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 allocative inefficiency, and the scale effect. The empirical results indicate that the scale effect and the effect of allocative inefficiency, 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 found to be the main source of TFP growth while both technical and allocative inefficiency decreased over time. Still though, 56.5% of output growth in attributed to input growth.

Introduction

Several recent studies (i.e., Fan, 1991; Ahmad and Bravo-Ureta, 1995; Wu, 1995; Kalirajan *et al*., 1996; Kalirajan and Shand, 1997) have attempted to explain and to identify the sources of output growth in agriculture. By using a production function approach, they have attributed output growth into the size effect (input growth), technical change, and improvements in technical efficiency. In this framework is however assumed implicitly that technical change and changes in technical efficiency consist the only components of total factor productivity (TFP) changes. Nevertheless, in a purely theoretical ground, returns to scale and allocative efficiency may also be significant sources of TFP growth and consequently, of output expansion. Bauer (1990) has provided such a decomposition of TFP changes within a cost function framework.

There are empirical evidence (e.g., Park and Kwon, 1995) that scale economies stimulate output growth even in the absence of technical change and improvements in technical efficiency as long as input use increases. Analogously, diseconomies of scale could slowdown output growth under similar circumstances, which is more likely to be the case for agriculture. The scale effect can correctly be omitted in the decomposition of TFP growth only in the case of constant returns to scale (Lovell, 1996). 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. Its relative contribution to output growth depends on both the magnitude of scale economies and the rate of input growth.

On the other hand, output gains may also be obtained 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 individual producers from improvements in overall performance. However, in highly protected sector, such as agriculture, allocative inefficiency tends to be an important source of TFP slowdown (Fulginiti and Perrin, 1993; Kalaitzandonakis, 1994). Nevertheless, in the presence of price support schemes, the improvement of allocative efficiency provides an additional incentive for output increases. The magnitude of allocative efficiency and the relative contribution of its improvement on output growth remain an open empirical question.

The theoretical framework employed in previously mentioned studies on output growth decomposition analysis cannot incorporate accurately the effects of returns to scale and of allocative inefficiency. In particular, Lovell (1996) has shown that in a production function framework, the effects of scale economies and of allocative inefficiency on TFP changes cannot be separated from each other even if there are available information on input prices. Indeed, the effect of returns to scale can only be identified if allocative efficiency is assumed, and this case there is no need for input price data. Then, output growth may be attributed to input growth, technical change, improvements in technical efficiency, and the effect of scale economies. In contrast, the effect of allocative inefficiency cannot be identified even if constant returns to scale are assumed. This seems a serious shortcoming of the production function approach on output growth decomposition analysis.

The aim of this paper is to propose Bravo-Ureta and Rieger's (1991) approach as an alternative to handle separately the effect of returns to scale and of allocative efficiency (along with input growth, technical change and technical efficiency) in output growth decomposition analysis and still relying on the econometric estimation of a production function frontier.[1] The direct outcome of integrating properly Bauer's (1990) and Bravo-Ureta and Rieger's (1991) and 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 allocative efficiency. As an indirect result, it is shown that the opportunity cost of duality between production and cost frontier functions may be less severe than the maintenance of constant-returns-to-scale assumption suggested by Fare and Primont (1996). That is, it may be the use of a self-dual production frontier that allows for variable returns to scale, but restricts input substitutability.

In Bravo-Ureta and Rieger's (1991) approach, the use of self-dual production frontier functions is important in deriving an analytical (closed form) solution for the corresponding cost frontier and in maintaining the distinction between technical and allocative efficiency. This may restrict however the functional specification of the underlying frontier production functions. In the present study, this shortcoming is partially overcame 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 (Fan and Pardey, 1997).

In addition, Bravo-Ureta and Rieger's (1991) approach has two advantages. *First*, the resulting inefficiency measures are unbiased from statistical noise as the limiting assumption of the deterministic frontier models (namely, that any deviation from the frontier is attributed to inefficiency), used initially by Kopp and Diewert (1982), is not anymore employed. Instead, a composed error term is used to account for both statistical noise and efficiency disturbances. *Second*, it enables the simultaneous derivation of (input-oriented) technical, allocative, and productive efficiency measures based solely on the econometric estimation of a production frontier function by using a single-equation procedure, under the expected profit maximization hypothesis. Notice that this was also a maintained hypothesis in previous output growth decomposition studies of Fan (1991), Ahmad and Bravo-Ureta (1995), Wu (1995), Kalirajan *et al*. (1996), and Kalirajan and Shand (1997).

The rest of this paper is organized as follows: the theoretical framework, integrating properly Bauer's (1990) and Bravo-Ureta and Rieger's (1991) approaches, is presented in the next section. The empirical model, based on Battesee and Coelli's

(1995) inefficiency effect model, is discussed in the third section. Data and their sources sources are described in the fourth section. A discussion of empirical findings and a comparison with previous studies on sources of output growth are given in the fifth section. Concluding remarks follow in the last section.

Theoretical Framework

The present study differs from all previous studies on output growth decomposition analysis in a distinct respect. The proposed analysis relies on input-oriented, Farell-type measures of technical, allocative and productive efficiency, while all previous studies have used the output-oriented, Timmer-type measures of technical efficiency.[2] The use of input-oriented efficiency measures is however 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 allocative efficiency (Lovell, 1996). In such a case, perfect competition in input and output markets ensures that production elasticities and factor shares are equal to each other (Chan and Mountain, 1983). Otherwise, a price adjustment effect should also be included to account for allocative inefficiencies (Bauer, 1990).

A Farrell-type, input-oriented measure of productive efficiency may be 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 if productive inefficiency is eliminated (Kopp, 1981).[3] Using Farrell's decomposition of efficiency, $E(Q,w,x,t) = T(Q,x,t)\cdot A(Q,w,x,t)$, where $T(Q,x,t) = w'x^T/w'x$ and $A(Q,w,x,t) = w'x^E(Q,w,t)/w'x^T$ are respectively the Farrell-type, input-oriented measures of technical and allocative efficiency, $0 < T(Q,x,t) \leq 1$, $0 < A(Q,w,x,t) \leq 1$ and x^T is the technically efficient input vectors. Moreover, $T(Q,x,t)$ and $A(Q,w,x,t)$ are both independent of factor prices scaling and have an analogous cost interpretation (Kopp 1981).

Following Bauer (1990), take the logarithm of each side of $E(Q,w,x,t) = C(Q,w,t)/C$ and totally differentiate it with respect to t:

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

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 $C_t(Q,w,t) = \partial \ln C(Q,w,t)/\partial t$. On the other hand, 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, $\dot{TFP} = \dot{Q} - \sum_{j=1}^{m} s_j \dot{x}_j$, and $\dot{E}(Q,w,x,t) = \dot{T}(Q,x,t) + \dot{A}(Q,w,x,t)$ results in:

$$\dot{Q} = \sum_{j=1}^{m} s_j \dot{x}_j + \left[1 - \varepsilon^{CQ}(Q,w,t)\right]\dot{Q} - C_t(Q,w,t) + \dot{T}(Q,x,t) + \\ + \dot{A}(Q,w,x,t) + \sum_{j=1}^{m}\left[s_j - s_j(Q,w,t)\right]\dot{w}_j \quad , \tag{3}$$

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).[4] Output increases (decreases) are associated *ceteris paribus* with increases (decreases) in at least an input's quantity. 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 (primal) rate of technical change, which is positive under progressive technical change.

The fourth and the fifth terms in (3) are positive (negative) as technical and allocative efficiency increases (decreases) over time. There is no *a priori* reason for both types of efficiency to increase or decrease simultaneously nor their relative contribution should be of equal importance for output growth. More importantly, in output growth decomposition analysis what really matter is not the degree of efficiency itself, but rate of change over time. That is, even at low levels of productive efficiency, output gains may be achieved by improving either technical or allocative efficiency or both. It seems difficult though to achieve substantial output growth gains at very high levels of technical and/or allocative efficiency.

The last term in (3) is the price adjustment effect. 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 allocative inefficiency (Bauer, 1990). Under allocative efficiency, the price adjustment effect is equal to zero as $s_j = s_j(Q, w, t)$. Otherwise, its magnitude is inversely related to the degree of allocative efficiency. The price adjustment effect is also equal to zero when input prices change at the same rate, since $\sum \lfloor s_j - s_j(Q, w, t) \rfloor = 0$.

To obtain quantitative measures of the terms 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, a Farrell-type, input-oriented measure of technical efficiency is derived by combining the estimated production frontier and the observed factor ratios at actual output levels, while a Farrell-type, input-oriented measure of productive efficiency is obtained by applying Shephard's lemma on the resulting cost frontier. Then, the input-oriented measure of allocative efficiency is derived by the ratio of productive to technical efficiency. On the other hand, estimates of the rate of technical change and the scale effect are also obtained from the resulting cost frontier.

Consider the following general stochastic production frontier function:

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

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, ϕ 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 i^{th} farm output from its production frontier, due to the existence of technical inefficiency. It is assumed that v_{it} and u_{it} are independently distributed from each other.

To obtain farm-specific estimates of the input-oriented measure of technical efficiency, computation of technically efficient input vector x^T is required. This is derived by solving simultaneously the following system of equations for each farm in the sample:

$$Q^*_{ti} = f(\bullet) - u_{it} = Q_{it} - v_{it} \tag{5}$$
$$\text{and } x_{1it} / x_{jit} = k_{jit}\ (j>1),$$

where Q^*_{it} is the maximum output that can be produced by the i^{th} farm given its production technology and input use (which is also equal to its observed output adjusted for the statistical noise), and k_{jit} is the ratio of observed inputs x_{1it} and x_{jit} at Q^*_{it}.[5] Then, $T = w'x^T / w'x$. On the other hand, farm-specific estimates of the input-oriented measure of productive efficiency are derived by using the resulting cost frontier, evaluated at Q^*_{it}. Given that $f(\bullet)$ is self-dual there is a close form solution for the cost frontier. Then, the productively efficient input vector, x^P, is obtained by applying Shephard's lemma. Finally, farm-specific estimates of allocative inefficiency are obtained by using Farrell decomposition $E(Q, w, x, t) = T(Q, x, t) \cdot A(Q, w, x, t)$.

The above results suggest that output- and input-oriented measures of technical efficiency may be obtained by using the duality between production and cost frontiers, not only in the case of constant returns to scale as shown by Fare and Primont (1996) but also, in the case of self-dual frontiers. Both measures may be obtained from either representation of technology by simply estimating one of them (most probably the production frontier with a single-equation procedure) and using the degree of returns to scale.[6] Hence, the opportunity cost of using the duality between production and cost frontiers in measuring efficiency may not be so severe as Fare and Primont (1996) initially suggested. Self-dual frontier functions allow for variable returns to scale, but restrict input substitutability; the latter is more easily acceptable in empirical studies.

Empirical Model

For the purposes of the present study, the underlying production frontier function is approximated by the quasi-translog functional form, proposed by Fan (1991), that is given as:

$$f(\bullet) = \alpha_0 + \sum_{j=1}^{m} \alpha_j \ln x_{jit} + \sum_{j=1}^{m} \beta_j t \ln x_{jit} + \gamma_1 t + \frac{1}{2}\gamma_2 t^2 \tag{6}$$

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

$$\ln C_{it} = B + \vartheta_t t + \vartheta_{tt} t^2 + \vartheta_Q \ln Q_{it} + \sum_{j=1}^{m} \vartheta_j \ln w_{jit} + \sum_{j=1}^{m} \vartheta_{jt} \ln w_{jit} t \tag{7}$$

where $B = (1/\vartheta_Q^2)(1/(\vartheta_k + \vartheta_{kt} t)) - \sum_{j=1}^{m-1} \ln\left((\vartheta + \vartheta_{jt_j} t)/(\vartheta_k + \vartheta_{kt} t)\right)(\vartheta + \vartheta_{jt} t) - \vartheta_0$ for $k \neq j$,

$\vartheta_t = \beta\vartheta_Q$, $\vartheta_{tt} = \beta_{tt}\vartheta_Q$, $\vartheta_i = \beta_i\vartheta_Q$, $\vartheta_{it} = \beta_{it}\vartheta_Q$, $\vartheta_Q = 1\Big/\sum_{i=1}^{m}(\beta_i + \beta_{it} t)$, $\vartheta_0 = \vartheta_Q \ln\beta_0$.

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. In this way and given the current state of technology and its physical endowments, every farm in the sample faces its own frontier and not a sample norm. The technical inefficiency effects are assumed to be independent, non-negative, truncations (at zero) of normal distributions with unknown variance and mean. Specifically,

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

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;[7] and ω_{it} is a random variable with zero mean and variance σ_w^2, defined by the truncation of the normal distribution such that $\omega_{it} \geq -\left(\delta_0 + \sum \delta_m z_{mit}\right)$. The above specification (8) implies that the means, $\mu_{it} = \delta_0 + \sum \delta_m z_{mlt}$, of the u_{it} are different for different farms but the variances, σ_w^2 are assumed to be the same.

The parameters of the stochastic production frontier model (6) and those of the technical inefficiency effects model (8) are estimated simultaneously by 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 $\sigma^2 \equiv \sigma_v^2 + \sigma_u^2$ and $\gamma \equiv \sigma_u^2 / \sigma^2$, where the γ -parameter has a value between zero and one. The closer the estimated value of the γ -parameter to one is, the higher the probability of the technical inefficiency effect to be significant in the stochastic frontier model is, and 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, $\lambda = -2\{\ln L(H_0) - \ln L(H_1)\}$, 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.[8] *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 and 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 *et al.* (1977) specification is obtained, where u_{it} follow a half-normal distribution.

Data Description

The data used in this study were extracted from a survey undertaken by the Institute of Agricultural Economics and Rural Sociology of 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 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.

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 plans taking place in the farm. It takes the value of one if an 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:

$$
\begin{aligned}
\ln C_{it} = {} & 1.8811 + 1.228 \ln Q_{it} + 0.145 \ln w_{Lit} + 0.029 \ln w_{Fit} + 0.012 \ln w_{Oit} + \\
& + 0.798 \ln w_{Ait} + 0.068t + 0.032t^2 + 0.001 \ln w_{Lit} t - 0.009 \ln w_{Fit} t - \\
& - 0.016 \ln w_{Oit} t - 0.074 \ln w_{Ait} t,
\end{aligned}
\tag{9}
$$

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

Hypotheses testing concerning model representation are reported on Table 2.[9] It is evident that the traditional average production does not represent adequately the structure of olive-growing farms in the sample. The null hypothesis that $\gamma = 0$ is rejected at 5% level of significance indicating that the technical inefficiency effects are in fact stochastic, as it is also depicted from the statistical significance of the γ – parameter.[10] Thus, a significant part of output variability among farms is explained by the existing differences in the degree of technical inefficiency. In addition, the hypothesis that the inefficiency effects are absents from the model (i.e., $\gamma = \delta_0 = \delta_m = 0$) is also rejected at 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 neither to Aigner *et al.* (1977) nor to Stevenson's (1980) model as the null hypothesis of $\delta_0 = \delta_m = 0$ and $\delta_m = 0$ $\forall m$, respectively, are rejected at 5% level of significance.

As a result, the explanatory variables included in the inefficiency effect models have non-zero coefficients and contribute significantly to the explanation of technical efficiency differences in olive-growing farming. The age of the farmer, as a proxy of experience and learning-by-doing, is one of the factors enhancing technical efficiency, while the negative sign of the squared term supports the notion of decreasing returns to experience (see Table 1). Education has also a positive and significant role to play in determining efficiency differentials among olive-growing farmers in Greece. Schooling helps farmers to use production information efficiently, as a more educated farmer acquires more information and is able to produce more from a given input vector. On the other hand, as was expected, the placement of farms in less favored areas affect negatively their degree of technical efficiency, while the existence of improvement plan within the farm affect technical efficiency positively.

The hypothesis that technical inefficiency is time-invariant is rejected as the null hypothesis of $\delta_T = 0$ is rejected at 5% level of significance (see Table 2). This means that output growth has been affected by changes in the degree of technical efficiency over time. During the period 1987-93, technical inefficiency tended to decrease over time as the estimated δ_T parameters is negative (see Table 1). Mean technical efficiency increased rather slowly from 76.6% in 1987 to 80.2% in 1993 (see Table 3), implying that its contribution into output growth would be relatively small. However, most farms in the sample (77-84%) have consistently achieved scores of technical efficiency greater than 70% during the period 1987-1983. More importantly, this portion of farms increased over time. This means that only a small portion of the farms in the sample faced severe technical inefficiency problems. The estimated mean technical efficiency was found to be 78.6% during the period 1987-1993. Thus, on average, a 21.4% decrease in total cost of production could have been achieved during the period, without altering the total volume of output, production technology and input usage.

Mean 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. But still, a 25.9% decrease in cost is feasible by a further re-allocation of inputs for any given level of output and input prices. The great majority of farmers in the sample (88-92%) have consistently achieved scores of allocative efficiency greater than 70% during the period 1987-1983. Thus, it seems that olive-growing farmers shown a satisfactory reaction and adjustment into market price signals. Nevertheless, mean allocative efficiency is smaller than corresponding point estimate of 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 rate of increase of allocative efficiency is greater than that of technical efficiency and thus, its relative contribution to output growth is expected to be relatively greater.

Mean productive 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 (about 41%) may be achieved by improving both technical and allocative efficiency. Given the estimates of technical and allocative efficiency, it seems that productive inefficiency is almost equally due to technical and allocative inefficiency. Productive 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 any 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 on 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 into output growth would be negative as far output increases and *vice versa*.

The decomposition analysis results for analyzing Greek olive-growing farms' output growth during the period 1987-1993 are given on Table 3. Those presented in the first column are based on (3). An average annual rate of 6.68% is observed for output growth. Our empirical findings suggest that most of output growth (56.5%) in olive-oil production is due to input increase. Only a portion of 33.1% is attributed to productivity growth, which grew with an average annual rate of 2.28%. These 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 element of total factor productivity growth in Greek olive-growing farms, 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, on the other hand, is negative as olive-growing farms in Greece exhibited decreasing returns to scale and 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 over-estimated.

Both technical and allocative inefficiencies have enhanced TFP and output growth during the period 1987-1993. The relative contribution of each one depends on their rate of change over time rather than their absolute magnitude. As shown in Table 3, the relative contribution of the allocative efficiency effect on output growth (11%) is greater than that of the technical efficiency (8.6%) as the average rate of increase of the former was found to be greater than that of the latter. Thus, productive efficiency accounts for 19.6% of average annual output growth among olive-growing farms in Greece. Moreover, the contribution of productive efficiency on TFP growth is comparable with that of technical change.

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, a 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 3), which does not account for the scale and the allocative inefficiency effects.[11]

The results of the present study indicate that the contribution of the allocative efficiency and the scale effect 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 would be under-estimated.[12] The corresponding figures are reported in column II on Table 3: the estimated average annual rate of TFP growth decreases from 2.28% to 2.14%. If, however, the rate of technical change was calculated residually, as in Fan (1991), the contribution of TFP would be over-estimated. In this case the estimated rate of technical change would be 3% instead of 1.57%, and the average annual rate of TFP growth would be 3.59% (see column III on Table 3). 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 *et al.* (1995), then the relative contribution of input growth would be overestimated (see column IV on Table 3).

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 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 sources of TFP 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, a quite 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.

Table 1: Maximum Likelihood Estimates of the 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	β_F	-0.007	0.016
α_L	0.110	0.017	β_O	-0.013	0.009
α_F	0.024	0.014	β_A	-0.060	0.040
α_O	0.010	0.007	γ_1	0.055	0.038
α_A	0.650	0.046	γ_2	0.026	0.014
β_L	0.001	0.020			
Inefficiency Model					
δ_0	-6.947	5.155	$\delta_{locatio}$	1.461	0.710
δ_{age}	0.274	0.206	$\delta_{improvemt}$	0.902	0.688
δ_{age^2}	-0.003	0.002	δ_{tim}	-0.747	0.333
$\delta_{educatic}$	-0.334	0.239			
γ	0.860	0.087	σ^2	1.163	0.667
Ln(θ)=-546.578					

Note: L refers to labor, F to fertilizer, O to other cost, and A to land.

Table 2: Model Specification Tests

Hypothesis	λ – Statistic	Critical Value (α=0.05)
$\gamma = 0$	37.82	$\chi_3^2 = 3.84$
$\gamma = \delta_0 = \delta_m = 0\ \forall m$	49.33	$\chi_8^2 = 15.5$
$\delta_0 = \delta_m = 0\ \forall m$	41.72	$\chi_7^2 = 14.1$
$\delta_m = 0\ \forall m$	35.20	$\chi_6^2 = 12.6$
$\delta_{time} = 0$	9.10	$\chi_1^2 = 3.84$
$\beta_j = \gamma_1 = \gamma_2 = 0\ \forall j = 1,4$	15.07	$\chi_6^2 = 12.6$
$\beta_j = 0\ \forall j = 1,4$	12.29	$\chi_4^2 = 9.49$
$\beta_j = \gamma_1 = \gamma_2 = \delta_{time} = 0\ \forall j = 1,4$	17.1	$\chi_7^2 = 14.1$
$\alpha_L + \alpha_F + \alpha_O + \alpha_A = 1$	21.42	$\chi_1^2 = 3.84$

Table 3: Measures of 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	0	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

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

	(I)[1]	(II)	(III)	(IV)
Output Growth[2]	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: [1] Each column in table presents the estimates obtained from (I) present formulation; (II) Ahmad and Bravo-Ureta (1995); (III) Fan (1991); (IV) Kalirajan*et al.* (1996).
[2] Numbers in parentheses are percentages.

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Endnotes

1 This approach has been used previously by Bravo-Ureta and Evenson (1994), Xu and Jeffrey (1998), and Sharma *et al.* (1999) to measure allocative efficiency from the econometric estimation of a production frontier.

2 Fare and Lovell (1978) have shown that are equal under constant returns to scale, while the output-oriented measure is greater (less) than the input-oriented measure under decreasing (increasing) returns to scale.

3 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 the use of regional, or even national, price data to be used in estimating efficiency measures, without altering the final outcome.

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

5 Specification in (4) ensures the stochastic nature of the production frontier and distinguishes Bravo-Ureta and Riger's (1991) from Kopp and Diewert's (1982) deterministic approach. 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 (i.e., by using Farrell decomposition), while the input-based measure of technical inefficiency is calculated residually in the latter case.

6 The assumption of expected profit maximization, which allows the single-equation estimation of the production frontier (Zellner *et al.*, 1966), implies cost minimization for risk-neutral producers under price uncertainty (Batra and Ullah, 1974).

7 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).

8 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 $\gamma = \mathbf{0}$. Then, the assumptotic distribution of λ is a mixed χ^2 (Coelli, 1995) and the appropriate critical values are obtained from Kodde and Palm (1986).

[9] 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 product structure tests are equivalent in terms of information provided each time, regardless of the function used to conduct these tests.

[10] Notice that the probability of the technical inefficiency effect 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).

[11] A similar comparison with Fan (1991) or Kalirajan *et al.* (1996) and Kalirajan and Shand (1997) approaches is not possible as technical change and the size effect are respectively calculated in a residual manner.

[12] It should be kept in mind that these comparison results are data specific and do not consist affirmative generalizations. This holds for all results related with comparison with previous studies.