score (θ=1) and we obtain the parameters estimations using maximum likelihood procedure with 1000 bootstrap replications.

In total, five variables were selected to represent the exogenous factors of production. Two variables, namely Age and $Land$ are quantitative whilst the variables $subsidies$, edu and sex have a dummy form. Table 4 presents the main descriptive statistics of the two continuous variables. As can be seen the mean age of the farmers is 56 years whilst values are ranging from 21 to 90 years. It should be noted that 64% of the farmers are over 50 years old and 46% are exceeding the 60 years. These figures denote that ageing is a dominant characteristic of local farmers. In addition, the mean land per farmer is estimated at 2.8 Ha. The variable present quite high variability as this is testified by the ratio of st. dv to mean and by the large distance between the minimum value (1) and the maximum value (400).

Table 4. Descriptive Statistics of the Continuous Exogenous Variables

Statistics	Age	$Land$
Mean	56	2.8
St.Dv.	15	4.7
Min	21	0.1
Max	90	40.0

Source: Own calculations

As for the dummy variables, the variable $subsidies$ takes the value of 1 when the total received subsidies per farmer exceeds 5,000€ and 0 if else. The variable edu receives a value of 1 if the farmer has completed university studies and 0 if else and finally the variable sex receives the value of 1 for male farmers and 0 for female farmers. Having defined the variables the regression analysis is performed by solving the Model 1.3:

$$Eff_i = \beta_o + \beta_1 Age_i + \beta_2 Land_i + \beta_3 Subsidies_i + \beta_4 Edu_i + \beta_5 Sex_i \quad \left(i = 1, 2, \ldots, 100\right)$$

Eff	=	Efficiency Scores θextracted by Model 1.2
$Age,\ Land$	=	The Continuous Independent Variables
$Subsidies,\ Edu,\ Sex$	=	The Dummy Independent Variables
β_o	=	The Constant Term
β_j	=	The Regression Coefficients Under Estimation $j = \left(1, \ldots, 5\right)$

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For comparative reasons both the estimations extracted by a simple truncated regression and these extracted by the bootstrapped regression are presented in Table 5. The value of the Wald Chi-Square statistic and the statistical significance of the estimation for both models denotes that we can reject the null hypothesis that all the parameters are equal to zero. As far as the estimated coefficients of the models are concerned, these are similar in both models in terms of the direction between the regressors and the dependent variable and the statistical significance of estimations. The only difference is the lowest statistical significance for the estimation of $\beta_{Subsidies}$ that was found under the bootstrapped model. In general, statistical significance was found for the β_{Land}, $\beta_{Subsidies}$ and β_{Sex} coefficients whereas for the other two variables the model application returned ambiguous estimations.

Table 5. Results of the Truncated Regression Model Application

	Truncated Regression		Bootstrapped Truncated Regression	
Parameter	Estimation	Std. Err.	Estimation	Std. Err.
β_{Age}	0.0001	0.0003	0.0001	0.0003
β_{Land}	-0.0033***	0.0002	-0.0033***	0.0005
$\beta_{Subsidies}$	0.1004***	0.0298	0.1004*	0.0590
β_{Edu}	-0.0023	0.0106	-0.0023	0.0005
β_{Sex}	0.0263**	0.0127	0.0263**	0.0121
β_{o}	0.9042***	0.0228	0.9042***	0.0271
σ	0.0473	0.0038	0.0473	0.0037
Loglikelihood	161.4406		161.4406	
Wald chi2(5)	251.8000		71.6300	
Prob> chi2	0.0000		0.0000	
Statistical significance: (***) at 0.01 level (**) at 0.05 level (*) at 0.10 level				

The $Land$ variable was found to be negatively connected to the farmers' efficiency, meaning that farmers with larger cultivation areas seem to be less effective than those with smaller areas. In addition, the positive estimation for $Subsidies$ coefficient denotes that as subsidies increase the farmers become more efficient. Moreover, the positive sign of the β_{Sex} estimation signifies that for the considered farmers' sample men tend to employ more efficient production means than women.

Finally, farmers' age seems to be positively connected to their efficiency whereas the opposite stands for their education level. Nevertheless, since both estimations lack of statistical significance no safe conclusions could be drawn for their relationship with the efficiency of farmers.

Conclusions

From the above analyses it is obvious that there is considerable potential for efficiency improvement regarding olive orchards cultivation. The representative characteristics of the sample signify the most important parameters needed to be changed in order efficiency to be increased. These parameters are better utilization of subsidies being received. Quite important is the fact that the *Land* factor is negatively related to efficiency scores. This outcome reflects the impact of the previous subsidy scheme, before the implementation of Agenda 2000, where the amount of subsidies received was coupled with the olive oil quantities being produced by the farmers. After the total decoupling of subsidies from production these amounts are stagnated even if the acreage of holdings is bigger. It is evident that even though the subsidy administration scheme has changed 12 years ago, the spillover effect of the previous status is still present. Finally, there is a need for training, especially for women, having as target the adoption of new knowledge about cultivation practices, aiming to bridge the gap between the two sexes.

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