Technical efficiency analysis and decomposition of productivity growth of Spanish olive farms

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Abstract

Spain occupies the first position in worldwide rankings of olive oil production and trade. This analysis assesses the relative technical efficiency with which this sector is operating. The concept of technical efficiency is critical to measuring the performance of a firm, determining the degree of innovative technology adoption and the overall production efficiency. Specifically, the main objective of this study is to assess the relative technical efficiency and to decompose the productivity growth of Spanish olive farms. Technical efficiency effects are assumed to be a function of firm-specific characteristics. Maximum-likelihood methods are applied to the estimation of the model. A primal approach is used to decompose total factor productivity (TFP) growth into its various components. Results indicate that farm location, age of manager, as well as the composition of the workforce affect efficiency levels. Technical efficiency changes and scale effects are found to be the main sources affecting TFP growth.

Additional key words: olive sector, primal approach, stochastic frontier methodology.

Resumen

Análisis de la eficiencia técnica y la descomposición del crecimiento de la productividad de las explotaciones olivareras españolas

España ocupa la primera posición mundial en la producción y el comercio de aceite de oliva. En este análisis se determina la eficiencia técnica relativa con la cual este sector está operando. El concepto de eficiencia técnica es crucial para evaluar el comportamiento de la empresa, determinar el grado de adopción de innovaciones tecnológicas y su eficiencia productiva. Concretamente, los objetivos principales de este estudio son la estimación de la eficiencia técnica relativa y la descomposición del crecimiento de la productividad en sus varios componentes para el caso de una muestra de explotaciones olivareras en España. El índice de eficiencia es considerado como una función de variables específicas relacionadas con la explotación. La estimación del modelo se realiza mediante la técnica de máxima verosimilitud. Después se utiliza una aproximación primal para descomponer el crecimiento de la productividad en sus varios componentes. Los resultados indican que la localización de la explotación, la edad del gerente, así como la composición de la mano de obra afectan a los niveles de la eficiencia. Por otra parte, los cambios en la eficiencia técnica y los efectos escala son los factores que más condicionan el crecimiento de la productividad.

Palabras clave adicionales: aproximación primal, frontera estocástica, sector olivar.

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 the Olistat database (Olistat dataset, 2006), 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 of a large number of small and medium-sized industries that are often located near to producing regions, 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 decoupled-oriented Common Agricultural Policy (CAP) reforms of the 1990s and 2003, which protected the sector by preventing the abandonment of olive groves in marginal areas, and supported sustainable development of the sector through promotion of healthy and quality products and prices.

In this paper relative technical efficiency and factor productivity changes are analyzed for a sample of Spanish farms specialized in olive production. Though some previous published studies have addressed efficiency issues in European agriculture (Tzouvelekas *et al.*, 1997; Karagiannis and Tzouvelekas, 2001; Karagiannis *et al.*, 2003;), no previous published paper has focused

on the Spanish olive sector[1]. 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 environmental protection in less-developed areas. Second, the thorough restructuring process 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, though the olive sector has been excluded from past 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 this study.

The olive sector in Spain

The EU occupies prominent positions in worldwide rankings of olive oil production and trade. According to the International Oleic Council data (IOC, 2006), EU harvests showed an upturn in the second half of the 1990s reaching 2.6 million tons in the 2001/02 marketing year, representing 88% of worldwide production. The EU is followed, at a distance, by Tunisia, Turkey, Syria and Morocco in terms of productive capacity. Spain accounted for 1.4 million tons in the same period, a 53% of EU's production and a 47% of world's output. Spain is also the top producer of table olives as 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. IOC data suggest that the EU accounts for more than half of worldwide olive oil exports, with the main destinations being the United States of America, Australia, Canada, Japan and Brazil. Spain and Italy are the largest EU exporters. During the 2001/02 marketing year, Spain exported 112,500 tons to non-EU countries and 488,000 tons to the EU. Hence, of total

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[1] A notable exception is the unpublished work by Calatrava-Leyva and Dios-Palomares (1997).

Spanish olive oil sales abroad, 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 within the EU over the last decade, mainly as a result of relevant increases in Spanish output.

The olive grove area represents around 13% of the total agricultural area in Spain (Spanish Ministry for Agriculture, 2003). Ninety-three percent of this area is devoted to olive oil production, while the rest is dedicated to table olive production. Spanish olive production has experienced a substantial growth since joining 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. The yield 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 from 102,000 ha in 1995 to 372,000 ha in 2000. Modernization of the sector has been partly promoted by an improvement 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, which are especially notable since the mid 1990s, have also contributed to increased production and trade. However, the very intense droughts 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, 2006), 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 fluctuated in accordance with output. There was a rise following the accession to the EU, which was prolonged by the droughts affecting Spain during 1994 and 1995. However, the increase in production after the drought caused prices to fall. Data from the European Commission (2002) show that prices for extra virgin olive oil fell from 2,770.4 € per ton in 1994/95 to 1,712.9 € in 2000/01. Increased production within the EU led to the 1998 reform of the EU's Common Market Organization (CMO) for oils and fats, in order to stabilize both production and the budget needed 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 (Aigner *et al.*, 1977; Meeusen 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 can be expressed as follows:

$$y_{it} = f(x_{it}, t; \beta) e^{v_{it} - u_{it}} \qquad [1]$$

where y_{it} is the output of the *i*-th firm ($i = 1, \ldots, N$) in period $t = 1, \ldots, T$; $f(x_{it}, t; \beta)$ 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 inefficiency. 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:

$$ET_{it} = \frac{y_{it}}{f(x_{it}, t; \beta) e^{v_{it}}} = e^{-u_{it}} \qquad [2]$$

It should be noted here that the specification of the stochastic frontier in [1] allows the 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 affects the u_{it}'s, which have mean, δz_{it}, and variance, σ_u^2. Specifically, the technical inefficiency term is assumed to respond to the following pattern of behavior: $u_{it} = g(\delta z_{it}) + \eta_{it}$, where z_{it} is a $(M \times 1)$ vector of farm-specific variables which may vary over time, δ is a $(1 \times M)$ vector of unknown coefficients, and $\eta_{it} \sim N(0, \sigma_\eta^2)$ 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 model (see the appendix for further detail). Although widely implemented using panel data, the Battese and Coelli (1995) model does not really exploit the nature of such data. Álvarez and Orea (2004) propose an alternative method to overcome such a limitation. In the empirical application, a restricted version of the fixed effects technique is used by incorporating regional dummies into the production technology function. The use of regional dummies involves the assumption that farms are heterogeneous across regions, while homogeneity is assumed within regions only for unobserved variables[2].

After estimating the stochastic production frontier farm's total factor productivity change is assessed, which involves evaluating to what extent input use has changed at a different rate than production. The sources of productivity change are also assessed. In doing so, the method proposed by Kumbhakar and Knox Lovell (2000) is followed. By using a Divisia index, total factor productivity change ($T\dot{F}P$) can be defined as the difference between the rate of change of output and the rate of change of an input quantity index. By omitting the subscripts indexing firms and time, the Divisia index can be represented as:

$$T\dot{F}P = \dot{y} - \sum_k S_k x_k \qquad [3]$$

where a dot over a variable indicates its rate of change over time, $S_k = \dfrac{w_k x_k}{E}$ is the observed expenditure share of input k, being $E = \sum_k w_k x_k$ the total input expenditure, and w_k the price of input k. By totally differentiating eq. [1] with respect to time and using expression [3] above, total factor productivity change can be expressed as:

$$T\dot{P}F = T\Delta + (\varepsilon - 1)\sum_k \left(\frac{\varepsilon_k}{\varepsilon}\right) \dot{x}_k +$$
$$+ \sum_k \left[\left(\frac{\varepsilon_k}{\varepsilon}\right) - S_k\right] \dot{x}_k + TE\Delta \qquad [4]$$

where:

$$T\Delta = \frac{\partial \ln f(x,t;\beta)}{\partial t},$$

$$\varepsilon_k = \varepsilon_k(x,t;\beta) = \frac{x_k\left(\partial f(x,t;\beta)/\partial x_k\right)}{f(x,t;\beta)},$$

$$\varepsilon = \varepsilon(x,t;\beta) = \sum_k \varepsilon_k(x,t;\beta), \text{ and } TE\Delta = -\frac{\partial u}{\partial t},$$

The first component of $T\dot{F}P$ is $T\Delta = \dfrac{\partial \ln f(x,t;\beta)}{\partial t}$, a measure of the rate of technical change or, in other words, a measure of the changes in the maximum attainable output. An upward (neutral) [downward] movement of the production frontier will be represented by $T\Delta > (=) [<] 0$. The second summand measures the contribution of scale economies to total factor productivity growth. It is represented by $(\varepsilon - 1)\sum_k \left(\dfrac{\varepsilon_k}{\varepsilon}\right) \dot{x}_k$, where $\varepsilon_k = \dfrac{x_k\left[\partial f(x,t;\beta)/\partial x_k\right]}{f(x,t;\beta)}$ is the output elasticity with respect to input, x_k. Returns to scale are measured by $\varepsilon = \sum_k \varepsilon_k(x,t;\beta)$, where $\varepsilon > (=)[<] 1$ involves increasing (constant) [decreasing] returns to scale. Expression $\sum_k \left(\dfrac{\varepsilon_k}{\varepsilon}\right) \dot{x}_k > (=)\left[<\right] 0$ indicates increases (constancy) [decreases] in input use. $T\dot{F}P$ will be increased if production is characterized by increasing (decreasing)

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[2] Other specifications were also tried, such as using the fixed effects technique, but yielded inferior results.

returns to scale and there is an expansion (contraction) in input use. The third term in [4], $\sum_k\left[\left(\frac{\varepsilon_k}{\varepsilon}\right)-S_k\right]\dot{x}_k$, measures allocative inefficiency and captures the effect of deviations in inputs' normalized output elasticities from their expenditure shares, or, in other words, the impacts of a deviation in input prices from the value of their marginal products. The fourth component, $TE\Delta=-\frac{\partial u}{\partial t}$ is the primal measure of the rate of change in technical efficiency-the gap between the production frontier and a firm's actual production. $TE\Delta$ will be > (=)[<]0 if technical inefficiency declines (remains unchanged) [increases] through time. $TE\Delta$ can be interpreted as the rate at which a producer moves toward or away from the production frontier. In summary, the $T\dot{F}P$ decomposition presented in [4] shows that total factor productivity can change as a result of a movement in the production frontier, a movement of current production towards or away from the frontier, the firms' ability to take advantage of economies of scale, as well as the ability to allocate inputs according to sound economic principles.

Empirical application

As noted above, the aim of this article is to assess relative technical efficiency and total factor productivity changes in the olive sector within Spain after the relevant changes experienced since the Spanish accession to the EU. Farm-level data are taken from the Farm Accounting Data Network (EU-FADN-DG Agriculture and Rural Development G-3) for the period 1999-2002. The concept of FADN was launched in 1965, when Council Regulation 79/65 of the Commission of the European Communities (CEC, 1965) established the legal basis for the organization of the network. Micro-economic data is collected annually for FADN from a sample of agricultural holdings in the EU. The information collected from each farm includes physical, structural, economic and financial data. FADN (2006) provides representative data of EU agricultural holdings along three dimensions: region, economic size and type of farming. This dataset classifies farms into different typologies that allow to identify the main types of farming. These typologies are defined in terms of the relative importance of the different enterprises

within the farm. Specifically, the relative importance of an enterprise is measured as the proportion of this enterprise's standard gross margin (SGM) over the farms' total SGM. The FADN farm classification type used in this analysis is farm type 33- specialist olives. FADN annual sample includes approximately 80,000 holdings that represent a population of about 5 million farms in the 25 member states, covering around 90% of the total utilized agricultural area (UAA), and accounting for more than 90% of the total agricultural production of the European Union. 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 population of Spanish agricultural holdings (FADN, 2006).

Though the analysis is based on microeconomic data, region and country level aggregates are also employed to define some variables used in the analysis. These aggregates are taken from the Spanish Ministry of Agriculture and Eurostat. The Spanish Ministry of Agriculture provided annual olive grove's land prices expressed in euros at the state level (see Spanish Ministry of Agriculture, 2005, for further detail) and average annual temperatures by region expressed in Celsius (see Spanish Ministry of Agriculture, 2004). Eurostat (2006) provided other annual input and output price indices. It is important to note here that this analysis faces some data limitations in the estimation of the stochastic production frontier. Specifically, since FADN does not register output prices, equal prices are assumed for all farms. In doing so, the analysis is unable to capture differences between olive varieties, qualities, etc.

The sample is composed by 576 observations that constitute an unbalanced panel which was built for the purpose of decomposing total factor productivity growth. The dataset contains 145 different farms. Observations are distributed in time as follows: 144 observations in 1999 and 2002, 145 in 2000, and 143 in 2001. Spanish regions are not equally represented within the sample. Andalusia is the most well represented region in the database with 303 observations, followed by Madrid (120 observations) and Catalonia (113 observations). At a distance follow Castilla La Mancha (20), Extremadura (10), Murcia and Aragón (with 5 observations each). The relevance of Andalusia within the sample is explained by the importance of olive oil production in this area.

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

$$Lny_{it} = \beta_0 + \sum_{k=1}^{K} \beta_k Lnx_{kit} +$$

$$+ \sum_{k=1}^{K} \sum_{j=1}^{K} \beta_{jk} Lnx_{kit} Lnx_{jit} + \beta_T t + \sum_{k=1}^{K} \beta_{Tk} Lnx_{kit} t + e_{it} \qquad [5]$$

where $k, j = 1,…,K$ indicate the conventional inputs used in the production process. The Translog function is tested against a Cobb-Douglas specification using the generalized likelihood ratio test[3]. The hypothesis that the production frontier has a Cobb-Douglas form is rejected at the 1% significance level against the alternative of a Translog functional form (see Table 3).

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 (1×21) vector that contains four inputs, an irrigation indicator expressed as the ratio of irrigated UAA to total UAA[4], average annual temperature by region and 14 interaction terms between inputs and inputs and time (t). The first input, x_1, includes fertilizers and pesticides; x_2 comprises variable crop-specific inputs other than fertilizers and pesticides; x_3 represents the hectares occupied by olive groves, 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. Market prices, also required to carry out the total factor productivity growth decomposition, are not registered in FADN (2006) dataset. To define w_1 and w_2 (i.e. pesticide and fertilizer and other variable input prices) as well as the output price index, national price indices are taken from Eurostat. Labor prices are approximated at the farm-level using FADN and by dividing a farm's labor expenses by the hours of labor. Land prices, as noted, are derived from the Spanish Ministry for Agriculture at the national level. All variables in the stochastic frontier are normalized with respect to their own mean and expressed in logs in the estimation process[5].

As noted above, the model by Battese and Coelli (1995) does not exploit panel data. In order to solve this problem, a restricted version of the fixed-effects technique is implemented which consists of using regional dummy variables to identify the different Spanish regions. In this regard it is assumed, only for unobserved variables, that farms are heterogeneous across regions and homogeneous within a particular area.

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 equal to 1 if the holding is renting agricultural land and zero otherwise (z_2), a dummy variable that indicates whether the farm is located in a less favored area (LFA) or not (z_3), the birth year of the holding's primary decision maker (z_4), time (z_5), and workforce composition (z_6) which is computed as the ratio of family labor hours to total labor hours. As suggested by previous literature (Serra *et al.*, 2005), direct costs of land rentals may create stronger incentives to work the land in a more efficient manner, relative to the opportunity costs borne by owned land. To the extent that this occurs, z_2 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_4. Younger farmers should be expected to be more prone to introduce changes in farm management techniques that increase efficiency, relative to elderly ones. 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. To the extent that family labour is more relevant in small, less competitive farms, it may be associated to a higher level of inefficiency. Results derived from the estimation of the model are presented in the following section.

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[3] As is well known, the test can be computed as $LR = -2[lnL(H_0) - lnL(H_1)]$, where $L(H_0)$ and $L(H_1)$ represent the values of the likelihood function under the null (H_0) and the alternative hypotheses (H_1) respectively.

[4] The model was also estimated using a slightly different definition of the variable irrigation. Specifically, a dummy variable equal to 1 if the farm irrigates land and zero otherwise was used. Results are very similar to the ones presented in this paper.

[5] Specifically, the following transformation is used: $x' = ln(x/\bar{x})$ where $\bar{x}$ is the sample mean of x.

Results

Summary statistics for the variables used in the analysis and other relevant farm characteristics are given in Table 1. This table shows that sample farms' average annual output totals around 33,517 €, an amount considerably below the 70,600 € generated by Spanish farms specialized in vegetables and horticulture, but above the gross income by citrus farms on the order of 7,160 €[6]. Table 1 also indicates that sample farms employ 3,383 labour hours per year, 69% of which come from family labour. Sample farms have, on average, 28 ha of land and irrigate 21% of the UAA. Only 8% of this land is rented, a percentage that can be considered low relative to the Italian olive sector that rents 16% of its cultivated land. Almost 60% of Spanish olive farms are located in a less favoured area. The average farmer's age in the sample is 54 years. Revenue per hectare of Spanish olive farms is 1,366.5 €, below the Italian olive farms' income (1,698.4 € ha^{-1}). However, the cost per hectare of the Italian olive farms (1,279 €) is greater than the Spanish one (730 €), yielding higher margins on a per hectare basis in Spain.

Results derived from simultaneously estimating the Translog production frontier and the technical inefficiency equation are presented in Table 2[7]. First-order parameters, β_k, have the anticipated positive sign and magnitude thus being between zero and one. Parameter estimates suggest that production is characterized by increasing returns to scale. The presence of constant returns to scale, i.e., $\sum_k \beta_k = 1$, $\sum_k \beta_{kt} = 0$ and $-2\beta_{kk} = \sum_{j=1}^{3} \beta_{kj}$, is tested using the generalized likelihood ratio statistic (see Table 3). The null hypotheses of constant returns to scale is rejected at the 5% significance level against the alternative of non-constant returns to scale, thus providing further evidence in favour of increasing returns to scale and implying that any increase in the size of Spanish olive farms would cause a decline in unit production costs.

Table 1. Description of the sample data (N = 576)

Variable	Unit of measure	Mean	Std. dev.	Minimum	Maximum
Variables used in the analysis					
Pesticides & fertilizers	€	2,926.85	6,213.49	0.00	102,026.00
Other crop-specific costs	€	2,890.26	4,524.46	0.00	69,739.50
Labour	h	3,383.16	1,743.99	698.00	19,117.00
Land	ha	28.08	44.69	2.00	377.00
Output	€	33,517.50	45,442.20	0.00	494,547.00
Workforce composition ratio		0.69	0.24	0.00	1.00
Irrigation ratio		0.21	0.34	0.00	1.00
Age[a]	years	54.10	14.48	26.00	102.00
Less favoured area dummy		0.59	0.49	0.00	1.00
Economic size	€	44,167.80	85,643.40	3,820.00	720,070.00
Rented area ratio		0.08	0.28	0.00	1.00
Fertilizer & pesticide price index		105.41	6.98	94.60	111.80
Other cost price index		111.34	3.82	105.30	115.20
Land price	€ ha^{-1}	16.46	1.07	14.78	17.90
Labour price	€ h^{-1}	3.48	2.10	1.00	8.84
Other variables describing sample farms					
Revenue per hectare	€ ha^{-1}	1,366.47	819.52	0.00	4,145.96
Cost per hectare	€ ha^{-1}	730.13	429.08	138.00	2,750.53

[a] FADN (2006) database actually provides the manager's birth year. This variable is converted to the manager's age only for the purpose of presenting more useful data in this table. *Source:* EU-FADN-D G Agriculture and Rural Development G-3, Eurostat and the Spanish Ministry for Agriculture.

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[6] Unless otherwise specified, data in this paragraph are derived from FADN.

[7] To preserve space, the coefficients for regional dummies are not presented but they are available from the authors upon request.

Table 2. Maximum likelihood estimates of the stochastic frontier model for olive farms in Spain, 1999-2002

Variables	Parameters	Estimate	Standard error
Frontier production function			
Constant	β_0	0.347425	(0.042262)***
Specific cost	β_{SC}	0.171972	(0.033491)***
Pesticides & Fertilizers	β_{PF}	0.129367	(0.045009)**
Land	β_{LND}	0.565790	(0.049412)***
Labour	β_{LB}	0.145050	(0.063004)**
Temperature	β_{TP}	3.198542	(0.266000)***
Time	β_{T}	−0.083612	(0.115794)
Irrigation	β_{I}	0.226936	(0.065388)***
Specific cost×Time	$\beta_{SC.T}$	0.122815	(0.046163)**
Pesticides & Fertilizers×Time	$\beta_{PF.T}$	0.290289	(0.056296)***
Land×Time	$\beta_{LND.T}$	−0.376697	(0.069740)***
Labour×Time	$\beta_{LB.T}$	−0.182010	(0.092737)**
Specific cost×Pesticides & Fertilizers	$\beta_{SC.PF}$	−0.061269	(0.041216)*
Specific cost×Land	$\beta_{SC.LND}$	−0.025694	(0.053353)
Specific cost×Labour	$\beta_{SC.LB}$	−0.058071	(0.056041)
Pesticides & Fertilizers×Land	$\beta_{PF.LND}$	−0.171580	(0.078295)**
Pesticides & Fertilizers×Labour	$\beta_{PF.LB}$	−0.007679	(0.088693)
Land× Labour	$\beta_{LND.LB}$	0.043860	(0.099127)
Specific cost×Specific cost	β_{SC2}	0.0585325	(0.020114)**
Pesticides & Fertilizers×Pesticides & Fertilizers	β_{PF2}	0.064353	(0.035875)*
Land×Land	β_{LND2}	0.095639	(0.050672)*
Labour×Labour	β_{LB2}	−0.176425	(0.086681)**
Inefficiency effects model			
Constant	δ_0	−0.549138	(0.102752)
Land rental	δ_{RP}	−0.066348	(0.317059)
Year of birth	δ_{YB}	−0.089964	(0.029152)***
Less favoured area	δ_{LFA}	3.002399	(0.927122)***
Time	δ_{T}	−0.004216	(0.001411)***
Workforce composition	δ_{LB}	2.393000	(0.785318)***
sigma-squared	σ^2	2.469331	(0.626970)***
gamma	γ	0.962202	(0.009781)***

log likelihood function = −337.9467
LR test of the one-sided error = 126.88018

***,** and * indicate that the parameter is significant at the 1, 5 and 10%, respectively.

Table 3. Model specification tests

Hypothesis	LR test-statistic	Critical value ($\alpha = 0.05$)
Absence of inefficiency effects, i.e., $\gamma = \delta_1 = \ldots \delta_M = 0$	126.88	$x_7^2 = 14.07$
Cobb-Douglas form, i.e., $\beta_{jk} = 0$ for all j and k	123.05	$x_{11}^2 = 19.68$
Constant returns-to-scale, i.e., $\sum_k \beta_k = 1$, $\sum_k \beta_{kt} = 0$ and $-2\beta_{kk} = \sum_{j=1}^{3} \beta_{kj}$	127.34	$x_5^2 = 11.1$
Zero-technical change, i.e., $\beta_t = \beta_{kt} = 0 \; \forall k$	106.49	$x_5^2 = 11.07$

The variance parameter, γ, is statistically significant and close to one[8], which suggests the relevance of technical inefficiency in explaining output variability among Spanish olive 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 technical change coefficient is not statistically different from zero. Estimated coefficients help us to understand the determinants of sample farms' technical inefficiency. As expected, the less-favoured area coefficient is positive which indicates that holdings facing different restrictions, such as environmental constraints, are less efficient relative to the other farms. The coefficient representing a farmer's birth year 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. Farms renting land are shown to be more efficient relative to farms owning cultivated land[9]. This provides evidence that land rental costs motivate more efficient operations relative to the opportunity costs of owned land. The negative coefficient for the variable time suggests that the technical inefficiency of olive farms tended to decrease throughout the period studied. The workforce composition coefficient is positive, indicating that farms with a higher proportion of unpaid labour are less efficient relative to the farms with a higher proportion of remunerated work.

In order to better interpret the results, the generalized likelihood ratio statistic is used to test for the relevance of inefficiency effects and technical change (Coelli, 1995). First, the null that inefficiency effects are absent from the model, i.e., $\gamma = \delta_1 = \ldots = \delta_M = 0$, is tested which involves that farms operate at the frontier. The null hypothesis of no technical inefficiency is rejected at the 5% level (see Table 3) against the alternative of inefficiency effects, thus providing evidence that both systematic and random technical inefficiency effects are indeed present in explaining output variability. Second, the null hypothesis that there is zero technical change in Spanish olive farms ($\beta_t = \beta_{kt} = 0 \ \forall k$) is tested against the alternative of non-neutral technical progress. The null is rejected at the 5% level. This implies the existence of non-neutral technical progress in the Spanish olive sector.

Estimated technical efficiency scores in the form of frequency distributions are reported in Table 4. The predicted technical efficiency takes an average value of 75.5% throughout the period studied, implying that output could increase substantially if technical inefficiency were eliminated. A majority of farmers have efficiency scores in the range of 70 to 90% (73% of the sample). Technical efficiency fluctuates over time from a peak of 77.8% in 2001 to a minimum of 72% in 2002. In accord with the findings by Calatrava-Leyva and Dios-Palomares (1997), who analyze the productive efficiency for a sample of Andalusian olive farms, technical inefficiency fluctuations over time move in parallel with olive yields in Spain. According to the Spanish Ministry for Agriculture, olive yields reached a peak of 3,100 kg ha^{-1} in 2001 and a minimum of 2,270 kg ha^{-1} in 2002. Technical efficiency levels are capturing these fluctuations with higher scores obtained in high yield years and lower scores corresponding to

Table 4. Mean technical efficiency by year and farms

Efficiency interval	1999	2000	2001	2002	Total
< 20	2	0	1	3	6
20-30	1	1	2	4	8
30-40	5	5	2	4	16
40-50	4	4	1	3	12
50-60	8	11	7	7	33
60-70	11	16	16	20	63
70-80	35	46	39	49	169
80-90	77	59	66	50	252
> 90	1	3	10	3	17
Mean	75.5	75.1	77.8	72.0	75.5

[8] This result is compatible with previous research. See Battese *et al*. (1997) and Coelli *et al*. (1998) for some examples.
[9] The coefficient, however, is not statistically significant.

low yield periods[10]. Álvarez and Arias (2003) have recently demonstrated that there is a positive relationship between technical efficiency scores and farms' size. Correlation coefficients between technical efficiency scores and farm size indicators such as output supply and farms' gross margin, support the results of these authors[11].

To the extent that the Spanish accession to the EU may have encouraged investment in the olive sector and thus an increase in the olive productive capacity, the analysis suggests that these improvements may not have been fully implemented. This may be due to a decrease in olive farm incomes as a result of a decline in both public subsidies after the 1998 CMO reform and a reduction in output prices following the relevant increases in production that took place after the mid 1990s. Technical efficiency scores for the main olive producing areas were also computed. Results suggest that farms located in Catalonia and Madrid have higher mean efficiency levels (above 75%) than the main producing region, Andalusia, with an efficiency of 74%.

Karagiannis and Tzouvelekas (2001) analyzed technical efficiency levels of Greek olive farms over the period 1987-1993. By using a panel data set of 125 olive-growing farms in Greece, they assessed the effect of functional form specification on the estimation of technical efficiency. The generalized quadratic Box-Cox transformation was used to test the relative performance of alternative, widely used, functional forms and to examine the effect of the choice on final efficiency estimates. The inputs included in their analysis are labor, fertilizers, other expenses and land. The authors derived efficiency scores on the order of 67% for the squared-root quadratic form, 87% when using a normalized quadratic, and 75% if working with a

Translog form. A comparison of efficiency scores in Table 4 with these authors' Translog results suggests similar levels of technical inefficiency for both Spanish and Greek farms. However, efficiency scores in Table 4 are lower than the results derived by Calatrava-Leyva and Dios-Palomares (1997), who, as noted above, assessed the productive efficiency for a sample of Andalusian olive farms. Their analysis is also based on a FADN (2006) dataset that provided a sample of 159 farms during 1993. They estimated a stochastic frontier model and specified the production frontier using a Cobb-Douglas form. The inputs included are capital, labour and crop-specific costs. These authors derive mean efficiency levels on the order of 90%. Lachaal *et al.* (2005) analyzed technical efficiency and its determinants using a sample of 178 olive farms in Tunisia, observed from 1994 to 1997. The authors used a stochastic frontier production function approach and the Translog form was applied to estimate the model. The inputs used are capital, labour and intermediate inputs. Results yielded technical efficiency ratings on the order of 82%.

Results of the TFP growth decomposition are reported in Table 5. As explained above, TFP growth is calculated as the sum of technical change, a scale component, as well as changes in technical and allocative inefficiency. Results show evidence in favor of an increase in total factor productivity growth throughout the period of analysis at an annual rate of 3.1%. It can be seen that, on average, both the technical efficiency change and, at a distance, the scale component were key contributors to TFP growth. Technical change also contributed to increase productivity. A positive value for the rate of technical change is an indicator of an upward shift of the olive production frontier, probably as a result of an

Table 5. Total factor productivity (TFP) changes

	2000	2001	2002	2000-2002 average
TFP[1]	0.031578	0.058083	0.003425	0.031029
TEC	0.029648	0.062668	0.001805	0.031373
TC	0.000212	0.000195	0.000048	0.000152
SC	−0.000048	0.000854	0.004123	0.001643
AI	0.001767	−0.005635	−0.002551	−0.002139

[1] TEC: technical efficiency change. TC: technical change. SC: scale component. AI: allocative inefficiency.

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[10] The correlation coefficient between sample farms' yields and technical efficiency scores was computed and found to be positive and statistically significant. Though results are not presented here, they are available upon request.

[11] Results are not presented here but are available upon request.

increase in investments following the Spanish accession to the EU. A positive value of the scale component means that olive farmers took advantage of the economies of scale by increasing farm size. Additionally, a positive value for the technical efficiency change component shows that the gap between the production frontier and olive farms' actual production was squeezed throughout the period of analysis. Allocative inefficiency exerted a negative effect on TFP growth, although its magnitude was smaller than that of the technical efficiency change. The presence of allocative inefficiency shows that, during the period of analysis, input prices were not equal to the value of their marginal product and thus that inputs were not allocated according to sound economic principles.

Concluding remarks

Spain occupies a prominent position in worldwide rankings of olive oil and table olive production. In this paper, relative technical efficiency and factor productivity changes were analyzed for a sample of Spanish farms specialized in olive production. Specifically, a stochastic frontier model was estimated to analyze technical efficiency and decompose the productivity growth into its various components following Kumbhakar and Knox Lovell (2000). An unbalanced panel of 576 observations was used in the empirical analysis.

Estimated average efficiency levels for sample farms are about 75.5% for the period 1999-2002. This mean efficiency score shows that there is ample scope to increase total output without the need to increase input use or alter the production technology. Some regions, such as Madrid and Catalonia, are found to perform more efficiently relative to Andalusia, which is the main production area. In accordance with Calatrava-Leyva and Dios-Palomares (1997) and Álvarez and Arias (2003), technical efficiency scores seem to be positively correlated with farms' size and yields. Parameters of the technical inefficiency equation suggest that several variables affect efficiency levels. These variables are farm location (i.e., whether it belongs to a less favoured area or not), age of manager, and workforce composition. Efficiency decreases when located in a less favored area, being an aged farmer or using family labour. On the other hand, the passage of time is found to increase efficiency scores. Hypothesis testing on inefficiency effects provides evidence that both systematic and random technical inefficiency effects are indeed present in explaining olive output variability. A comparison of the results derived in this analysis with previous research reveals similar levels of technical inefficiency for Spanish and other Mediterranean olive farms.

As for productivity growth, results show an increase in average productivity of about 3.1% per year during the period of study. Productivity growth was mainly driven by the technical efficiency change and the scale component. These results suggest that input use increased where economies of scale exist and that the distance between actual production and the production frontier was reduced during the period of analysis. The positive contribution of the scale component is not surprising given that production for sample farms is characterized by increasing returns to scale.

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Appendix

The likelihood function of the problem can be expressed as follows (Battese and Coelli, 1993).

$$L^*(\theta;y_{it}) = -\frac{1}{2}(\sum_{i=1}^{N}T_i)\left[ln\,2\pi + ln\,\sigma^2\right] - \frac{1}{2}\sum_{i=1}^{N}\sum_{t=1}^{T}\left[(y_{it} - x_{it}\,\beta + z_{it}\,\delta)^2/\sigma^2\right] - \sum_{i=1}^{N}\sum_{t=1}^{T}(ln\Phi(d_{it}) - ln\Phi(d_{it}^*)) \quad [A1]$$

where $= \theta = (\beta,\ \delta,\ \sigma^2,\ \gamma)$, $d_{it} = z_{it}\delta/(\gamma\sigma^2)^{1/2}$, $\sigma^2 = \sigma_v^2 + \sigma_u^2$, $\gamma = \sigma_u^2/\sigma^2$ $(0 \le \gamma \le 1)$ and $d_{it}^* = [(\sigma_v^2 z_{it}\delta - \sigma_u^2(y_{it} - x_{it}\beta))/\sigma^2]/[\gamma(1-\gamma)\sigma^2]^{1/2}$. 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:

$$E\left[e^{-u_{it}}\middle| v_{it} - u_{it}\right] = \left[exp\left\{-\mu_{*it} + \frac{1}{2}\sigma_*^2\right\}\right]\left[\frac{\Phi\left[(\mu_{*it}/\sigma_*) - \sigma_*\right]}{\Phi(\mu_{*it}/\sigma_*)}\right] \quad [A2]$$

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

FRONTIER version 4.1 is employed to estimate the stochastic frontier model. SAS version 8 is used to decompose productivity growth.