Decomposition of Olive Oil Production Growth into Productivity and Size Effects : A Frontier Production Function Approach

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Les sources de la croissance de la production d'huile d'olive : une approche par la méthode des frontières de production

Résumé – Cet article examine la contribution relative de l'efficacité technique, des changements technologiques et de l'augmentation des intrants dans la croissance de la production d'huile d'olive grecque en utilisant la méthode des frontières de production appliquée à un panel d'exploitations agricoles. La technologie de production est représentée par une forme fonctionnelle de type translog tandis qu'un modèle à tendance temporelle unique est estimé par la procédure du maximum de vraisemblance. Les résultats empiriques montrent que l'efficacité totale de la production d'olives en Grèce est demeurée stable depuis 1987. L'examen des sources de croissance de la production révèle que celle-ci provient surtout de la contribution des intrants conventionnels, la productivité totale des facteurs n'ayant augmenté que lentement durant les années 1987-1993.

Mots-clés :
huile d'olive, Grèce, productivité, changement technologique, efficacité technique

Decomposition of Olive Oil Production Growth into Productivity and Size Effects: A Frontier Production Function Approach

Summary *– This paper investigates the relative contribution of technical efficiency, technological change and increased input use to the output growth of the Greek olive-oil sector using a stochastic frontier production function approach applied to panel data. A flexible translog functional form is used to represent the underlying production technology and maximum likelihood procedure is implemented to estimate a single time trend model. Empirical results show that the overall efficiency of olive-growing farms in Greece remained stable during the period 1987-1993, while an inquiry into the sources of production growth shows that the contribution of conventional inputs was the main source of that growth, since total factor productivity increased in a slow rate during the study period.*

Key-words:
olive oil, Greece, productivity, technical change, technical efficiency

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OLIVE oil has traditionally been a major food crop in Greek agriculture. Average annual production in the period 1976-1994 was 270,000 million tonnes, which represents almost 15 % of the world total, third after Spain and Italy (IOOC, 1995). Since Greek accession to the European Union (EU) in 1981, the olive oil market has undergone a series of significant changes through the operation of the Common Agricultural Policy (CAP). The most important change arising from CAP implementation was the sharp increase in agricultural support prices, with an annual change of 21.1 % during the period 1980-1990 (Georgakopoulos, 1990). Farmers' expectations of higher profits, through the introduction of high support prices, resulted in a persistent increase in total national olive oil production.[(1)]

However, CAP has come lately under strong pressure and governments within the EU are attempting to switch from an inward oriented to a more neutral trade regime. Recent and forthcoming reforms motivated by the GATT agreement are directed toward abolishing price regulation and achieving long-run structural adjustment in the agricultural sector by reducing price support and production grants. Therefore, an important policy issue in coming years for Greece, as a full member state of the EU, is to make the agricultural sector more competitive and market oriented. At the same time growing consumer desire in Western Europe and North America for the nutritional characteristics of olive oil is expected to shift demand in these areas.[(2)] Furthering production growth and simultaneously increasing exports could be a reasonable objective for Greek agricultural policy in forthcoming years.

In this context, knowledge of the relative contributions of total factor productivity and input use to output growth would provide a comprehensive view of the structure of the olive oil sector and can be shown to help farm managers and policy makers in Greece to ascertain appropriate policy measures. The objective of this paper is to capture the relative contributions of input growth, technological change and technical efficiency to olive oil production growth for a balanced panel data set of 125 Greek olive-growing farms using a stochastic frontier production function approach.

The empirical literature has mainly focused either on the measurement of farm technical efficiency (Dawson *et al.*, 1991; Bravo-Ureta and

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[(1)] From 1980 to 1992, the average growth rate of olive oil production was 3.75 %, almost 2 % higher than the EU average figure for agriculture (Commission of EC, 1995).

[(2)] Imports of olive oil in the US increased from 31,000 tones in 1980 to 115,000 tones in 1994. In Western Europe the relevant figures were 134,000 and 402,000 tones, respectively (IOOC, 1995).

Evenson, 1994), or on the effect of technological change on output growth (Blayney and Mittelhammer, 1990; Kumbhakar and Heshmati, 1996). Studies reporting such a decomposition for agriculture include Fan (1991), Wu (1995) and Ahmad and Bravo-Ureta (1995). However, the above studies utilized a Cobb-Douglas form, with the exception of Fan, who used a strongly separable translog production function. Furthermore, various effects explaining output growth were estimated in a residual base.

In this paper, a flexible translog functional form is utilized to represent the underlying technology, while a single time trend is used to capture the effect of technological changes. In addition, none of the effects explaining output growth are estimated in a residual base. These effects constitute an unexplained portion of output growth accounting for sub-equilibrium effects associated with the existence of quasi-fixed inputs and capacity under-utilization, learning-by-doing effects, cost of adjustments etc. The rest of the paper is organized as follows: first, by drawing from the relevant literature, the theoretical underpinnings associated with the methodology and estimation procedures are discussed; the data and empirical model are presented; results are set out and interpreted; and finally, some conclusions are drawn.

METHODOLOGICAL FRAMEWORK AND ESTIMATION PROCEDURES

Production frontier and technical efficiency

The current interest in efficiency measurement finds its origin in Farrell (1957) who introduced the concept of the production frontier. Ever since, considerable progress has been made towards refining the production frontier methodology (for review see Battese, 1992; Bravo-Ureta and Pinheiro, 1993). Among the alternative methods proposed for the estimation of stochastic frontier models (and the subsequent measurement of technical efficiency), the stochastic decomposition methodology has gained popularity among researchers because it offers an explanation of technical efficiency based on economic theory. In this framework, each farm faces its own frontier rather than a sample norm (Aigner *et al.*, 1977).

Battese and Coelli (1992) refined the model in a panel data context, allowing for temporal variation in levels of technical efficiencies. According to this method, when a balanced panel data set is available the concept of technical efficiency can be modeled in the following way:

$$Y_{it} = f\,(X_{it}\,;\,\beta)\,\cdot\,e^{\varepsilon_{it}}$$

$$\varepsilon_{it} \equiv v_{it} - u_{it}$$

and

$$u_{it} = \eta_{it} \cdot u_i = \left[e^{-\eta(t-T)}\right] \cdot u_i \tag{1}$$

where

Y_{it} is the output of the i^{th} farm (i = 1, 2, …, N) at time t (t = 1, 2,…, T),

X_{it} are the levels of inputs used,

β is the vector of unknown parameters,

ε_{it} is the stochastic composed error term,

and e designates the exponential function.

The components v_{it} and u_{it} are assumed to be independent of each other, where v_{it} is a symmetric normally distributed component $\left\{v \sim N\left(0, \sigma_v^2\right)\right\}$ capturing random output variation beyond the control of farmers (weather, diseases etc.), and u_{it} is a truncated normal distributed component $\left\{u \sim N\left(\mu, \sigma_u^2\right)\right\}$ representing the stochastic shortfall of output from the frontier due to technical inefficiency.(3) The parameter η reflects the time trend of the individual farm efficiencies.

Given the assumptions for the statistical distribution of u_{it} and v_{it} and the maximum likelihood(4) (ML) estimates of the production frontier, u_{it} can be obtained using the predictor (Battese and Coelli, 1992):

$$E\left[u_i/\varepsilon_i\right] = \mu_i^* + \sigma_i^* \left[\frac{\left(\varphi - \mu_i^*/\sigma_i^*\right)}{1 - \Phi\left(- \mu_i^*/\sigma_i^*\right)}\right] \tag{2}$$

where $\mu_i^* = \dfrac{\mu\sigma_v^2 - \eta_i'\varepsilon_i\sigma^2}{\sigma_v^2 + \eta_i'\eta_i\sigma^2}$ and $\sigma_i^{*2} = \dfrac{\sigma_v^2\sigma^2}{\sigma_v^2 + \eta_i'\eta_i\sigma^2}$

The functions $\varphi(\cdot)$ and $\Phi(\cdot)$ denote, respectively, the probability (pdf) and cumulative density functions (cdf) of the standard normal random variable, evaluated at $\left(- \mu_i^*/\sigma_i^*\right)$. The farm specific technical efficiency for the t^{th} year can be then calculated as $TE_{it} = e^{-u_{it}}$.

(3) It should be noted that the distribution of the one-sided error term, while necessary for the maximum likelihood estimation of farm efficiencies, might not be reasonable in some settings. As shown by Greene (1990), efficiency levels are susceptible to distributional assumptions and, unless there is economic basis for drawing any particular distribution, the choice is not a clear cut.

(4) For the formulation of the likelihood function, Battese and Coelli (1992) utilized the parameterization of Battese and Corra (1977) who replace the variances of the two components in the error term, σ_v^2 and σ_u^2, with $\sigma^2 \equiv \sigma_v^2 + \sigma_u^2$.

Technical change

Technical change has traditionally been described by a single time trend. Following the development of flexible functional forms, it was generalized over a period of years by the introduction of quadratic terms in time and interaction with inputs. An alternative approach is the utilization of various index numbers which, however, requires strong assumptions about the underlying technology (Caves *et al.*, 1982). In this study, we consider single time trend representation of technical change using a translog functional form to represent the underlying technology. Hence, equation (1) can be written as (Kim, 1992):

$$
\begin{aligned}
y_{it} = \beta_0 + \sum_{j=1}^{J} \beta_j x_{jit} + \beta_t t + \frac{1}{2}\beta_{tt} t^2 + \frac{1}{2}\sum_{j=1}^{J}\sum_{k=1}^{J} \beta_{jk} x_{jit} x_{kit} \\
+ \sum_{j=1}^{J} \beta_{jt} x_{jit} t + v_{it} - u_{it}
\end{aligned} \tag{3}
$$

where inputs and output are expressed in natural logarithms; i denotes farms; t denotes time; j and k denote inputs. Given the estimated parameters in the above equation, the rate of technical change is defined as the percentage change in output due to an increment of time with inputs held constant. That is,

$$
\partial y_{it} / \partial t = \beta_t + \beta_{tt} t + \sum_{j=1}^{J} \beta_{jt} x_{jit} \tag{4}
$$

According to its effect on relative input utilization, the rate of technical change can be decomposed further into effects due to pure and biased technical change (the first two terms and the last term of the RHS of (4), respectively). The former shows the effect of technology accumulation *per se*, while the latter shows its effects through the use of various inputs, indicating changes in their productivity.[(5)]

Accounting for total production growth

According to Farrell's decomposition of productive efficiency, technical efficiency is defined as:

$$
TE = Y / f(X, t) \tag{5}
$$

[(5)] It should be noted that the identification of the separate effects of neutral technical changes and change in technical efficiency can be problematic. A complete separation of these effects is not feasible without further complicating the estimation process (Heshmati, 1994; Lovell, 1996).

By taking the natural logarithms and totally differentiating with respect to time the above equation, we get:

$$\frac{d\ \ln TE}{dt} = \frac{d\ \ln Y}{dt} - \sum_j \frac{\partial \ln f(X,t)}{\partial X_j}\frac{dX_j}{dt} - \frac{\partial \ln f(X,t)}{\partial t} \qquad (6)$$

which can be written by rearranging slightly as (Bauer, 1990):

$$\dot{Y} = T\dot{E} + \dot{f}(X,t) + \sum_j \kappa_j (X_j,t)\,\dot{X}_j \qquad (7)$$

where the first term of the RHS captures the effect of time-varying technical efficiency on production growth; the second term represents technological change which can be further decomposed into neutral and biased technological change (as in equation (4)); and the last term captures the effect of input change on production growth as the sum of input growth rates weighted by the relevant production elasticities, κ_j.

DATA AND VARIABLE DEFINITIONS

The data used in this study were extracted from a survey undertaken by the Agricultural Economics and Social Research Institute. Our analysis focuses on a sample of 125 olive-growing farms, located in the four most productive regions of Greece (Peloponissos, Crete, Sterea Ellada and Aegean Islands). Observations were obtained on annual basis for the period 1987-1993. The sample was selected with respect to production area, the total number of farms within the area, the number of olive trees on the farm, the area of cultivated land and the share of olive oil production in farm output.

As we posed at the outset, a translog functional form (equation (3)), which represents a second-order approximation of the true function around a particular point (here the sample means), was chosen for the representation of the underlying technology. The dependent variable is the annual olive oil production measured in kilograms. The aggregate inputs[6] included as explanatory variables are: (a) total *labor*, comprising hired (permanent and casual), family and contract labor, measured in working hours. It includes all farm activities such as plowing, fertilization, chemical spraying, harvesting, irrigation, pruning, transportation, administration and other services; (b) *fertilizers*, including nitrogenous, phosphate, potash, complex and others, measured in kilograms; (c) *other*

[6] We cannot avoid measurement bias due to non-separability and jointness in the production technology of most of the inputs. However, the high production share of olive oil (greater than 75 % of total farm production) guarantees a minimum of measurement error in capital inputs.

cost expenses, consisting of pesticides, fuel and electric power, irrigation taxes, depreciation expenses,[7] interest payments, fixed assets interest, taxes and other miscellaneous expenses, measured in drachmas (constant 1990 prices); (d) *land*, including only the share of farm's land devoted to olive-tree cultivation measured in stremmas (one stremma equals 1,000 m^2). Summary statistics of the variables are presented in Table 1. To avoid problems associated with units of measurement, quantity data was converted to Divisia indices using cost shares to aggregate quantity indices of the inputs (Selvanathan and Rao, 1994; Balk, 1998).

Table 1.
Summary statistics of the data

Variables	*Output (Kg)*	*Area (Str)*[a]	*Labor (Hrs) Human*	*Labor (Hrs) Machine*	*Fertilizers (Kg)*	*Other Costs (Drs)*[b]
Mean values	1741.5	33.2	885.3	147.2	2,501.4	77.256
Standard Deviation	1147.2	17.4	547.2	123.0	1,745.2	36,858
Maximum	9975	97	4012	536	12,400	174,582
Minimum	798	6	420	10.0	150	45,000

[a] One stremma is 0.1 ha; [b] One Greek drachma is $0.003.

EMPIRICAL RESULTS

Production frontier estimates

The ML estimates[8] of equation (3) are given in Table 2. The Davidon-Fletcher-Powell algorithm, which has the principal advantage of eliminating the second order derivatives of the likelihood function,[9] was used to approximate the maxima. Eleven out of twenty-one variables are found to be statistically significant. Multi-collinearity is not a problem in our study.[10] Restrictive forms, such as the Cobb-Douglas and the constant returns to scale translog, were rejected at the 5 % significance level using the Chow test.

[7] The rate of depreciation applied to machinery varied between 10 and 13 % depending on the size of the farm. For buildings and inventories the depreciation rate was 7 % on the stock value.

[8] The ML estimates were obtained using the program FRONTIER Version 4.1, which was kindly provided by T. J. Coelli.

[9] The likelihood function is derived by Battese and Coelli (1992) and is not reproduced here.

[10] Regressing each of the explanatory variables with the remaining ones, we obtained R^2 values less than 0.60 indicating that multicollinearity is not severe (Kmenta, 1986).

Table 2. Stochastic frontier translog production functions for olive growing farms in Greece

Parameter	*Estimates*		*Parameter*	*Estimates*	
β_O	0.485	(0.131)*	β_{CC}	0.007	(0.005)***
β_L	0.142	(0.042)*	β_{AA}	0.015	(0.051)
β_F	0.067	(0.034)**	β_T	0.017	(0.012)***
β_C	0.091	(0.058)***	β_{TT}	0.030	(0.108)
β_A	0.535	(0.106)*	β_{TL}	-0.006	(0.035)
β_{LF}	-0.0001	(0.011)	β_{TF}	0.003	(0.026)
β_{LC}	0.002	(0.004)	β_{TC}	-0.016	(0.012) ***
β_{LA}	-0.025	(0.033)	β_{TA}	-0.084	(0.065)***
β_{LL}	0.011	(0.006)**	$\sigma^2 \equiv \sigma_v^2 + \sigma_u^2$	0.323	(0.094)*
β_{FC}	-0.002	(0.004)	$\gamma \equiv \sigma_u^2 / \sigma^2$	0.408	(0.104)*
β_{FA}	-0.017	(0.038)	μ	0	-
β_{FF}	0.008	(0.004)**	η	0.016	(0.024)
β_{CA}	0.004	(0.021)	Log-Likelihood	-583.07	

L: labor, F: fertilizers, C: other costs, A: area, T: time.
In parentheses are the consistent standard errors (White, 1980),
*significant at 1 % level, **significant at 5 % level, ***significant at 10 % level.

The ratio of farm specific variability to total variability, γ, is positive and significant at the 5 % level, implying that farm specific technical efficiency is important in explaining the total variability of output produced. Thus, the stochastic frontier function is empirically justified. Further, the statistical significance of modeling farm effects is examined using likelihood ratio tests. Several hypotheses are considered for different model specifications. The traditional average response model in which farms are assumed to be fully technically efficient is rejected ($H_0: \gamma = \mu = \eta = 0$), while the assumption that farm effects follow a truncated half-normal distribution is also rejected ($H_0: \mu \neq 0$).

Marginal products, calculated at geometric means, are all positive and diminishing. The corresponding figures are 0.362, 1.854, 2.057 and 0.454 for labor, fertilizer, other capital inputs, and land, respectively.[(11)] Average estimates over farms of the production elasticities and returns to scale (RTS) for each year of observation are presented in Table 3. These

(11) In addition, the bordered Hessian matrix of the first and second-order partial derivatives was negative semi-definite indicating diminishing marginal productivities.

figures indicate that land had contributed the most to olive oil production followed by labor, other capital inputs and fertilizers. On the other hand, returns to scale are diminishing, following a decreasing trend over time (in 1987 the relevant estimate was 0.907, while in 1993 it decreased to 0.856). The estimate was found to be higher for the small and medium farms located in Aegean Islands and Crete. The Allen partial elasticities of substitution (AES) evaluated at the mean values of inputs are also presented in Table 3. All point estimates are positive as one might expect theoretically.

Table 3. Production elasticities and Allen partial elasticities of substitution of olive-growing farms in Greece

Year	1987	1988	1989	1990	1991	1992	1993
Production Elasticities							
Labor	0.125	0.121	0.123	0.118	0.123	0.120	0.119
Fertilizer	0.065	0.066	0.065	0.069	0.067	0.066	0.066
Other Costs	0.082	0.080	0.081	0.072	0.077	0.075	0.071
Area	0.634	0.627	0.614	0.610	0.599	0.603	0.600
RTS	0.907	0.893	0.884	0.869	0.867	0.863	0.856
Elasticities of Substitution							
σ_{LF}	0.734	0.740	0.748	0.801	0.802	0.751	0.750
σ_{LC}	0.997	0.926	1.001	0.945	0.975	1.001	0.943
σ_{LA}	1.365	1.385	1.400	1.439	1.433	1.441	1.466
σ_{FC}	1.611	1.645	1.657	1.696	1.678	1.660	1.898
σ_{FA}	1.382	1.421	1.420	1.433	1.433	1.451	1.446
σ_{CA}	1.157	1.197	1.215	1.242	1.243	1.259	1.260

Technical efficiency

The estimated farm-specific technical efficiency measures for each year of observation are presented in Table 4 in the form of frequency distribution within a decile range while Figure 1 shows the relevant probability histogram. These estimates have been rather stable since 1987.[12] Specifically, in 1993 the average technical efficiency was found to be 76.8 %, quite close to the corresponding value in 1987 (74.94 %). Further, the comparison among regions shows that Crete has the highest average technical efficiency over time. A possible explanation of this stability in intra-farm technical efficiency variation might lie with the perennial nature of the olive tree, which reduces significantly producer's

(12) It is clear from Table 2 that the estimate of time-varying coefficient, η, is not statistically significant. In addition, the likelihood ratio test rejected the assumption of time-varying farm efficiencies for both truncated ($\mu \neq 0$) and half-normal ($\mu = 0$) distributions.

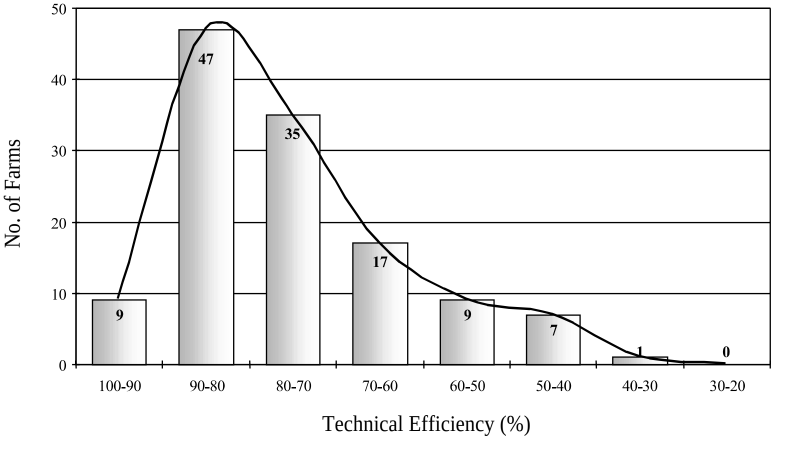
adoptability to changing market conditions. Another possible explanation could be the considerable intervention in the olive oil sector after Greek accession the EU, which makes farmers less responsive to market signals.[13]

Table 4. Frequency distribution of technical efficiency of olive-growing farms in Greece by year and region

	100-90	90-80	80-70	70-60	60-50	50-40	40-30	Min*	Max*	Mean*
1987	8	44	37	19	7	9	1	34.9	93.2	74.9
1988	9	44	38	17	7	9	1	35.5	93.3	75.3
1989	9	46	36	17	8	8	1	36.1	93.4	75.6
1990	9	47	35	17	9	7	1	36.7	93.5	75.9
1991	9	49	34	16	9	7	1	37.3	93.6	76.2
1992	9	50	34	16	8	7	1	37.9	93.7	76.5
1993	10	52	33	14	8	7	1	38.5	93.8	76.8
Gr	9	47	35	17	9	7	1	36.7	93.5	75.9
R_1	7	20	17	6	3	6	1	36.7	93.3	75.5
R_2	1	17	5	5	2	0	0	52.3	91.8	79.1
R_3	0	5	10	3	2	0	0	50.1	88.6	73.9
R_4	1	5	3	3	2	1	0	46.7	93.5	73.6

R_1: Peloponissos, R_2: Crete, R_3: Sterea Ellada, R_4: Aegean Islands and Gr: Greece; * expressed in %.

Figure 1. Technical efficiency estimates (average values over farms and time)



(13) Kalaitzandonakes (1993) argued that protectionism can have a positive effect on productivity growth only in small farms with small capital stock that face low prices, while for large farms protectionism tends to generate technical inefficiencies and thus productivity losses.

Nevertheless, individual technical efficiency estimates exhibit considerable variation among farms. On average these estimates ranged between 36.69 and 93.46 % (the lowest value was found in Peloponissos and the highest in Aegean Islands). Between years that variation remained constant though quite considerable. This could imply differences among production units with regard to non-conventional inputs (socio-economic and demographic characteristics of the farmers), which are directly related to producers' managerial capacity.[14]

Technological change and output growth

Estimates of the rate of technical change (equation (4)) show technological progress throughout the study period at an average annual rate of 1.80 % (Table 5). That rate increased from 1.11 % in 1987 to 2.27 % in 1993 and was "using" towards fertilizers and "saving" for all other inputs. The rate of technological change is further decomposed into pure and non-neutral components. The sample means over time were both found to be positive. Considering the trend over time, neutral technical change exhibited a shift from negative to positive values, while biased technical change was rather stable around the value of 1.5 %. Generally, small farms located in Peloponissos and Sterea Ellada experienced slightly larger technological progress.

The relative contribution of input growth, technical change and technical efficiency to total production growth are also presented in Table 5. For the whole country, the average total production growth rate between 1987 and 1993 was 6.88 % per year. The significant variation among years is due to the perennial cycle of the olive tree mentioned previously. This growth stems mainly from the 3.91 % increase in the use of inputs and the 1.8 % of technological progress, since technical efficiency changes are negligible (0.32 %). Total factor productivity increased at an average annual rate of 2.12 % between 1987 and 1993. About 85 % of the total change is attributed to technological progress and the remaining 15 % to increasing efficiency.

Determination of the size effects (input changes) on total production growth is also presented in Table 5. The increase in labor use explains only 8.58 % of total production growth since in poor crop years it exhibited a negative change. Fertilizers contribute on average the highest amount to the total input growth (almost the 24 %). The increase in land area also has a considerable effect, but it seems to exhibit a decline

[14] Using a sample of thirty olive-growing farms in Crete, Tzouvelekas *et al*. (1997) found that the age and education of the household head, the specialization and the size of the farm, the existence of improvement plan, and land fragmentation were important in explaining efficiency variation among farms.

over time due to acreage limitations. For other capital inputs no clear pattern emerges from that table, but the table does show a positive change on average (0.88 %). Given the binding nature of land constraint and the increasing concern within the EU over the environmental effects of fertilizer and pesticide use, these findings underline the need for new sources of production growth in the future.

Table 5. Production growth decomposition of olive growing farms in Greece

Year	87-88	88-89	89-90	90-91	91-92	92-93	87-93
Total Production growth							
	3.59	7.72	5.58	9.15	6.85	8.41	6.88
Total Input growth							
Labor	-1.66	2.54	-1.29	2.21	-0.12	1.83	0.59
Fertilizer	1.31	-0.97	2.85	-0.13	2.45	4.47	1.66
Other Costs	1.1	2.22	0.69	3.11	0.16	-2.01	0.88
Land	1.02	1.59	0.88	0.82	0.3	0.1	0.79
Total	1.77	5.38	3.13	6.01	2.79	4.39	3.91
Total Factor productivity							
	1.43	1.58	2.21	1.87	3.04	2.58	2.12
Technological change							
Neutral	-0.40	-0.10	0.12	0.12	1.17	0.54	0.24
Biased	1.51	1.35	1.78	1.43	1.56	1.73	1.56
Total	1.11	1.26	1.89	1.55	2.73	2.27	1.80
Technical efficiency change							
	0.32	0.32	0.32	0.31	0.31	0.31	0.32
Unexplained residuals							
	0.39	0.77	0.23	1.28	1.02	1.44	0.86

All figures are expressed in %.

Finally, a significant part of output growth (12.5 % on average) remains unexplained in the case of Greek olive-growing farms. This may be due to subequilibrium effects mentioned previously that are not incorporated in the analysis. Unfortunately, data limitations do not allow us to proceed in this direction.

Just and Zilberman (1983) have noted that the risk reduction in introducing technological innovations can have important positive implications in the adoption of new technologies. Nevertheless, and just as important, policies that increase farm efficiency, such as incentives for investment in human capital, will also increase adoption of new technologies and therefore farm productivity.

CONCLUDING REMARKS

Farmers' expectations of higher profits through the introduction of high support prices resulted in a consistent increase in total national olive oil production from 1987 until 1993. This production growth is translated into increased input use and, to a lesser extent, technological change. The efficiency of Greek olive growers has been low and constant during the study period.

Although CAP implementation gave an incentive to farmers to increase their production, on the other hand it prevented them from operating under *laissez-faire* conditions (lack of external competition and thus entrepreneurial motives), which resulted, along with the peculiar structure of Greek olive-groves, in a persistent level of inefficiency.

Considering that market intervention will decrease, international competition will increase, and environmental regulations will be tightened, long-run adjustments to the olive oil sector are difficult to predict. The potential for increasing production by increasing traditional inputs is limited. The contribution of land is expected to decline further in the future, while an increase in labor will have only limited effect on total production. As well, the use of modern inputs like fertilizers and pesticides is anticipated to be further tightened by environmental regulations. Increased machinery input might have some effect on production if and only if it increases land productivity (*i.e.* mechanization of irrigation). The introduction of technological innovations and improved efficiency in the use of the available inputs seem to be the only tracks for considerably increasing olive oil production.

The introduction of technological innovations is necessary but not sufficient for considerable olive oil production growth. Farmers will have to improve their efficiency so that they can exploit the full potential of given or new technologies. The role of private and governmental institutions in assisting farmers to improve their managerial skills is crucial.

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