Technical efficiency analysis and decomposition of productivity growth of Spanish olive farms[1]

Fatima Lambarraa

Centre de Recerca en Economia i Desenvolupament Agroalimentaris CREDA-UPC-IRTA
Parc Mediterrani de la Tecnologia, Edifici ESAB, Avinguda del Canal Olímpic s/n
08860 Castelldefels, Spain
Phone: 34-93-552-1208, Fax: 34-93-552-1001, e-mail: fatima.lambarraa@upc.edu

Teresa Serra

Centre de Recerca en Economia i Desenvolupament Agroalimentaris CREDA-UPC-IRTA,
Castelldefels, Spain

José Maria Gil Roig

Centre de Recerca en Economia i Desenvolupament Agroalimentaris CREDA-UPC-IRTA,
Castelldefels, Spain

Paper prepared for presentation at the 98th EAAE Seminar 'Marketing Dynamics within the Global Trading System: New Perspectives', Chania, Crete, Greece as in: 29 June – 2 July, 2006

Technical efficiency analysis and decomposition of productivity growth of Spanish olive farms [2]

Fatima Lambarraa

Centre de Recerca en Economia i Desenvolupament Agroalimentaris CREDA- UPC- IRTA
Parc Mediterrani de la Tecnologia, Edifici ESAB, Avinguda del Canal Olímpic s/n
08860 Castelldefels, Spain
Phone: 34- 93- 552- 1208, Fax: 34- 93- 552- 1001, e- mail: fatima.lambarraa@upc.edu

Teresa Serra

Centre de Recerca en Economia i Desenvolupament Agroalimentaris CREDA- UPC- IRTA,
Castelldefels, Spain

José Maria Gil Roig

Centre de Recerca en Economia i Desenvolupament Agroalimentaris CREDA- UPC- IRTA,
Castelldefels, Spain

**Paper prepared for presentation at the 98th EAAE
(European Association of Agricultural Economists) Seminar.**

Chania, Greece June 29th - July 2nd, 2006

Abstract

The concept of technical efficiency is critical to measuring the firm performance, determining the degree of innovative technology adoption and the overall production efficiency. Traditionally, technical efficiency has been measured as the ratio of observed output to maximum feasible output. Stochastic frontier models have been widely utilized to assess this issue. Our research evaluates technical efficiencies in the Spanish olive sector. Specifically, the main objective of this study is to estimate a stochastic frontier production model by using a farm- level panel of data. The non- negative technical efficiency effects are assumed to be a function of firm- specific variables. A sample of Spanish farms observed from 1999 to 2002 is obtained from the FADN dataset and used in the estimation of the model. Maximum- likelihood methods are applied in the estimation of the parameters of the model. A primal approach is used to decompose Total Factor Productivity (TFP) growth. Results indicate that farm location, age of manager, tenure regimes of land and whether the farm has adopted organic farming techniques affect efficiency levels. Technical efficiency change, allocative efficiencies and scale effects are found to be the main sources of TFP growth, while technical change seems to be of minor importance. Results also suggest that Spanish olive farms are less efficient relative to other EU farms. This suggests that improvements in the Spanish olive productive capacity after the accession to the EU were not fully implemented in the period of analysis. This may be due to a decline in olive farm

---

incomes as a result of a decline in both public subsidies and in output prices after the mid 1990s.

Introduction

The olive sector has a significant social, economic and environmental relevance within the European Union (EU). This relevance can be justified by different reasons. First, olive cultivation, which is widespread throughout the Mediterranean region, constitutes a key element of the EU agricultural model. According to Olistat, the area under olive groves accounts for approximately 5.4 million hectares, representing around 4% of the EU utilizable agricultural area. Spain, with more than 2.4 million hectares concentrates almost 45% of the EU olive groves extension. This sector involves around a third of all EU farmers, with about 2.5 million producers (Directorate- General for Agriculture, 2002), of which 380,000 are located in Spain. Second, olive production is concentrated in less-developed areas. With only a few exceptions, a majority of producer areas are under Objective 1 of the EU Regional Policy. In these regions, olive cultivation provides an important source of employment. Olive picking creates seasonal employment in winter, thus complementing with seasonal jobs provided by other agricultural activities. Third, because the olive processing industry is composed by a large number of small and medium- sized industries that are often located near to producing areas, it further contributes to the economic development of these areas. Fourth, traditional olive groves are very valuable as a tool in addressing environmental problems such as desertification and loss of biodiversity. As a result, abandonment of traditional olive holdings may bring increased environmental deterioration. Fifth, olive cultivation has a

number of distinctive features that create some disadvantages to the sector relative to other agricultural activities. These features include the structural inflexibility inherent to olive groves that restricts the capacity to adapt to market conditions; a high dependence of yields on both weather conditions and alternate bearing; a marked heterogeneity of holdings across space; or an intense fragmentation of the sector both at the farm and industry level. Finally, the olive sector is a major cultural factor in the Mediterranean countries, with a role that goes beyond agricultural production to embrace tourist and gastronomic activities, as well as social and cultural events. The EU has long recognized such distinctive characteristics of olive farming and has provided this sector with specific regulations and support measures. An example is provided by the exclusion of the olive sector from the 1990s and the 2003 decoupled- oriented CAP reforms in order to support the sector, prevent the abandonment of olive groves in marginal areas, and support sustainable development of the sector through promotion of healthy and quality products and prices.

In this paper we analyze technical efficiencies and factor productivity changes for a sample of Spanish farms specialized in olive production. Though some previous published studies have addressed efficiency issues in the European agriculture (Van der Vlist et al., 2005; Karagiannis et al., 2003; Karagiannis et al., 2001; Tzouvelekas et al.; 1997), to our knowledge, no previous paper has focused on the Spanish olive sector. The analysis of this sector is considered economically relevant for at least three reasons. First, because of its economic, social

and environmental importance. As explained below, Spain is the top worldwide producer and exporter of olive oil and olives. It is thus very interesting to assess the efficiency with which this leading sector is operating. The sector is also key to economic development and environment protection in less-developed areas, being thus important to measure its firm performance. Second, the thorough restructuring process through which the Spanish olive sector has undergone during the last decades (see next section for further detail) has resulted in increased production and yields. This is likely to have altered the efficiency of operations granting research on this topic. Finally, as it will be explained, though the olive sector has been excluded from the 1990s and 2000s decoupling-oriented CAP reforms, the tendency to replace production aids by direct aids should not be underestimated. In a more decoupled scenario, the efficiency with which olive holdings operate would be more relevant and a crucial factor in determining the continuity of olive holdings over time. This increases the interest of our study.

The olive sector in Spain

The EU occupies prominent positions in worldwide rankings of olive oil and table olives production and trade. According to the International Oleic Council data (IOOC), EU harvests showed an upturn in the second half of the 1990s reaching 2.5 million tones in the 2001/02 marketing year, representing 82% of worldwide production. The EU is followed, at a distance, by Tunisia, Turkey, Syria and Morocco in terms of

productive capacity. Spain accounted for almost 1.4 million tones in the same period, a 54% of EU production and a 47% of world's output. The EU is also the top producer of table olives, with a share in world production of 52% in 2001/02. Here too, Spain represents the first producer since it generates 75% of the EU's output and almost 40% of worldwide production.

Olive oil tends to be consumed in production areas. As a result, external trade represents less than 20% of world production. IOOC data suggest that the EU accounts for more than half of worldwide olive oil exports, the main destinations being the United States of America, Japan, Canada and Australia. Spain and Italy are the largest EU exporters. During the 2001/02 marketing year, Spain exported 112,500 tones to non-EU countries and 488,000 tones to the EU. Hence, of total Spanish olive oil exports, more than 81% went to the EU. It is a fact that the olive oil sector in the EU has undergone substantial changes since the Spanish accession to the Community. Specifically, it has become the largest world producer and a key player in the worldwide olive oil trade. Additionally, total olive production has increased substantially in the EU over the last decade, mainly as a result of relevant increases in Spanish output.

Olive grove area represents around 13% of the total agricultural area in Spain (Spanish Ministry for Agriculture, 2003). A 93% of this area is devoted to olive oil production, being the rest dedicated to the production of table olives. As noted above, Spanish olive production has experienced a substantial growth since the adhesion to the EU. The increases in output are the result of both an increase in new plantations

(even after 1998 when new plantations were excluded from EU production aids) and an increase in yields per hectare. Yields increase is the outcome of a series of changes in production methods such as improvements in growing techniques, the replacement of old trees by new ones and, specially, the increase in irrigated olive groves (which can yield threefold or fourfold increases in output). According to the Spanish Ministry for Agriculture, irrigated land increased form 102,000 ha in 1995 to 372,000 ha in 2000. Modernization of the sector has been partly promoted by an increase in prices and a sharp increase in the production aid resulting from the accession to the EU and the application of EU regulations. Changes in dietary preferences favoring olive oil, specially notable since the mid 1990s, have also contributed to increased production and trade. However, the very intense drought suffered by Spain in 1994 and 1995 delayed the arrival of the new production potential to the market until after the 1996/97 marketing year. Structural changes undergone by the sector have increased the economic size of the holdings. According to the Farm Accounting Data Network (FADN), Spanish farms specialized in olive groves increased their economic size from about 7 European size units (ESU) in 1991 to 14 ESU in 2000. Prices perceived by Spanish producers have also fluctuated in accord with production. There was a rise following accession to the EU, which was prolonged by the draught affecting Spain during 1994 and 1995. However, the increase in production after the draught caused prices to fall. Data from the European Commission show that prices for extra virgin olive oil fell from 2770.4 euros per ton in 1994/95 to 1712.9 in 2000/01. Increased production within the EU led to

the 1998 reform the EU's Common Market Organization (CMO) for oils and fats in order to stabilize both production and the budget devoted to support the sector. This reform involved, among other changes, a reduction in the production aid per unit, the exclusion of new plantings from the areas entitled to receive production aid, the replacement of the former intervention system by a private storage mechanism, and the elimination of consumption aids.

Methodology

The performance of a firm has been conventionally assessed through the concept of efficiency. Technical efficiency represents the capacity and willingness of an economic unit to produce the maximum attainable output from a given set of inputs and technology (Koopmans, 1951). A commonly used technique to measure a firm's technical efficiency is the stochastic frontier methodology which we adopt (Aigner, Lovell and Schmidt, 1997; Meusen and van den Broeck, 1977). This well-known technique assumes that, for a given combination of inputs, the maximum attainable production by a firm is delimited from above by a parametric function of known inputs involving unknown parameters and a measurement error. The more distant actual production is from this stochastic frontier, the greater a firm's technical inefficiency. A stochastic frontier production function formulated within a panel data context can be expressed as follows:

$$Y_{it} = f(x_{it}, \beta, t)e^{v_{it}-u_{it}} \tag{1}$$

where Y_{it} is the output of the i-th firm ($i=1,...,N$) in period $t=1,...,T$, $f(x_{it}, \beta, t)$ represents the production technology, x_{it} is a $(1 \times K)$ vector of inputs and other factors influencing production associated with the i-th firm in period t, β is a $(K \times 1)$ vector of unknown parameters to be estimated, v_{it} is a vector of random errors that are assumed to be iid $N(0, \sigma_v^2)$, and u_{it} is a vector of independently distributed and nonnegative random disturbances that are associated with output-oriented technical inefficiencies. Specifically, u_{it} measures the extent to which actual production falls short of maximum attainable output. The technical efficiency of a producer at a certain point in time can be expressed as the ratio of actual output to the maximum potential output:

$$ET_{it} = \frac{Y_{it}}{f(x_{it}, \beta, t)} = \frac{f(x_{it}, \beta, t)e^{-u_{it}}}{f(x_{it}, \beta, t)} = e^{-u_{it}} \tag{2}$$

It should be noted here that the specification of the stochastic frontier in (1) allows technical inefficiency of a firm to change over time. Time is also included as an explanatory variable in the production function, which allows to measure trends in productivity change. Following Battese and Coelli (1995), exogenous influences are incorporated in the model to explain changes in producer performance. In this regard, it is assumed

that technical inefficiency effects, the u_{it}s, have mean δz_{it} and variance

σ_u^2. Specifically, according to these authors, the technical inefficiency

term responds to the following pattern of behavior: $u_{it} = \delta z_{it} + \eta_{it}$, where z_{it}

is a $(1 \times M)$ vector of farm-specific variables which may vary over time, δ

is a $(M \times 1)$ vector of unknown coefficients, and $\eta_{it} : N(0, \sigma_\eta^2)$ is a random

variable defined by the truncation of the normal distribution such that

the truncation point is $-\delta z_{it}$. Maximum likelihood techniques are used for

a simultaneous estimation of the stochastic frontier and the technical

inefficiency models (see Battese and Coelli, 1993 for more details on the

likelihood function):

$$L^*(\theta; y_{it}) = -\frac{1}{2}\left(\sum_{i=1}^{N} T_i\right)\left[\ln 2\pi + \ln\sigma^2\right] - \frac{1}{2}\sum_{i=1}^{N}\sum_{t=1}^{T_i}\left[\left(y_{it} - x_{it}\beta + z_{it}\delta\right)^2 / \sigma^2\right] - \sum_{i=1}^{N}\sum_{t=1}^{T_i}\left(\ln\Phi(d_{it}) - \ln\Phi(d_{it}^*)\right)$$

(3)

Where θ represents $(\beta, \delta, \sigma^2, \gamma)$, $d_{it} = z_{it}\delta/(\gamma\sigma^2)^{1/2}$,

$d_{it}^* = \left(\left[\sigma_v^2 z_{it}\delta - \sigma_u^2(y_{it} - x_{it}\beta)\right]/\sigma^2\right)/\left[\gamma(1-\gamma)\sigma^2\right]^{1/2}$, $\sigma^2 \equiv \sigma_v^2 + \sigma_u^2$ and $\gamma \equiv \sigma_u^2/\sigma^2$,

where $0 \leq \gamma \leq 1$. Following previous research, variance parameters of the

likelihood function are estimated in terms of σ^2 and γ. Within this

framework, a predictor for equation (2) is given by the following

expression:

$$E\left[e^{-u_{it}}\big|v_{it}-u_{it}\right]=\left[\exp\left\{-\mu_{*it}+\frac{1}{2}\sigma_*^2\right\}\right]\left[\frac{\Phi\left[\left(\mu_{*it}/\sigma_*\right)-\sigma_*\right]}{\Phi\left(\mu_{*it}/\sigma_*\right)}\right]$$

(4)

where $\mu_{*it}=\dfrac{\sigma_v^2(\delta\,'z_{it})-\sigma_u^2(\eta_{it})}{\sigma_v^2+\sigma_u^2}$ and $\sigma_*^2=\dfrac{\sigma_v^2\sigma_u^2}{\sigma_v^2+\sigma_u^2}$.

After estimating the model, we measure productivity change and determine its various sources following Kumbhakar et al (2000):

$$\overset{\circ}{TFP}=T\Delta+(\varepsilon-1)\sum_k(\frac{\varepsilon_n}{\varepsilon})\overset{\circ}{x}_k+\sum_k\left[(\frac{\varepsilon_k}{\varepsilon})-S_k\right]\overset{\circ}{x}_k+TE\Delta$$

(5)

where a dot over a variable indicates its rate of change. $\overset{\circ}{TFP}$ represents total factor productivity change. The first component of $\overset{\circ}{TFP}$ is

$T\Delta=\dfrac{\partial f(x,t;\beta)}{\partial t}$, a measure of the rate of technical change which captures trends in productivity change. The second summand measures the contribution of scale economies to total factor productivity growth. It is

represented by $(\varepsilon-1)\sum_k\dfrac{\varepsilon_n}{\varepsilon})\overset{\circ}{x}_k$, where $\varepsilon_k=\varepsilon_k(x,t;\beta)=\dfrac{x_k\left(\partial f(x,t;\beta)/\partial x_k\right)}{f(x,t;\beta)}$

represents the output elasticity with respect to input x_k and

$\varepsilon=\varepsilon(x,t;\beta)=\sum_k\varepsilon_k(x,t;\beta)$ provides a measure of a firm's returns to scale.

The third term measures allocative efficiency, or the deviation of input

prices from their marginal products. Allocative inefficiencies are

computed as: $\sum_k \left[(\frac{\varepsilon_k}{\varepsilon}) - S_k \right] \overset{\circ}{x}_k$, where $E = \sum_k w_k x_k$ is total expenditure in

inputs, w_k is the unit price of input k and $S_k = \frac{w_k x_k}{E}$ is a measure of the

expenditure share of input k. The fourth component, the primal measure

of the rate of change in technical efficiency is given by $TE\Delta = -\frac{\partial u}{\partial t}$.

Empirical application

As noted above, the aim of this article is to assess technical efficiencies of
the olive sector in Spain after the relevant changes experienced by this
sector since the Spanish accession to the EU. We use farm-level data
taken from the Farm Accounting Data Network for the period 1999-2002.
FADN dataset annually collects micro-economic data from a sample of
agricultural holdings in the European Union. It provides representative
data of EU agricultural holdings along three dimensions: region, economic
size and type of farming. It should be noted however, that FADN only
considers "professional" holdings with enough size to constitute the
grower's principal activity and provide enough revenue to meet his
household needs. As a result, FADN data only represents about 65% of the
Spanish holdings.

Though the analysis is based on individual data, region and country level aggregates are also employed to define some variables used in the analysis. These aggregates are derived from the Spanish Ministry of Agriculture and Eurostat. The Spanish Ministry of Agriculture provided land prices. Eurostat provided other input and output price indices. Our sample is composed by 576 observations that constitute an unbalanced panel of data. The use of a panel of data in efficiency estimation offers advantages over a cross section, since it allows technical efficiencies to change both as a result of individual characteristics as well as a result of the passage of time.

Following previous literature (Fan, 1991; Karagiannis and Tzouvelekas, 2001), the production frontier function in (1) is specified as a quasi-translog function that takes the form:

$$Y_{it} = \beta_0 e^{\beta_t t} \prod_{k=1}^{K} X_{kit}^{(\beta_k + \beta_{kt} t)} e^{v_{it} - u_{it}} \tag{6}$$

Production, Y_{it}, is defined as an implicit quantity index by dividing total olive sales in currency units by the olive price index. Vector x_{it} is defined as a (1×4) vector that contains four inputs. The first input, x_1 includes fertilizers and pesticides, x_2 comprises other variable specific inputs other than fertilizers and pesticides, x_3 represents the hectares occupied by olive groves area and x_4 symbolizes labor input and is measured in

labor hours per year. Input use variables x_1 and x_2 are expressed as implicit quantity indices by dividing the consumption of these inputs in currency units by their respective price indices. Input prices, required to carry out the total factor productivity growth decomposition, are not registered in FADN dataset. To define w_1 and w_2, i.e. pesticide and fertilizer and other variable input prices, we use national price indices taken from Eurostat. Labor prices are approximated by dividing a farm's labor expenses by the hours of labor. Land prices are derived from the Spanish Ministry for Agriculture. All variables in the stochastic frontier are normalized with respect to their own mean and expressed in logs in the estimation process.

The technical inefficiency effects function is specified as a linear function $u_{it} = \sum_{m=1}^{M} \delta z_{mit} + \eta_{it}$, with $M = 6$. The components of z_{it} include a constant (z_1), a dummy variable that takes the value of 1 if the holding is engaged in organic farming techniques and 0 otherwise (z_2), a dummy variable equal to 1 if the holding is renting agricultural land and zero otherwise (z_3), a dummy variable that indicates whether the farm is located in a less favored area (LFA) or not (z_4), the birth year of the holding's primary decision maker (z_5), and time (z_6). Organic farming practices involve changes in input use such as the replacement of synthetic inputs by other inputs such as labor, the use of crop rotation

methods, etc. After discarding synthetic inputs and converting their operations to organic farming, farmers may experience some loss in yields. This may exert a negative influence on a farm's technical efficiency. As suggested by previous literature (Serra, Goodwin and Featherstone, 2005), direct costs of land rentals may create stronger incentives to work the land in an efficient manner, relative to the opportunity costs borne by owned land. To the extent that this occurs, z_3 is expected to increase a farm's efficiency. Farms located in less favored areas are likely to suffer from different restrictions such as environmental constraints, low productive capacity, aged population, etc. that may reduce the efficiency of operations. A farmer's age is also likely to influence technical efficiency, which we measure through variable z_5. Younger farmers should be expected to be more prone to introduce changes in crop management techniques that increase efficiency, relative to elderly ones. Finally, the variable time is also expected to influence technical efficiency. Since farm managers are likely to learn from their errors, the passage of time should be expected to improve technical efficiency. Results derived from the estimation of the model are presented in the following section.

Results

Results derived from simultaneously estimating the quasi- translog production frontier and the inefficiencies equation are presented in table

1. First-order parameters β_k are all positive and statistically significant thus indicating that production is increasing in all inputs: pesticides and fertilizers, other variable inputs, land and labour. The variance parameter, γ, is statistically significant and close to one, which suggests the relevance of technical inefficiencies in explaining output behaviour for our sample of farms. It also suggests that one should not rely solely on the average production function response as an adequate representation of the sample data. The positive sign of the technical change coefficient indicates that the value of output has tended to increase over the four year period.

Estimated δ coefficients help us understand the determinants of our sample farms' technical inefficiencies. As expected, the less-favored area coefficient is positive which indicates holdings facing different restrictions such as environmental constraints are less efficient relative to the other farms. The coefficient representing a farmer's age suggests that older farmers are more inefficient in comparison to younger ones. As suggested above, younger farmers may be more likely to introduce efficiency-improving changes in their holdings relative to aged ones. The organic farming coefficient is positive. This provides evidence that the adoption of practices that promote and enhance agro-ecosystems' health involves technical efficiency gains. Farms renting land are shown to be more efficient relative to farms owning cultivated land. This provides evidence that land rentals motivate more efficient operations relative to the opportunity costs of owned land. The negative coefficient for the

variable year suggests that technical inefficiencies of olive farms tended to decrease throughout the period studied.

Following previous research (Coelli, 1995), we use the generalized likelihood ratio statistic to test for the null that inefficiency effects are absent from the model, i.e., $\gamma = \delta_1 = \text{...} = \delta_M = 0$. The generalised likelihood-ratio statistic takes the value of 85.89, which allows to reject the null and supports the alternative hypothesis that Spanish olive farms suffer from inefficiencies. The predicted technical efficiencies take an average value of 69% throughout the period studied (Table 2). A majority of farmers have efficiency scores above 70- 90% (59% of the sample), which is compatible with previous research findings (Karagiannis and Tzouvelekas, 2001). Consistently with previous research (see Battesse and Coelli 1995), the evolution of technical efficiencies shows a light fluctuation over time, ranging from a peak of almost 73.4% in 1999 to a low 65.4% in 2002. As noted above, olive production is highly dependent on weather variables and alternate bearing that cause production per hectare to fluctuate over time[3]. Technical efficiency levels are capturing these fluctuations with higher scores obtained in high yield years and lower scores corresponding to low yield periods.

Karagiannis and Tzouvelekas (2001) assessed technical efficiency levels of Greek farms over the period 1987- 1993. A comparison of our results with these authors' suggests higher levels of technical inefficiency for our sample of Spanish olive farms. The same conclusion is reached if

---

[3] According to the Spanish Ministry for Agriculture data, yields per hectare in the 1999 to 2003 period fluctuated from a low 20.1 to a high 31.1.

one compares our results with those derived by Van der Vlist, Withagen and Folmer (2005) for a sample of Dutch farms specialized in vegetables production. This suggests that improvements in the Spanish olive productive capacity after the accession to the EU were not fully implemented in the period of analysis. This may be due to a decline in olive farm incomes as a result of a decline in both public subsidies after the 1998 CMO reform and a decline in output prices after the relevant increases in production that took place after the mid 1990s.

Results of the TFP growth decomposition are reported in Table 3. Mean TFP growth rates increased through time from 0.7% in 1999 to 1.3% in 2002. As noted above, TFP increases can be decomposed into technical change, scale, technical efficiency and allocative efficiency changes. It can be seen that technical change is positive though very small for the period studied. The scale effect, which is bigger than technical changes, shows that sample farms have taken advantage of scale economies throughout the period of analysis. Allocative efficiencies, whose average magnitude is very close to the scale effect, also point towards increases in the efficiency with which production factors are allocated. Finally, the rate of change of technical efficiency, the most relevant component in the TFP growth decomposition, indicates substantial improvements in technical efficiencies.

Concluding remarks

19

Spain occupies prominent positions in worldwide rankings of olive oil and table olives production (with a 58% of EU and 45% of the world-wide olive production, and a 70% of EU and 34% of the world-wide olive table production in 2004). In this paper, we analyze technical efficiencies and factor productivity changes for a sample of Spanish farms specialized in olive production. We use a primal approach. Specifically, we estimate a stochastic frontier model to analyze technical efficiencies and decompose the productivity growth following Kumbhakar et al. (2000). An unbalanced panel of 576 observations is used in the empirical analysis. Estimated average efficiency levels for our sample farms are about 69% for the period 1999-2002. A comparison of our results with previous research on the olive sector in Greece reveals higher levels of technical inefficiency for our sample of Spanish olive farms than for Greek olive farms. This suggests that improvements in the Spanish olive productive capacity after the accession to the EU were not fully implemented in the period of analysis. This may be due to reduced olive prices and subsidies after a period of attractive incomes following the Spanish accession to the EU.

Results also indicate that the variables that affect efficiency levels are: farm location (i.e., whether it belongs to a less favoured area or not), age of manager, rent paid and whether the farm has adopted organic farming techniques. Being located in a less favoured area, adopting organic farming techniques or being an aged farmer is found to decrease efficiency. On the other hand, renting land and the passage of time are found to increase efficiencies. As for productivity growth, results show an

increase in average productivity of about 1.0% per year during the period of study, with technical efficiency change, allocative efficiencies and scale effects being the most relevant components of this growth.

References:

Aigner, D.J., Lovell, C.A.K., and Schmidt, P.J. (1977). Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics* 6: 21- 37.

Battese, G.E. and Coelli T. (1995). A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Empirical Economics* 20: 325- 332.

Battese, G.E. and Coelli, T. (1993). A stochastic frontier production function incorporating a model for technical inefficiency effects. (Working paper). *Econometrics and applied statistics* 69. Univeristy of New England. Armidale.

Bauer, P.W. (1990). Recent developments in the econometric estimation of frontiers. *Journal of Econometrics* 46(1/2): 39- 56.

Coelli, T. (1995). Estimators and hypothesis test for a stochastic frontier function: a Monte Carlo analysis, *Journal of Productivity Analysis* 6(4): 247- 268.

Directorate- General for agriculture.(ed.) (2006). The olive oil and table olives sector. (Working paper). http://europa.eu.int/comm/agriculture/markets/olive/index_en.htm. Accessed 1 abril 2006.

European Commission. (2002). The olive oil sector in the European Union. http://europa.eu.int/comm/agriculture/publi/fact/olive/index_en.htm. Accessed 1 abril 2006.

Eurostat. (2006). Dataset. http://epp.eurostat.cec.eu.int. Accessed 1 october 2006.

FADN. (2006). Dataset (unpublished data). http://europa.eu.int/comm/agriculture/rica.

Fan, S. (1991). Effects of Technological Change and Institutional Reform on Production Growth in Chinese Agriculture. *American Journal of Agricultural Economics* 73: 266- 75.

International Oleic Council (IOOC). (2006). Dataset. http://www.internationaloliveoil.org/ oliveworld_recipes01.asp . Accessed 1 abril 2006.

Karagiannis, G. and Tzouvelekas, V.(2001) Self- Dual Stochastic Production Frontiers and Decomposition of Output Growth: The Case of Olive- Growing Farms in Greece. *Agricultural and Resource Economics Review* 30(2): 168- 178.

Karagiannis, G., Kien, C. and Tzouvelekas, V (2003). On the choice of functional form in stochastic frontier modeling. *Empirical Economics* 28: 75- 100.

Koopmans, T.C. (1951). An analysis of production as an efficient combination of activities. T.C. Koopmans ed. Activity analysis of production and allocation, Cowles Commission for Research in Economics, Monograph n. 13, New York, Wiley.

Kumbhakar, S.C. and Knox Lovell, C.A. (2000). *Stochastic frontier analysis*. New York, Cambridge University Press.

Meeusen, W. and Van den Broeck, J. (1977). Efficiency estimation from Cobb-Douglas production functions with composed error. *International Economic Review* 18(2): 435- 444.

Olistat (2006). Dataset. Accessed 1 abril 2006. http://mars.jrc.it/marspac/olivine/Olistat.htm .

Serra,T., Goodwin, B., and Featherstone. A. M. (2005). Agricultural Policy Reform and Off- farm Labour Decisions. *Journal of Agricultural Economics*. 56(2): 271–285.

Spanish Ministry for Agriculture. (2006). Data. http://www.mapa.es/. Accessed 1
october 2006.

Tzouvelekas, V., Giannakas, K., Midmore, P. and K. Mattas. (1997) Technical
Efficiency Measures for Olive-Growing Farms in Crete, Greece. *International Advances in Economic Research* 3(3): 154-169.

Van der Vlist, A., Withagen, C., and Folmer. H. (2005). Testing Porter´s
hypothesis: A stochastic frontier panel data analysis of Dutch horticulture.
The XIth Congress of the EAAE. European association of agricultural
economists, Copenhagen.

Table 1. Maximum Likelihood Estimates the Production Frontier Model for Olive Farms in Spain, 1999- 2003

Variables	Parameters	Estimate	Standard Error
Production Frontier			
Constant	β_0	0.535663	(0.04134959)*
Specific cost	β_{SC}	0.197351	(0.02848957)*
Pesticides & Fertilizers	β_{PF}	0.368264	(0.04331106)*
Land	β_{LND}	0.372394	(0.05051601)*
Labour	β_{LB}	0.1584408	(0.07467910)*
Time	β_T	0.2281728	(0.05371179)*
Specific cost*Time	$\beta_{SC.T}$	0.1305851	(0.04486798)*
Pesticides & Fertilizers *Time	$\beta_{PF.T}$	0.2814309	(0.06427588)*
Land*Time	$\beta_{LND.T}$	- 0.4251829	(0.07756294)*
Labour*Time	$\beta_{LB.T}$	- 0.0485768	(0.10464542)
Technical efficiency			
Constant	δ_0	- 1.6576097	(1.4305176)
Organic farming	δ_{OF}	2.2223123	(0.6477559)*
Rent paid	δ_{RP}	- 4.9887782	(1.8764161)*
Year of birth	δ_{YB}	- 0.0387208	(0.0235556)*
Less Favoured Area	δ_{LFA}	1.4425666	(0.7753664)*
Time	δ_T	- 0.0048668	(0.0021792)*
sigma- squared	σ^2	4.8531050	(1.9636074)*
gamma	γ	0.9739373	(0.0098921)*
log likelihood function = - 460.916			
LR test of the one- sided error = 85.489			

Note:* indicates that the parameter is significant at the 5%.

Table 2. Mean technical efficiency by year and farms.

	1999	2000	2001	2002	Total
<20	3	0	2	4	9
20- 30	2	7	3	4	16
30- 40	3	2	10	7	22
40- 50	6	7	17	13	43
50- 60	6	12	9	15	42
60- 70	21	32	20	30	103
70- 80	36	61	30	35	162
80- 90	67	24	52	34	177
90>	0	0	1	1	2
Mean	73.4%	68.5%	68.4%	65.4%	69%

Table3. TFP changes

		2000	2001	2002	2000- 20002
TFP		0.007395	0.010069	0.013330	0.010265
	TEC	0.004866	0.004866	0.004866	0.004866
	TC	0.000109	0.000106	0.000097	0.000104
	SC	0.000017	0.002367	0.002940	0.001775
	AE	0.002240	0.002727	0.000542	0.001836

Where: TFP represents total factor productivity change, TEC represents technical efficiency change,

TC is technical change, SC is scale component and AE is allocative efficiency