Self-Dual Stochastic Production Frontiers and Decomposition of Output Growth: The Case of Olive-Growing Farms in Greece

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This paper provides a decomposition of output growth among olive-growing farms in Greece during the period 1987–1993 by integrating Bauer's (1990) and Bravo-Ureta and Rieger's (1991) approaches. The proposed methodology is based on the use of self-dual production frontier functions. Output growth is attributed to the size effect, technical change, changes in technical and input allocative inefficiency, and the scale effect. Empirical results indicate that the scale and the input allocative inefficiency effects, which were not taken into account in previous studies on output growth decomposition analysis, have caused a 7.3% slowdown and a 11.0% increase in output growth, respectively. Technical change was found to be the main source of TFP growth while both technical and input allocative inefficiency decreased over time. Still though, a 56.5% of output growth is attributed to input growth.

Several recent studies have attempted to explain and to identify the sources of output growth in agriculture. By using a stochastic production frontier approach, Fan (1991), Ahmad and Bravo-Ureta (1995), Wu (1995), Kalirajan, Obwona and Zhao (1996), and Kalirajan and Shand (1997) have attributed output growth into size effect (input growth), technical change and improvements in technical efficiency. Within such a framework it is, however, implicitly assumed that technical change and changes in technical efficiency are the only sources of total factor productivity (TFP) changes. Bureau, Fare and Grosskopf (1995), Arnade (1998), Fulginiti and Perrin (1998), Lambert and Parker (1998) and Tauer (1998) have used a similar decomposition of TFP changes based on the Malmquist TFP index. In contrast to all the above studies using the parametric approach, there have been some studies based on the Malmquist TFP index that have also taken into account scale effects (i.e., Piesse, Thirtle and van Zyl 1996; Piesse, Thirtle and Turk 1996; Thirtle, Piesse and Turk 1996; Fulginiti and Perrin 1997).

It is well recognized that returns to scale and allocative efficiency may also be significant sources of TFP growth. Scale economies stimulate output growth even in the absence of technical change and improvements in technical efficiency as long as input use increases. However, diseconomies of scale, which are more likely in agriculture, could slow down output growth under similar circumstances. The scale effect can correctly be omitted in the decomposition of TFP growth only in the case of constant returns to scale (Lovell 1996). However, since the range of scale economies is not known *a priori*, it seems appropriate to proceed by statistically testing the hypothesis of constant returns to scale. If this hypothesis is rejected, the scale effect is present and should be taken into account.[1] Its relative contribution to output growth

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[1] From all the above studies only few have treated the scale effect properly. Piesse, Thirtle and Turk (1996) and Thirtle, Piesse and Turk (1996) have correctly included it in TFP measurement as they presented empirical evidence for increasing returns to scale. Tauer (1998), how-

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depends on both the magnitude of scale economies and the rate of input growth.

Output gains may also be achieved by improving allocative efficiency. As noticed by Bravo-Ureta and Rieger (1991), focusing only on technical efficiency understates the benefits that could be derived by producers from improvements in overall performance. However, in a highly protected sector, such as agriculture, allocative inefficiency tends to be an important source of TFP slowdown (Fulginiti and Perrin 1993; Kalaitzandonakis 1994). Except for output price support schemes, input prices susceptible to government policy could also be a serious cause of failure on the part of farmers to minimize cost, by affecting input mix and thus the extent of allocative inefficiency.[2] Nevertheless, the magnitude of allocative efficiency and the relative contribution of its improvement on output growth remain an open empirical question.

In both parametric and non-parametric approaches there are some problems in accounting simultaneously for the effect of scale economies and allocative efficiency in TFP changes. First, despite its flexibility in modeling the structure of technology, the nonparametric approach based on the Malmquist TFP index cannot account for the extent of allocative inefficiency since the Malmquist index is a primal concept (Tauer 1998). Second, the primal stochastic frontier approach cannot incorporate accurately the effects of returns to scale and input allocative inefficiency. In particular, these cannot be separated from each other within a production frontier framework, even if there are available information on input prices (Lovell 1996). Indeed, the effect of returns to scale can only be identified if input allocative efficiency is assumed, and in this case there is no need for input price data. However, the effect of input allocative inefficiency cannot be identified even if the assumption of constant returns to scale is maintained. Third, even though cost frontiers can satisfactorily deal with input allocative efficiency and non-constant returns to scale technologies when panel data are available (Kumbhakar and Lovell 2000, pp. 166–75), they do so through the estimation of a system of equations which is a more complicated econometric problem than the single-equation estimation of production frontiers, and also requires more data (i.e., input prices).

The aim of this paper is to propose Bravo-Ureta and Rieger's (1991) approach as an alternative within the primal stochastic frontier approach to handle separately the effect of returns to scale and input allocative efficiency (along with input growth, technical change and technical efficiency) in output growth decomposition analysis. This approach relies on self-dual production frontiers (e.g., Cobb-Douglas) to provide estimates of output-oriented technical efficiency, input-oriented technical efficiency, input allocative efficiency and cost efficiency by using single-equation estimation procedures. Then this information along with those related to technical change and scale economies can be incorporated into a cost function framework for decomposing TFP changes (see Bauer 1990) by simply exploiting the self-duality property. The direct outcome of integrating properly Bauer's (1990) and Bravo-Ureta and Rieger's (1991) approaches would be a complete and accurate analysis of the sources of output growth at the extra cost of information on input price data, which are necessary to identify the effect of input allocative efficiency.

In Bravo-Ureta and Rieger's (1991) approach, the use of self-dual production frontier functions is necessary in deriving an analytical (closed form) solution of the corresponding cost frontier. The inflexibility of self-dual frontiers may, however, lead to biased estimates of the output-oriented measure of technical efficiency as the unmodeled complexity of production technology will appear in the composed error term (Kumbhakar and Lovell 2000, p. 143). In the present study, this shortcoming is partially overcome by using a generalized Cobb-Douglas (or quasi translog) frontier production function, proposed by Fan (1991). This functional specification allows for variable returns to scale, input-biased technical change, and time varying production and substitution elasticities, but it restricts the latter to be unchanged over farms. Nevertheless, it permits statistical tests for the hypotheses of zero rate of technical change and constant returns to scale. Thus, this specification represents a reasonably flexible alternative to approximate the underlying technology.

Bravo-Ureta and Rieger's (1991) approach has however two main advantages. First, the resulting output-oriented technical efficiency estimates are unbiased from statistical noise as the restricted assumption of the deterministic frontier models (i.e., any deviation from the frontier is attributed to in-

ever, has excluded it based on previous evidence (Tauer 1993) for constant returns to scale.

[2] In the present study case of olive-growing farms in Greece allocative inefficiency is not policy-induced but is the outcome of farmers' failure to minimize cost. However, it was a long period of seed and fertilizer subsidization in Greek agriculture that ended in 1986, since it was incompatible with the spirit of the Common Agricultural Policy. Our analysis covers the period 1987–1993 but the lower degree of input allocative inefficiency found for 1987 and 1988 (see table 3 below) may, in part, be due to an adjustment period following aforementioned policy changes.

efficiency), used initially by Kopp and Diewert (1982), has been relaxed.[3] Instead, a composed error term is used to account for both statistical noise and output-oriented technical inefficiency. Second, it enables simultaneous derivation of input-oriented technical, input allocative, and cost efficiency based solely on the econometric estimation of a production frontier function by single-equation methods, under the assumption of expected profit maximization.[4] If, instead, Schmidt and Lovell's (1979, 1980) approach is used to estimate the Cobb-Douglas production frontier, then a system-of-equations estimation method should be employed.

The rest of this paper is organized as follows: the theoretical framework is presented in the next section. The empirical model discussed in the third section is based on Battese and Coelli's (1995) inefficiency effects model. Data and their sources are described in the fourth section. A discussion of empirical findings and a comparison with previous parametric studies' forms of output growth decomposition are given in the fifth section. Concluding remarks follow in the last section.

Theoretical Framework

The present study differs from all previous studies using stochastic production frontiers to decompose output growth in a distinct respect. The proposed analysis relies on the input-oriented, Farell-type measures of technical efficiency, while all previous studies have used the output-oriented, Timmer-type measures of technical efficiency.[5] The use of the input-oriented measure of technical efficiency is necessary in integrating properly Bauer's (1990) and Bravo-Ureta and Rieger's (1991) approaches as the output-oriented measure of technical efficiency allows for a separate (from input growth) measurement of the scale effect only in the presence of input allocative efficiency (Lovell 1996). In such a case, perfect competition, in both input and output markets, ensures that production elasticities and factor cost shares are equal to each other (Chan and Mountain 1983). Otherwise, a price adjustment effect should also be included to account for input allocative inefficiencies (Bauer 1990).

Cost efficiency is defined as $E(Q,w,x,t) = C(Q,w,t)/C = w'x^E(Q,w,t)/w'x$ (Bauer 1990; Lovell 1996), where $0 < E(Q,w,x,t) \leq 1$, $C(Q,w;t)$ is a well-defined cost frontier function, C is the observed cost, Q is output quantity, w is a vector of input prices, t is a time index that serves as a proxy for technical change, and x^E and x are the cost minimizing and the observed input vectors, respectively. $E(Q,w,x,t)$ is independent of factor prices scaling and has a cost interpretation in the sense that $1 - E(Q,w,x,t)$ indicates the percentage reduction in cost associated with the removal of all inefficiencies (Kopp, 1981).[6] In addition, $E(Q,w,x,t) = T(Q,x,t)\cdot A(Q,w,x,t)$ (Farrell 1957), where $T(Q,x,t) = w'x^T/w'x$ is the input-oriented measure of technical efficiency with $0 < T(Q,x,t) \leq 1$, $A(Q,w,x,t) = w'x^E(Q,w,t)/w'x^T$ is input allocative efficiency with $0 < A(Q,w,x,t) \leq 1$, and x^T is the technically efficient input vector. Moreover, $T(Q,x,t)$ and $A(Q,w,x,t)$ are both independent of factor prices scaling (Kopp 1981).

Following Bauer (1990), by taking the logarithms of each side of $E(Q,w,x,t) = C(Q,w;t)/C$ and totally differentiate it with respect to t results in:

$$\dot{E}(Q,w,x,t) = \varepsilon^{CQ}(Q,w,t)\dot{Q} + \sum_{j=1}^{m} s_j(Q,w,t)\dot{w}_j + \dot{C}(q,w,t) - \dot{C}, \tag{1}$$

where a dot over a variable or function indicates a time rate of change, $\varepsilon^{CQ}(Q,w,t) = \partial \ln C(Q,w,t)/\partial \ln Q$, $s_j(Q,w,t) = \partial \ln C(Q,w,t)/\partial \ln w_j$, and $-\dot{C}(Q,w,t) = \partial \ln C(Q,w,t)/\partial t$ is the rate of cost

[3] Specification (4) below ensures the stochastic nature of the production frontier and distinguishes Bravo-Ureta and Riger's (1991) approach from Kopp and Diewert's (1982) deterministic model. Another distinguished feature between them is that the former is based on the estimation of a production (primal) frontier while the latter on a dual (cost) frontier. As a result, the input-based measure of allocative inefficiency is obtained residually in the former case, while the input-based measure of technical inefficiency is calculated residually in the latter.

[4] The assumption of expected profit maximization, which allows the single-equation estimation of the production frontier (Zellner, Kmenta and Dreze 1966), implies cost minimization under price uncertainty (Batra and Ullah 1974) and thus allows us to go back and forth between the stochastic production and cost frontiers in a theoretically consistent way. Notice that expected profit maximization was also a maintained assumption in all previously mentioned studies using the parametric approach.

[5] Following Kopp (1981), the output-oriented Timmer-type measure of technical efficiency is defined as the ratio of observed output to maximum feasible output and the input-oriented Farrell-type measure is defined as the maximum amount by which an input vector can be decreased proportionally and still producing the same amount of output. Fare and Lovell (1978) shown that the output- and the input-oriented measures of technical efficiency are equal under constant returns to scale, while the former is greater (less) than the latter under decreasing (increasing) returns to scale.

[6] That is, scaling all factor prices equally or each factor price individually will have no effect on the input-oriented measure of inefficiency. This property of input-oriented measures is due to their radial nature and it will be proved important in panel data studies where there are no price data for individual producers. Apparently, it allows regional, or even national, price data to be used in measuring efficiency without altering the final outcome.

diminution. However, by taking the logarithm of $C = w'x$ and totally differentiating with respect to t yields:

$$\dot{C} = \sum_{j=1}^{m} s_j \dot{x}_j + \sum_{j=1}^{m} s_j \dot{w}_j. \tag{2}$$

Substituting (2) into (1) and using the conventional Divisia index of TFP growth ($\dot{TFP} = \dot{Q} - \Sigma_{j=1}^{m} s_j \dot{x}_j$) and the relation $\dot{E}(Q,w,x,t) = \dot{T}(Q,x,t) + \dot{A}(Q,w,x,t)$ results in:

$$\begin{aligned}\dot{Q} = & \sum_{j=1}^{m} s_j \dot{x}_j + [1 - \varepsilon^{CQ}(Q,w,t)]\dot{Q} - \dot{C}(Q,w,t) \\ & + \dot{T}(Q,x,t) \\ & + \dot{A}(Q,w,x,t) + \sum_{j=1}^{m}[s_j - s_j(Q,w,t)]\dot{w}_j,\end{aligned} \tag{3}$$

which is an output growth representation of the decomposition relationship developed by Bauer (1990).

The first term in (3) captures the contribution of aggregate input growth on output changes over time (size effect).[7] The more essential an input is in the production process the higher its contribution is on the size effect. The second term measures the relative contribution of scale economies on output growth (scale effect). This term vanishes under constant returns to scale as $\varepsilon^{CQ}(Q,w,t) = 1$, while it is positive (negative) under increasing (decreasing) returns to scale, as long as aggregate input increases, and *vice versa.* The third term refers to the dual rate of technical change (i.e., cost diminution), which is positive under progressive technical change.

The fourth and the fifth terms in (3) are positive (negative) as technical and input allocative efficiency increases (decreases) over time. There is no *a priori* reason for both types of efficiency to increase or to decrease simultaneously (Schmidt and Lovell 1980), or that their relative contribution should be of equal importance for output growth. More importantly, in output growth decomposition analysis what really matters is not the degree of efficiency itself, but its rate of change over time. That is, even at low levels of efficiency, output gains may be achieved by improving either technical or input allocative efficiency, or both. It seems difficult though to achieve substantial output growth gains at very high levels of technical and/or input allocative efficiency.

The last term in (3) is the price adjustment effect (Bauer 1990). The existence of this term is closely related to the definition of TFP, which is based on observed input and output quantities. It indicates that the aggregate measure of inputs is biased in the presence of input allocative inefficiency. The price adjustment effect is equal to zero if there is no input allocative inefficiency as $s_j = s_j(Q,w,t)$. Otherwise, its magnitude is inversely related to the degree of input allocative efficiency. The price adjustment effect is also zero if input prices change at the same rate; in this case $\Sigma[s_j - s_j(Q,w,t)] = 0$.

To obtain quantitative measures of each term in (3), Bravo-Ureta and Rieger's (1991) approach is based on the estimation of a self-dual production frontier function and the resulting cost frontier. Specifically, consider the following general stochastic production frontier function:

$$Q_{it} = f(x_{jit},t;\alpha)exp(v_{it} - u_{it}), \tag{4}$$

where $f(\bullet)$ represents its functional form, Q_{it} is the observed output produced by the ith farm at year t, x_{jit} is the quantity of the jth input used by the ith farm at year t, α is the vector of parameters to be estimated, and $e_{it} = v_{it} - u_{it}$ is a stochastic composite error term. The v_{it} depicts a symmetric and normally distributed error term (i.e., statistical noise), which represents those factors that cannot be controlled by farmers and left-out explanatory variables. The u_{it} is a one-side, non-negative, error term representing the stochastic shortfall of the ith farm output from its production frontier, due to the existence of technical inefficiency. The u_{it} captures farm-specific output-oriented technical efficiency. It is further assumed that v_{it} and u_{it} are independently distributed from each other.

Farm-specific estimates of input-oriented technical efficiency are obtained by computing the technically efficient input vector x^T. This is derived by combining the estimated production frontier and the observed factor ratios at actual output levels, and by solving simultaneously the following system of equations for each farm in the sample:

$$\begin{aligned} Q_{it}^{*} &= f(\bullet) - u_{it} \\ &= Q_{it} - v_{it} \text{ and } x_{1it}/x_{jit} \\ &= k_{jit} (\mathrm{j} > 1), \end{aligned} \tag{5}$$

where Q_{it}^{*} is the maximum output that can be produced by the ith farm given its production technology and input use (Q_{it}^{*} is also equal to observed output adjusted for the statistical noise), and k_{jit} is the ratio of observed inputs x_{1it} and x_{jit} at Q_{it}^{*}. Then, $T = w'x^T/w'x$. However, farm-specific estimates of cost efficiency are derived by using the resulting

[7] Aggregate input growth is measured as a Divisia index; this follows directly from the standard definition of TFP. The fact that actual (observed) factor cost shares are used as weights of individual input growth gives rise to the sixth term in (3).

cost frontier, evaluated at Q^*_{it}. Given that $f(\bullet)$ is self-dual there is a closed form solution for the cost frontier and then the cost efficient input vector, x^E, is obtained by applying Shephard's lemma. Finally, farm-specific estimates of input allocative inefficiency are obtained by using Farrell's (1957) decomposition, i.e., $E(Q,w,x,t) = T(Q,x,t) \cdot A(Q,w,x,t)$.

Empirical Model

For the purposes of the present study, the underlying production frontier function is approximated by the generalized Cobb-Douglas form (Fan 1991), i.e.,:

$$(6) \quad f(\bullet) = \alpha_0 + \sum_{j=1}^{m} \alpha_j \, ln \, x_{jit} + \alpha_t t + \frac{1}{2}\alpha_{tt} t^2 + \sum_{j=1}^{m} \alpha_{jt} \, ln \, x_{jit} t$$

This may also be viewed as a translog specification without cross terms, i.e. a strongly separable-inputs translog production frontier function. Assuming that all regularity conditions hold, a closed form solution of the cost minimization problem subject to (6) yields the following (dual) cost frontier function:

$$(7) \quad ln \, C_{it} = B + \beta_Q \, ln \, Q_{it} + \sum_{j=1}^{m} \beta_j \, ln \, w_{jit} + \beta_t t + \beta_{tt} t^2 + \sum_{j=1}^{m} \beta_{jt} \, ln \, w_{jit} t$$

where $B = 1/\beta_Q^2(1/\beta_k + \beta_{kt}t) - \Sigma_{j=2}^{m} ln(\beta_j + \beta_{jt}t/\beta_k + \beta_{kt}t)(\beta_j + \beta_{jt}t) - \beta_0$ for $k \neq j$, $\beta_j = \alpha_j\beta_Q$, $\beta_Q = 1/\Sigma_{j=1}^{m}(a_j + \alpha_{jt}t)$, $\beta_{jt} = \alpha_{jt}\beta_Q$, $\beta_t = \alpha_t\beta_Q$, $\beta_{tt} = \alpha_{tt}\beta_Q$ and $\beta_0 = \beta_Q \, ln\alpha_0$.

Battese and Coelli (1995) suggested that the technical inefficiency effects, u_{it}, in the stochastic production frontier model (4) could be replaced by a linear function of explanatory variables, reflecting farm-specific characteristics. The technical inefficiency effects are assumed to be independent, non-negative truncations (at zero) of normal distributions with unknown variance and mean. Specifically,

$$(8) \qquad u_{it} = \delta_o + \sum_{m=1}^{M} \delta_m z_{mit} + \omega_{it},$$

where z_{mit} are farm and time specific explanatory variables (e.g., functions of farms and management characteristics) associated with technical inefficiencies; δ_0 and δ_m are parameters to be estimated;[8] and ω_{it} is a random variable with zero mean and variance σ^2_ω, defined by the truncation of the normal distribution such that $\omega_{it} \geq -(\delta_0 + \Sigma\delta_m z_{mit})$. Equation (8) implies that the means, $\mu_{it} = \delta_0 + \Sigma\delta_m z_{mit}$, of the u_{it} are different for different farms but the variances, σ^2_ω are assumed to be the same.

After substituting (6) and (8) into (4) the resulting model is estimated by a single-equation estimation procedure using the maximum likelihood method and the FRONTIER (version 4.1a) computer program developed by Coelli (1992). The variance parameters of the likelihood function are estimated in terms of $\sigma^2 = \sigma^2_v + \sigma^2_u$ and $\gamma = \sigma^2_u/\sigma^2$, where the γ-parameter has a value between zero and one. The closer the estimated value of the γ-parameter is to one, the higher the probability of the technical inefficiency effect to be significant in the stochastic frontier model, thus the average response production function is not an adequate representation of the data.

Several hypotheses can be tested by using the generalized likelihood-ratio statistic, $\lambda = -2\{1nL(H_0) - \ln L(H_1)\}$, where $L(H_0)$ and $L(H_1)$ denote the values of the likelihood function under the null (H_0) and the alternative (H_1) hypothesis, respectively.[9] First, if $\gamma = 0$ technical inefficiency effects are non-stochastic and (4) reduces to the average response function in which the explanatory variables in the technical inefficiency model are also included in the production function. Second, if $\gamma = \delta_0 = \delta_m = 0$ for all m, the inefficiency effects are not present. Consequently, each farm in the sample is operating on the frontier, thus the systematic and random technical inefficiency effects are zero. Third, if $\delta_m = 0$ for all m, the explanatory variables in the model for the technical inefficiency effects have zero coefficients. In this case, farm-specific factors do not influence technical inefficiency and (5) reduces to Stevenson's (1980) specification, where u_{it} follow a truncated normal distribution. Fourth, if $\delta_0 = \delta_m = 0$ the original Aigner, Lovell and Schmidt's (1977) specification is obtained, where u_{it} follow a half-normal distribution.

[8] Biased estimates of δ_m parameters may be obtained by not including an intercept parameter δ_0 in the mean, μ_{it}, and in such a case the shape of the distribution of the inefficiency effects is unnecessarily restricted (Battese and Coelli 1995).

[9] If the given null hypothesis is true, the generalized likelihood-ratio statistic has approximately a χ^2 distribution, except the case where the null hypothesis involves also $\gamma = 0$. Then, the asymptotic distribution of λ is a mixed χ^2 (Coelli 1995) and the appropriate critical values are obtained from Kodde and Palm (1986).

Table 1. Maximum Likelihood Estimates of a Cobb-Douglas Production Frontier Function for Olive-Growing Farms in Greece, 1987–1993

Parameter	Estimate	Standard Error	Parameter	Estimate	Standard Error
Stochastic Frontier					
α_0	0.505	0.064*	α_{FT}	−0.007	0.016
α_L	0.118	0.017*	α_{OT}	−0.013	0.009
α_F	0.024	0.014*	α_{AT}	−0.060	0.040
α_O	0.010	0.007**	α_T	0.055	0.038**
α_A	0.650	0.046*	α_{TT}	0.026	0.014**
α_{LT}	0.001	0.020			
Inefficienty Effects Model					
δ_0	−6.947	5.155**	$\delta_{location}$	1.461	0.710*
δ_{age}	−0.274	0.206	$\alpha_{improvement}$	0.902	0.688
δ_{age^2}	0.003	0.002**	δ_{time}	−0.747	0.333**
$\delta_{education}$	−0.334	0.239			
γ	0.860	0.087*	σ^2	1.163	0.667*
$\text{Ln}(\theta) = -546.578$					

Note: L refers to labor, F to fertilizer, O to other cost, and A to land.
*Significant at 1% level of significance
**Significant at 5% level of significance

Data Description

The data used in this study were extracted from a survey undertaken by the Institute of Agricultural Economics and Rural Sociology, Greece. Our analysis focuses on a sample of 110 olive-growing farms, located in the four most productive regions of Greece (Peloponissos, Crete and Sterea Ellada). Observations were obtained on an annual basis during 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.

The dependent variable is the annual olive oil production measured in kilograms. The aggregate inputs 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 cost* expenses, consisting of pesticides, fuel and electric power, irrigation taxes, depreciation, 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 0.1 ha).

The following variables are included in the inefficiency effect model: first, farmer's age and its square measured in years. Second, farmer's education measured in years of schooling. Third, a dummy variable determining the location of olive-oil farms, which takes the value of one if the farm locates in less-favored area and zero otherwise. Fourth, a dummy variable indicating the existence of an improvement plan taking place in the farm. It takes the value of one if any improvement plan is in order and zero otherwise. Fifth, a time trend to capture the temporal pattern of technical inefficiency.

Empirical Results

The estimated parameters of the stochastic quasi-translog production frontier function are presented in table 1. The estimated first-order parameters (α_j) are having the anticipated (positive) sign and magnitude (being between zero and one), and the bordered Hessian matrix of the first and second-order partial derivatives is negative semi-definite indicating that regularity conditions hold at the point of approximation (i.e., sample mean). That is, marginal products are positive and diminishing and the production frontier is locally quasi-concave. The estimated variance of the one-side error term is found to be $\sigma_u^2 = 1.001$ and that of the statistical noise $\sigma_v^2 = 0.162$. The logarithm of the likelihood function indicates a satisfactory fit for the quasi-translog specification. Finally, given (7), the corresponding cost frontier is:

$$(9) \quad \ln C_{it} = 18.811 + 1.228\ln Q_{it} + 0.145\ln w_{Lit} + 0.029\ln w_{Fit} + 0.012\ln w_{Oit} + 0.798\ln w_{Ait} + 0.068t + 0.032t^2 + 0.001\ln w_{Lit}t - 0.009\ln w_{Fit}t - 0.016\ln w_{Oit}t - 0.074\ln w_{Ait}t,$$

where L stands for labour, F for fertilizer, O for other costs, and A for land.

Hypotheses testing concerning model representation are reported in table 2.[10] It is evident that the conventional average production does not represent adequately the structure of olive-growing farms in the sample. The null hypothesis that $\gamma = 0$ is rejected at the 5% level of significance indicates that the technical inefficiency effects are in fact stochastic, as it is also depicted from the statistical significance of the γ-parameter.[11] Thus, a significant part of output variability is explained by the existing differences in the degree of technical inefficiency. In addition, the hypothesis that the inefficiency effects are absent from the model (i.e., $\gamma = \delta_0 = \delta_m = 0$) is also rejected at the 5% level of significance. This indicates that the majority of farms in the sample operate below the technically efficient frontier. Finally, notice that specification (4) cannot be reduced either to Aigner, Lovell and Schmidt's (1977) or to Stevenson's (1980) model, as, respectively, the null hypothesis that $\delta_0 = \delta_m = 0$ and $\delta_m = 0\ \forall m$ are rejected at the 5% level of significance.

The age of the farmer, as a proxy of experience and learning-by-doing, is one of the factors enhancing technical efficiency, while the positive sign of the squared term supports the notion of decreasing returns to experience (see table 1). Education also has a positive impact on technical efficiency. Schooling helps farmers to use information efficiently since a better educated farmer acquires more information and is able to produce more from a given input vector. However, the location of farms in less favored areas negatively affect their technical efficiency scores, while undertaking an improvement plan within the farm does not seem to affect technical efficiency as the

Table 2. Model Specification Tests

Hypothesis	λ-Statistic	Critical Value ($\alpha = 0.05$)
$\gamma = 0$	37.82	$\chi_3^2 = 7.05$*
$\gamma = \delta_0 = \delta_m = 0\ \forall m = 1, \ldots, 6$	49.33	$\chi_8^2 = 14.85$*
$\delta_0 = \delta_m = 0\ \forall m = 1, \ldots 6$	41.72	$\chi_7^2 = 14.10$
$\delta_m = 0\ \forall m = 1, \ldots 6$	35.20	$\chi_6^2 = 12.60$
$\delta_{time} = 0$	9.10	$\chi_1^2 = 3.84$
$\alpha_{jt} = \alpha_t = \alpha_{tt} = 0 \forall j = 1, \ldots 4$	15.07	$\chi_6^2 = 12.60$
$\alpha_{jt} = 0 \forall j = 1, \ldots 4$	12.29	$\chi_4^2 = 9.49$
$\alpha_{jt} = \alpha_t = \alpha_{tt} = \delta_{time} = 0 \forall j = 1, \ldots 4$	17.1	$\chi_7^2 = 14.10$
$\sum_{j=1}^{m} \alpha_j = 1\ \forall j = 1, \ldots, 4$	21.42	$\chi_1^2 = 3.84$

*These values are taken from Kodde and Palm (1986).

corresponding estimated parameter is statistically insignificant at the 5% level of significance. The hypothesis that technical inefficiency is time-invariant is rejected as the null hypothesis that $\delta_T = 0$ is rejected at the 5% level of significance (see table 2). During the period 1987–1993, output-oriented technical efficiency tended to increase over time as the estimated δ_T parameter is negative (see table 1).

Mean input-oriented technical efficiency increased rather slowly from 76.6% in 1987 to 80.2% in 1993 (see table 3), implying that its contribution to output growth would be relatively small. However, most farms in the sample (77–84%) have consistently achieved technical efficiency scores greater than 70% during the period under consideration. More importantly, this portion of farms increased over time. The estimated mean input-oriented technical efficiency was found to be 78.6% during the period 1987–1993. Thus, on average, a 21.4% decrease in total cost could have been achieved during this period by decreasing proportionally the quantity of inputs used and without altering the total volume of production.

The estimated mean input allocative efficiency was found to be 74.1% (see table 3), implying that Greek olive-growing farms in the sample have achieved a relatively good allocation of existing resources. The great majority of farmers in the sample (88–92%) have consistently achieved scores of input allocative efficiency greater than 70% during the period 1987–1993. Thus, it seems that olive-growing farmers have shown a satisfactory reaction and adjustment to market price signals. Nevertheless, mean input allocative effi-

[10] All hypotheses testing is conducted in terms of the estimated production frontier function and the results reported in table 1. Given the self-duality of the estimated production frontier, all tests concerning the structure of production are equivalent in terms of information provided each time, regardless of the function used to conduct these tests.

[11] Notice that the probability the technical inefficiency effects to be significant in the stochastic frontier model is high since the estimated value of the γ-parameter is close to one (see table 1).

Table 3. Measures of Cost Efficiency and Returns to Scale for Greek Olive Growing Farms, 1987–1993

	1987	1988	1989	1990	1991	1992	1993	1987–1993
					Technical Efficiency			
<20	0	0	0	0	0	0	0	0
20–30	0	0	0	0	0	0	0	0
30–40	2	1	1	1	1	0	1	0
40–50	5	5	1	1	1	1	1	0
50–60	5	3	6	4	4	5	7	0
60–70	13	13	10	12	13	14	8	8
70–80	32	33	32	37	37	34	29	55
80–90	49	54	57	46	45	46	53	47
>90	4	2	3	9	9	10	11	0
Mean	76.6	77.5	78.2	78.8	79.2	79.8	80.2	78.6
					Allocative Efficiency			
<20	0	0	0	0	0	0	0	0
20–30	0	0	0	0	0	0	0	0
30–40	4	0	1	1	1	0	1	0
40–50	3	6	2	2	2	1	1	0
50–60	6	6	8	8	6	9	8	1
60–70	21	20	19	20	23	17	15	20
70–80	53	48	41	50	43	45	41	75
80–90	23	30	38	25	29	34	35	14
>90	0	0	1	4	6	4	9	0
Mean	71.6	72.8	74.6	73.7	74.5	75.4	76.2	74.1
					Productive Efficiency			
<20	5	2	1	1	2	0	1	0
20–30	3	5	3	4	3	2	4	0
30–40	6	7	8	8	4	8	7	1
40–50	15	14	14	10	17	14	9	8
50–60	29	26	24	34	31	28	24	46
60–70	37	35	36	27	21	24	28	49
70–80	15	21	21	19	22	25	28	6
80–90	0	0	2	7	9	7	1	0
>90	0	0	1	0	1	2	8	0
Mean	56.2	57.3	59.1	59.1	60.1	61.1	62.4	59.3
					Returns to Scale			
	0.838	0.824	0.816	0.811	0.806	0.803	0.800	0.814

ciency is smaller than corresponding point estimate of input-oriented technical efficiency, indicating that olive-growing farms did better in achieving the maximum attainable output for given inputs than in allocating existing resources. However, the average annual rate of increase of input allocative efficiency is greater than that of input-oriented technical efficiency, thus its relative contribution to output growth is expected to be relatively greater.

The estimated mean cost efficiency was found to be around 59% (see table 3). This figure represents the ratio of minimum to actual cost of production and implies that significant cost savings (41%) may be achieved by improving both technical and allocative efficiency. Given the estimates of input-oriented technical efficiency and of input allocative efficiency, it seems that cost inefficiency is almost equally due to technical and allocative inefficiency. Cost efficiency increased over time from 56.2% in 1987 to 62.4% in 1993. Nevertheless, only a very small portion of farms in the sample attended a score greater than 80%.

The hypothesis of a linearly homogeneous production frontier is rejected at the 5% level of significance (see table 2), implying the existence of non-constant returns to scale. As a result, the scale effect is a significant (in statistical grounds) source of output growth and it should be taken into account in (3). According to the results reported in

Table 4. Decomposition of Output Growth for Greek Olive-Growing Farms, 1987–1993

	(I)	(II)	(III)	(IV)
Output Growth[b]	6.88			
	(100.0)			
Aggregate Input Growth	3.89			4.54
	(56.5)			*(68.0)*
of which Labor	0.82			
Fertilizer	1.22			
Other Cost	0.38			
Land	1.48			
Total Factor Productivity Growth	2.28	2.16	3.59	2.16
	(33.1)	*(31.4)*	*(52.2)*	*(32.0)*
Of which Rate of Technical Change	1.57	1.57	3.00	1.57
	(22.8)	*(22.8)*	*(43.6)*	*22.8)*
Autonomous part	0.66			
Biased part	0.91			
Scale Effect	−0.52			
	(−7.6)			
Change in Technical Efficiency	0.59	0.59	0.59	0.59
	(8.6)	*(8.6)*	*(8.6)*	*(8.6)*
Change in Allocative Efficiency	0.76			
	(11.0)			
Price Adjustment Effect	−0.12			
	(−1.7)			
Unexplained Residual	0.72	0.83		
	(10.5)	*(12.1)*		

Notes: [a]Each column in table presents the estimates obtained from (I) present formulation; (II) Ahmad and Bravo-Ureta (1995); (III) Fan (1991); (IV) Kalirajan Obwona and Zhao (1996).
[b]Numbers in parentheses are percentages.

table 3, production is characterized by decreasing returns to scale, which on average was 0.814 during the period 1987–93. This implies that the contribution of the scale effect to output growth would be negative as far as output increases and *vice versa.*

The decomposition analysis results are reported in table 4. Those presented in the first column are based on (3). An average annual rate of 6.88% is observed for output growth during the period 1987–1993. Our empirical findings suggest that most of the output growth (56.5%) is due to input increases. Only a portion of 33.1% is attributed to productivity growth, which grew with an average annual rate of 2.28%. These results imply that, during the period under consideration, Greek olive-growing farmers have chosen the most expensive way to expand production, namely the increase of input use. Thus, substantial output increases may still be achieved *ceteris paribus* by improving TFP; this has important policy implications as far as sources of productivity growth are identified.

Technical change was found to be the main source of TFP growth accounting for about 22.8%. The average annual rate of technical change is found to be 1.57%, and its largest portion was caused by the biased, rather than the autonomous, counterpart. The scale effect, however, is negative as olive-growing farms in Greece exhibited decreasing returns to scale and the aggregate input increased over time. On average, diseconomies of scale slowed down annual output growth by a rate of 7.6%, and TFP by almost 23%. These rather significant figures would have been omitted if constant returns to scale were falsely assumed. In such a case, TFP and output growth would have been overestimated.

Both technical and allocative efficiencies have enhanced TFP and output growth. Their relative contribution to output growth depends on their rate of change over time, rather than their absolute magnitude. As shown in table 4, the relative contribution of input allocative efficiency on output growth (11%), is greater than that of input-oriented technical efficiency (8.6%), as the average annual rate of increase of the former was found to be greater than that of the latter. By combining their effects, it can be seen that improvements in cost efficiency account for 19.6% of average annual output growth. Notice also that the contribution of cost efficiency on TFP growth is comparable with that of technical change (see table 4).

The price adjustment effect was found to have a very small impact on TFP and output growth. On average, the price adjustment effect accounted for 1.7% of output change. However, given the existence of allocative inefficiency, its impact cannot be neglected in obtaining an accurate measure of TFP growth rate. After accounting for all theoretically proposed sources of TFP growth and for the size effect, 10.5% of observed output growth remained unexplained. Nevertheless, the unexplained portion of output growth is smaller than the unexplained residual obtained by using Ahmad and Bravo-Ureta's (1995) approach (see table 4), which does not account for the scale and the allocative inefficiency effects.[12]

The results of the present study indicate that the contribution of input allocative efficiency and scale economies into output growth cannot by any means be negligible as 3.4% of annual output are attributed to their combined effect. If, for any reason, these two effects were not incorporated into output growth decomposition analysis, as in Ahmad and Bravo-Ureta (1995), the contribution of TFP on output growth would be underestimated.[13] The corresponding figures are reported in column II on table 4; the estimated average annual rate of TFP decreases from 2.28% to 2.16%. If, however, technical change was calculated residually, as in Fan (1991), its contribution to TFP would be overestimated. In this case the estimated rate of technical change would be 3% instead of 1.57%, and the average annual rate of TFP would be 3.59% (see column III on table 4). The latter accounts for 52.2% of output growth. Finally, if the allocative efficiency and the scale effects were not incorporated in decomposition analysis, and the size effect was measured residually, as in Kalirajan, Obwona and Zhao (1995), then the relative contribution of input growth would be overestimated (see column IV on table 4).

Concluding Remarks

This paper proposes an alternative methodology for decomposing observed output growth by integrating Bauer's (1990) and Bravo-Ureta and Rieger's (1991) approaches. Within this framework, output growth is decomposed into input growth, technical change, scale economies, technical and allocative efficiency, and a price adjustment effect by relying on the econometric estimation of a self-dual production frontier. This methodology is applied to a panel data set for olive-growing farms in Greece during the period 1987–1993. Empirical findings indicate that both the scale and the (input) allocative efficiency effects, which have not been analyzed in previous studies, have a significant role in explaining output growth; it is found that, on average, they have caused a 7.6% slowdown and a 11% enhancement, respectively. Thus, there may be significant differences in TFP growth by not accounting simultaneously for these two effects.

Despite any errors that may arise by not accounting for the allocative inefficiency and scale effects when parametrically measuring TFP growth, misconceptions also arise about the potential sources of TFP and output growth. This incomplete identification of TFP sources of growth, both in terms of the factors that affect its evolution over time and their relative contribution, poses some concerns about the efficacy of various measures used by policy makers to enhance productivity. In the case of olive-growing farmers in Greece, for example, quite a significant source of output growth is excluded from the development policy agenda when the effect of allocative inefficiency is not taken into consideration in decomposition analysis.

[12] A similar comparison with Fan (1991) or Kalirajan, Obwona and Zhao (1996) and Kalirajan and Shand (1997) approaches is not possible as technical change and the size effect are respectively calculated in a residual manner in these studies.

[13] It should be noticed that these comparison results are data specific and they cannot be affirmative generalizations. This holds for all the results related with the comparison with previous studies.

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