PARAMETRIC DECOMPOSITION OF THE INPUT-ORIENTED MALMQUIST PRODUCTIVITY INDEX: WITH AN APPLICATION TO GREEK AQUACULTURE

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Chris Pantzios died in December 15, 2004. Chris was a wonderful friend and partner in research. It has been very difficult to complete this paper without him.

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Using a stochastic frontier approach and a tranlog input distance function, this paper implements the input-oriented Malmquist productivity index to a sample of Greek aquaculture farms. It is decomposed into the effects of technical efficiency change, scale efficiency change, input-mix and, technical change, which is further attributed to neutral, output- and input-induced shifts of the frontier. Implementable expressions for the aforementioned components are obtained using a discrete changes-approach that is consistent with the usual discrete-form data. Empirical findings indicate that the productivity of the farms in the sample increased during the period 1995-99 at a moderate rate of about two percent, and it was shaped up primarily by the input mix-effect and technical change.

JEL classification:

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1. Introduction

The Malmquist productivity index, introduced by Caves, Christensen and Diewert (1982), started gaining popularity only after the influential work of Fare *et al*. (1992), who developed a tractable way to estimate it by non-parametric techniques (i.e., Data Envelopment Analysis, DEA) and provided an intuitive decomposition of it into two mutually exclusive sources (i.e., technical change and technical efficiency changes). Since then a considerable amount of effort (e.g., Ray and Desli, 1997; Balk, 2001, 2004; Lovell, 2003; Grosskopf, 2003) has been devoted to extend this decomposition and to develop a more detailed analysis of its sources of growth. Even though there is a general cohesion on measuring the effect of technical efficiency changes, several alternatives (more or less intuitive) exist for measuring the effects of technical change and of scale economies. However, as clearly noted by Balk (2004) there is no unique way of decomposing any measure of productivity change.

Concerning the implementation of the Malmquist productivity index, on the other hand, it is evident from the survey of Fare, Grosskopf and Roos (1998) that the majority of empirical studies have used DEA. In a non-parametric context, estimates of the Malmquist productivity index as well as its sources of growth are obtained by computing appropriate ratios of distance function values corresponding to constant- and variable-returns-to-scale technologies. The advantages of the non-parametric approach stem from its ability *first*, to function in cases with insufficient degrees of freedom; *second*, to overcome extreme invariability in the data and *third*, to model production technology without imposing a particular functional form. Nevertheless, it lacks statistical hypotheses testing regarding the significance of the assembling parts of the Malmquist productivity index as sources of change.

Several more recent studies (i.e., Coelli, Rao and Battese, 1998; Rossi, 2001; Balk, 2001; Fuentes, Grifell-Tatje and Perelman, 2001; Orea, 2002) have used the parametric (i.e., econometric). Unlike DEA, the parametric approach does not require the estimation of constant-returns-to-scale production technology. Instead estimates of various components, and consequently of the Malmquist productivity index, are obtained from a fitted distance function with variable returns to scale.[1] In fact, two distinct routes have been used within the parametric approach. *First*, Coelli, Rao and Battese (1998, p. 234) and Rossi (2001), following Nishimizu and Page (1982), estimated the Malmquist productivity index by using geometrical means of time derivatives for any two adjacent periods. *Second*, Balk (2001), Fuentes, Grifell-Tatje and Perelman (2001) and Orea (2002) used discrete differences of the fitted distance function values evaluated at adjacent periods' input and output quantity data. Since economic data do not come in the form of continuous records, the use of time derivatives to estimate discrete changes may be misleading.

The advantages of the parametric approach stem for the fact that *first*, it allows for an appropriate treatment of measurement errors and random noise and *second,* it permits formal statistical hypotheses testing.[2] The latter is particularly important as it can be tested whether *(i)* technical efficiency is time varying; *(ii)* there is technical change; and *(iii)* production technology exhibits (local) constant returns to scale.[3] In each case, one (or more) of the components constituting the Malmquist productivity index will remain unchanged and thus, it will not contribute to growth. For example, if technical efficiency is found to be time invariant, then the contribution of the technical efficiency change effect on productivity would be zero. Similarly, if the rate of technical change is statistically not different than zero, then the technical change effect vanishes. Finally, if production exhibits (local) constant returns to scale, then there is no scale effect. Even though these features have not explored in previous parametric studies, it is clear that have important implications in obtaining appropriate empirical results and in dealing with policy measures design to enhance productivity.

The aim of this paper is to extend the methodology of Fuentes, Grifell-Tatjé and Perelman (2001) to accomplish the remaining assembling parts of the Malmquist productivity index, namely scale efficiency change and input-mix effects. We also develop the necessary hypotheses testing regarding the statistical significance of the various sources of growth. For these purposes, parametric restrictions are derived for testing the hypotheses of constant returns to scale, ray homogeneous technology, no technical change, and implicit Hicks input- and output-neutral technical change. It is expected that these hypotheses testing strengthen further the parametric approach.

The proposed procedure is applied to a sample of Greek seabass and seabream farms for the period 1995-1999. During the last two decades, seabass and seabream industry has been one of the faster growing industries in Greece and since the first half of the 1990s it has dominated the aquaculture sector. Output grew dramatically and the number of seabass and seabream farms almost doubled in the first half of the 1990s. Eventually Greece became the largest producer of seabass and seabream in Europe accounting for around 50% of total European production and also the largest exporter. Identifying the sources of growth in such a fast expanding industry is of considerable importance for gaining insights on its development process and also for designing future policies.

The rest of the paper is organized as follows. In section 2 we present the decomposition of the Malmquist productivity index in an input-oriented framework. In the next section, we show how the assembling components of the input-oriented Malmquist index can be computed from the parameter estimates of a translog input distance function. The data used in this study are presented in section 4. In section 5 we provide an empirical application by measuring the productivity of Greek seabass and seabream farms. Concluding remarks follow in the last section.

2. Decomposition of the input-oriented Malmquist productivity index

Following Balk (2001), the input-oriented Malmquist productivity index M_I^t, for any two successive time periods *t* and *t+1*, can be expressed as:[4]

$$M_I^t(x^{t+1},y^{t+1},x^t,y^t)=TC_I^{t,t+1}(x^{t+1},y^{t+1})\cdot TEC_I(x^{t+1},y^{t+1},x^t,y^t)\cdot \\ SEC_I^t(x^t,y^{t+1},y^t)\cdot ME_I^t(x^{t+1},x^t,y^{t+1}) \qquad (1)$$

where x and y denote inputs and outputs respectively, the subscript I refers to input orientation, and the four components on the right-side of (1) are defined as:

$$TC_I^{t,t+1}=\frac{D_I^{t+1}(x^{t+1},y^{t+1})}{D_I^t(x^{t+1},y^{t+1})} \qquad (2a) \qquad\qquad TEC_I=\frac{D_I^t(x^t,y^t)}{D_I^{t+1}(x^{t+1},y^{t+1})} \qquad (2b)$$

$$SEC_I^t=\frac{ISE^t(x^t,y^{t+1})}{ISE^t(x^t,y^t)} \qquad (2c) \qquad\qquad ME_I^t=\frac{ISE^t(x^{t+1},y^{t+1})}{ISE^t(x^t,y^{t+1})} \qquad (2d)$$

The technical change component, $TC_I^{t,t+1}$, corresponds to the radial shift in the input requirement set measured with period *t+1* data. As the same level of output can be produced with less (more) amount of inputs, technical progress (regress) results. The former (latter) corresponds to values of $TC_I^{t,t+1}$ that are greater (less) than one.[5]

Fare *et al*. (1997) developed a further decomposition of $TC^{t,t+1}$. In particular, they shown that (2a) can be rewritten as:

$$TC_I^{t,t+1}(y^{t+1},x^{t+1})=TCM(y^t,x^t)\cdot OB(y^t,x^{t+1},y^{t+1})\cdot IB(x^t,y^t,x^{t+1}) \qquad (3)$$

where

$$TCM(x^t,y^t)=\frac{D_I^{t+1}(x^t,y^t)}{D_I^t(x^t,y^t)} \qquad (4a)$$

$$OB(x^t,y^t,y^{t+1})=\left[\frac{D_I^{t+1}(x^{t+1},y^{t+1})}{D_I^t(x^{t+1},y^{t+1})}\cdot\frac{D_I^t(x^{t+1},y^t)}{D_I^{t+1}(x^{t+1},y^t)}\right] \qquad (4b)$$

$$IB(x^t,y^t,x^{t+1})=\left[\frac{D_I^{t+1}(x^{t+1},y^t)}{D_I^t(x^{t+1},y^t)}\cdot\frac{D_I^t(x^t,y^t)}{D_I^{t+1}(x^t,y^t)}\right] \qquad (4c)$$

The $TCM(y^t,x^t)$ term is a *technical change magnitude index* that provides a local measure of the rate of technical change. As the input requirement set contract (expand) along a ray through period t data, values greater (less) than one are assigned to the magnitude index. The terms $OB(y^t,x^{t+1},y^{t+1})$ and $IB(x^t,y^t,x^{t+1})$ are the *output* and the *input bias indices*, respectively. These terms compare the magnitude of technical change along a ray through period *t+1* data to the magnitude of technical change along a ray through period *t* data. If technical change is neutral (biased), the input requirement set shifts in or out by the same (different) proportion along a ray through period *t+1* data as it does along the ray through period *t* data (Grifell-Tatje and Lovell, 1997). The values of (4b) and (4c) are equal to one and thus they make no contribution to productivity if technology exhibits respectively implicit Hicks input neutral change, and implicit Hicks output neutral technical change and constant returns to scale (CRS) (Fare *et al*., 1997).

The technical efficiency change component, *TEC*, measures firms' ability to improve technical efficiency from period *t* to period *t+1*. Given that input-oriented technical efficiency is defined as $1/D_I^t(x^t, y^t)$, technical efficiency between two successive time periods increases (decreases) as long as *TEC* is greater (less) than one.

The remaining two components, SEC_I^t and ME_I^t, are defined in terms of the input-oriented scale efficiency measure (ISE^t), which evaluates the productivity of an observed input-output bundle (x^t, y^t) relative to that of the technically optimal scale (or the most productive scale size). At the technically optimal scale, production technology exhibits CRS and average ray-productivity reaches its maximum. ISE^t is defined as:

$$ISE^t(x^t, y^t) = \frac{D_I^t(x^t, y^t)}{\breve{D}_I^t(x^t, y^t)} \tag{5}$$

where the symbol (˘) indicates an input distance function associated with CRS (also referred to as the cone technology). Then, following Balk (2001), SEC_I^t is defined as:[6]

$$SEC_I^t(x^t, y^{t+1}, y^t) = \frac{\breve{D}_I^t(x^t, y^t)}{\breve{D}_I^t(x^t, y^{t+1})} \cdot \frac{D_I^t(x^t, y^{t+1})}{D_I^t(x^t, y^t)} \tag{6}$$

If SEC_I^t is greater (less) than one, then the output bundle at period *t+1* lies closer to (farther away from) the point of technical optimal scale than the output bundle of period *t* does and thus scale efficiency increases (decreases). That is, SEC_I^t measures how the input-oriented measure of scale efficiency changes over time, conditional on a certain input mix.

On the other hand, the input-mix effect, ME_I^t, measures how the distance of a frontier-point to the frontier of the cone technology changes when input mix changes, conditional on the same output mix. It is formally defined as (Balk, 2001):

$$ME_I^t(x^{t+1}, x^t, y^{t+1}) = \frac{\breve{D}_I^t(x^t, y^{t+1})}{\breve{D}_I^t(x^{t+1}, y^{t+1})} \cdot \frac{D_I^t(x^{t+1}, y^{t+1})}{D_I^t(x^t, y^{t+1})} \tag{7}$$

That is, the input-mix effect measures the change in the input-oriented measure of scale efficiency from a change in input mix when outputs remain unchanged. As with the previous assembling parts of (1), values of ME_I^t greater (less) than one indicate a positive (negative) contribution of the input-mix effect into productivity changes. For any given output vector, $ME_I^t > (<) 1$ is associated with improvement (deterioration) of scale efficiency as input mix changes. Finally, notice that if technology exhibits CRS then both SEC_I^t and ME_I^t are identically equal to one.[7]

The combined effect of the scale efficeicny change and of input-mix, defined as:

$$SEC_I^t(x^t, y^{t+1}, y^t) \cdot ME_I^t(x^{t+1}, x^t, y^{t+1}) = \frac{SE_i^t(x^{t+1}, y^{t+1})}{SE_I^t(x^t, y^t)} = S\Delta(x^t, y^t, x^{t+1}, y^{t+1}) \tag{8}$$

was referred by Lovell (2003) as the *activity* or *volume effect*. It is essentially an "overall" scale effect, which includes a radial scale effect and an input-mix effect. For this reason it was called "scale change factor" by Ray and Desli (1997).

By substituting (2b), (4a), (4b), (4c), (6) and (7) into (1), it may be verified that the input-oriented Malmquist productivity index can be simply expressed as:

$$M_I^t(x^{t+1}, y^{t+1}, x^t, y^t) = \frac{\breve{D}_I^t(x^t, y^t)}{\breve{D}_I^t(x^{t+1}, y^{t+1})} \tag{9}$$

which is equivalent to the original definition used by Fare *et al*. (1992), namely by the ratio of the distance function values of the corresponding (virtual) cone technology, in periods *t* and *t+1*.[8] This is a well-defined productivity index satisfying the desirable properties of identity, monotonicity, and proportionality, and under certain conditions that of separability.[9]

3. Parametric estimation of the Malmquist productivity index

The parametric estimation of the Malmquist productivity index (1) requires the prior specification and estimation of the input distance function. To weaken as much as possible the implications of assuming a particular functional form for the underlying input distance function, a flexible function form such as the translog is chosen. The translog input distance function involving k=1,…,K inputs and m=1,…,M outputs over t=1,…, T time-periods is defined as (e.g., Coelli and Perelman, 1999; 2000):

$$\begin{aligned}\ln D_I^t(x^t, y^t) = a_0 + \sum_{k=1}^{K} a_k \ln x_k^t + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K} a_{kl} \ln x_k^t \ln x_l^t + \sum_{k=1}^{K}\sum_{m=1}^{M} \delta_{km} \ln x_k^t \ln y_m^t \\ + \sum_{m=1}^{M} \beta_m \ln y_m^t + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{M} \beta_{mn} \ln y_m^t \ln y_n^t + \gamma_0 t + \frac{1}{2}\gamma_{00} t^2 \\ + \sum_{k=1}^{K} \eta_k \ln x_k^t\, t + \sum_{m=1}^{M} \mu_m \ln y_m^t\, t\end{aligned} \tag{10}$$

The regularity conditions associated with input distance function require homogeneity of degree one in input quantities and symmetry, which in turn imply the following restrictions on the parameters of (10):

$$\sum_{k}^{K} a_k = 1, \ \sum_{k}^{K} a_{kl} = 0, \ \sum_{k}^{K} \delta_{km} = 0 \text{ and } \sum_{k}^{K} \eta_k = 0 \tag{11}$$

$$\alpha_{kl} = \alpha_{lk} \text{ and } \beta_{mn} = \beta_{nm} \tag{12}$$

For notational convenience (10) may be rewritten as $\ln D_I^t = TL(x^t, y^t, t; \theta)$, where $TL(\cdot\ )$ denotes the translog specification and $\theta = (a, \beta, \gamma, \delta, \eta, \mu)$ is the vector of the parameters to be estimated.

The homogeneity restrictions can be imposed by dividing the left-hand side and all input quantities in the right-hand side of (10) by the quantity of that input used as a *numeraire*. Given linear homogeneity, (10) may be written as:

$$-\ln x_K^{i,t} = TL(x_+^{i,t} y^{i,t}, t; \theta) - \ln D_I^{i,t}(x^{i,t}, y^{i,t}) \tag{13}$$

where $x_+^{i,t} = x_k^{i,t} / x_K^{i,t}$ for all $k \neq K$ and the superscript i is used to index farms. Since $\ln D_I^{i,t}(x^{i,t}, y^{i,t})$ is unobservable one may write $\ln D_I^t(x^{i,t}, y^{i,t}) = -u_{i,t}$ (Coelli and Perelman, 1999, 2000), where u_{it} is a one-sided, 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. Then, the stochastic input distance function model may be written as:

$$-\ln x_K^{i,t} = TL(x_+^{i,t} y^{i,t}, t; \theta) + u_{i,t} + v_{i,t} \tag{14}$$

where v_{it} depicts a symmetric and normally distributed error term (i.e., statistical noise), representing a combination of those factors that cannot be controlled by farms, omitted explanatory variables and measurement errors in the dependent variable.[10] It is also assumed that v_{it} and u_{it} are distributed independently of each other.

The temporal pattern of u_{it} is important in (2b) as the changes in technical efficiency over time rather than the degree of technical efficiency *per se* matters. For this purpose Cuesta (2000) specification, which is an extension of Battese and Coelli (1992) formulation, is adopted to model the temporal pattern of technical inefficiency, i.e.,

$$u_{it} = \left(\exp\left[-\xi_i (t - T)\right]\right) u_i \tag{15}$$

where ξ_i are firm-specific parameters capturing the temporal variation of individual technical efficiency ratings, and $t \in [1, 2, ..., \mathrm{T}]$.[11] The main advantage of (15) is that allows for firm-specific patterns of temporal variation in technical efficiency. If the parameter ξ_i is positive (negative), technical efficiency tends to improve (deteriorate) over time. If $\xi_i = 0$, technical efficiency is time-invariant and the term in (2b) is equal to one and thus technical efficiency does not contribute to productivity changes. When $\xi_i = \xi$ for all *i*, (15) collapses to Battese and Coelli (1992) model with a common time-pattern of technical inefficiency across producers.[12]

Following Balk (2001) and Fuentes, Grifell-Tatje and Perelman (2001), the parameter estimates of the input distance function along with the observed values of input and output quantities can be used for the estimation of the assembling parts of the Malmquist productivity index as follows. For technical change, the magnitude index may be expressed as (Fuentes, Grifell-Tatje and Perelman, 2001):

$$\begin{aligned} TCM(x^t, y^t) = \frac{D_I^{t+1}(x^t, y^t)}{D_I^t(x^t, y^t)} &= \exp\left[\ln D_I^{t+1}(x^t, y^t) - \ln D_I^t(x^t, y^t)\right] \\ &= \exp\left[TL(x^t, y^t, t+1; \theta) - TL(x^t, y^t, t; \theta)\right] \end{aligned} \tag{16}$$

The input and output variables in the tranlog specifications involved in (16) belong to the same period; therefore only terms associated with the time-variable do not vanish. Thus, upon canceling out common terms and re-arranging results to:

$$TCM(x^t, y^t) = \exp\left[\gamma_0 + \gamma_{00}\left(t + \frac{1}{2}\right) + \sum_k^K \eta_k \ln x_k^t + \sum_m^M \mu_m \ln y_m^t\right] \tag{17}$$

The output bias index $OB(y^t, x^{t+1}, y^{t+1})$ in (4b) may be expressed as:

$$\begin{aligned} OB(y^t, x^{t+1}, y^{t+1}) &= \exp\big[\ln D_I^{t+1}(x^{t+1}, y^{t+1}) + \ln D_I^t(x^{t+1}, y^t) - \\ &\qquad - \ln D_I^t(x^{t+1}, y^{t+1}) - \ln D_I^{t+1}(x^{t+1}, y^t)\big] \\ &= \exp\big[TL(x^{t+1}, y^{t+1}, t+1; \theta) + TL(x^{t+1}, y^t, t; \theta) - \\ &\qquad - TL(x^{t+1}, y^{t+1}, t; \theta) - TL(x^{t+1}, y^t, t+1; \theta)\big] \end{aligned} \tag{18}$$

By substituting the tranlog specifications involved in (18), canceling out common terms and re-arranging yields:

$$OB(y^t, x^{t+1}, y^{t+1}) = \exp\left[\sum_m^M \mu_m (\ln y_m^{t+1} - \ln y_m^t)\right] \tag{19}$$

Similarly, the input bias index $IB(x^t, y^t, y^{t+1})$ in (4c) is given as:

$$IB(x^t, y^t, y^{t+1}) = \exp\left[\sum_k^M \eta_k (\ln x_k^{t+1} - \ln x_k^t)\right] \tag{20}$$

Hence, the technical change component (2a) of the Malmquist productivity index in (1) can be practically computed as the product of expressions (17), (19), and (20).

Following Fuentes, Grifell-Tatje and Perelman (2001), technical efficiency chagne is calculated as the ratio of two successive distance functions:

$$\begin{aligned} TEC_I = \frac{D_I^t(x^t, y^t)}{D_I^{t+1}(x^{t+1}, y^{t+1})} &= \exp\big[\ln D_I^t(x^t, y^t) - \ln D_I^{t+1}(x^{t+1}, y^{t+1})\big] \\ &= \exp\big[TL(x^t, y^t, t; \theta) - TL(x^{t+1}, y^{t+1}, t+1; \theta\big] \end{aligned} \tag{21}$$

Given the stochastic nature of (14), the predicted value of the input distance function can be estimated either as a conditional expectation:

$$D_I^{i,t}(x^{i,t}, y^{i,t}, t) = E\left[\exp(-u_{i,t}) \middle| u_{i,t} + v_{i,t}\right]$$

or as the fitted value of input distance function using (13) and (14). The former has been used by Fuentes, Grifell-Tatje and Perelman (2001), while latter is employed in the present study. It seems though that the fitted value procedure is computationally less demanded than the conditional expectation procedure.[13]

Balk (2001) suggested that the remaining two components of the Malmquist productivity index (i.e., *SEC* and *ME*) can be computed by using estimates of the input-oriented scale efficiency with no need to re-estimate the input distance function by imposing CRS, as in the non-parametric approach.[14] Extending Ray (1999) and Balk (2001) procedure to an input-oriented framework, it can be shown that, for a translog input distance function, the scale efficiency of an input-output bundle $(\bar{x}, \bar{y})$ may be computed as:

$$ISE^t(\bar{x}, \bar{y}) = \exp\left[\frac{1}{2\beta}\left(\frac{1-\varepsilon^t(\bar{x}, \bar{y})}{\varepsilon^t(\bar{x}, \bar{y})}\right)^2\right] \tag{22}$$

where $\beta = \sum_m^M \sum_n^M \beta_{mn}$ and

$$\varepsilon^t(\bar{x}, \bar{y}) = -\left(\sum_m^M \frac{\partial \ln D_I^t(\bar{x}, \bar{y})}{\partial \ln y_m}\right)^{-1} = \left(\sum_m^M \left[\beta_m + \sum_k^K \delta_{km} \ln x_k + \sum_n^M \beta_{mn} \ln y_n + \mu_m t\right]\right)^{-1}$$ is

the scale elasticity. Since by definition $ISE^t(\bar{x}, \bar{y}) \leq 1$ it follows that $\ln ISE^t(\bar{x}, \bar{y}) \leq 0$, which in turn implies that $\beta < 0$. (22) implies that the scale efficiency of a particular input-output bundle can be computed from the value of the local scale elasticity ε pertaining to this bundle. The latter can be evaluated at any data point from the estimates of the parameters of the input distance function.

Given (22), the scale efficiency change and the input-mix effects can be computed as follows. First, (2c) is rewritten as:

$$SEC_I^t(x^t, y^t, y^{t+1}) = \exp\left[\ln ISE^t(x^t, y^{t+1}) - \ln ISE^t(x^t, y^t)\right] \tag{23}$$

Then, (23) and (22) yield:

$$SEC(x^t, y^t, y^{t+1}) = \exp\left\{\frac{1}{2\beta}\left[\left(\frac{1}{\varepsilon^t(x^t, y^{t+1})} - 1\right)^2 - \left(\frac{1}{\varepsilon^t(x^t, y^t)} - 1\right)^2\right]\right\} \qquad (24)$$

Similarly, (2d) can be written as:

$$ME_I^t(x^t, x^{t+1}, y^{t+1}) = \exp\left[\ln ISE^t(x^{t+1}, y^{t+1}) - \ln ISE^t(x^t, y^{t+1})\right] \qquad (25)$$

Then, (25) and (22) result in:

$$ME_I(x^t, x^{t+1}, y^{t+1}) = \exp\left\{\frac{1}{2\beta}\left[\left(\frac{1}{\varepsilon^t(x^{t+1}, y^{t+1})} - 1\right)^2 - \left(\frac{1}{\varepsilon^t(x^t, y^{t+1})} - 1\right)^2\right]\right\} \qquad (26)$$

Thus, *SEC* and *ME* can be computed from evaluating the expression of the scale elasticity at the input-output bundles involved in each of these two components.

Having computed the assembling parts of the Malmquist productivity index through (17), (19), (20), (21), (24) and (26), the parametric approach permits formal testing of the statistical significance of various sources of productivity changes. In particular, *TC=1* and its contribution to productivity changes is null when the three assembling parts, namely *TCM*, *OB* and *IB*, are all equal to one. The former implies that $\ln TCM(x^t, y^t) = 0$, which in turn requires the following parameter restrictions on (17):

$$\gamma_0 = \gamma_{00} = \eta_k = \mu_m = 0 \qquad (27)$$

for all *k* and *m*. On the other hand, according to Fare *et al*. (1997), *OB* (*IB*) equals unity when the technology exhibits CRS and implicit Hicks output-neutral technical change (implicit Hicks input-neutral technical change). Implicit Hicks output- and input-neutral technical change imply respectively that (Chambers and Fare, 1994):

$$D_O^t(x^t, y^t, t) = D_O^t(x^t, y^t) / A(x^t, t) \qquad (28a)$$

$$D_I^t(x^t, y^t, t) = D_I^t(x^t, y^t) B(y^t, t) \qquad (28b)$$

where $D_O(x, y, t)$ refers to the output distance function. Given that $D_O(x, y, t) = 1/D_I(x, y, t)$ when CRS prevails, by applying (28a) into (10) results in the following parameter restrictions for *OB=1*:

$$\mu_m = 0 \text{ for all } m, \ \sum_m^M \beta_m = -1 \text{, and } \sum_m^M \delta_{km} = \sum_m^M \beta_{mm} = 0 . \quad (29)$$

Analogously, by applying (28b) into (10) the following parameter restrictions are required for *IB=1*:

$$\eta_k = 0 \text{ for all } k \quad (30)$$

Thus, for *TC=1* we should have CRS, joint input and output Hicks neutral technical change, and $\gamma_0 = \gamma_{00} = 0$.[15]

On the other hand, if technical efficiency is time invariant, then *TEC=1* and its contribution to productivity changes is null. Given (15), the hypothesis of time invariant technical efficiency implies that $\xi_i = 0$ for all *i*. In addition, both *SEC* and *ME* are identically equal to unity if the technology exhibits CRS. In terms of the input distance function, this requires to be homogenous of degree –1 in input quantities. For (10) this implies the following parameter restrictions:

$$\sum_m^M \beta_m = -1 \text{, and } \sum_m^M \delta_{km} = \sum_m^M \beta_{mm} = 0 . \quad (31)$$

Hence, CRS are important for the statistical significance of three components in (1), namely *SEC*, *ME* and *OB*.

4. Data Description

The data used in this paper are taken from a questionnaire survey conducted annually by the Greek Ministry of Agriculture, Department of Fishery. From this survey, a sample of 14 seabass and seabream farms is randomly selected for the period 1995-1999, forming a balanced panel data set of 70 0bservations. This sample corresponds to about one fourth of fish farms producing seabass and seabream in Greece during the period examined. For each farm, the available information includes production and annual sales of seabass and seabream; quantities of stocking rate; fish feed consumption; total cage area; and the number of workers employed. Summary statistics of these variables are presented in Table 1.

Two outputs and four inputs are included in (10). The two outputs are the total annual production of *seabass* and *seabream,* measured in tonnes. The four inputs are: (*a*) *labor*, measured as the number of workers employed in the farm; (*b*) *stocking rate,* measured as the number of (seabass and seabream) juveniles utilized annually; (*c*) *fish feed* consumption*,* measured in tonnes and; (*d*) the total *cage area* used in production, measured in m^2. Seabass and seabream stocking rates were aggregated by computing Divisia indices, using cost shares as weights. Moreover, output and input data were converted into indices by choosing a representative fish farm as a base to normalize these series. The choice of the representative fish farm was based on total sales and the smallest deviation from the sample mean.

5. Empirical Results

The ML parameter estimates of the translog input distance function (10) are reported in Table 2. At the point of approximation, the estimated translog input distance function is found to be non-increasing in output quantities and non-decreasing in input quantities. In addition, at the point of approximation, the Hessian matrix with respect to output quantities is found to be negative-definite and that with respect to input quantities to be positive-definite. These indicate respectively the concavity and the convexity of the estimated translog input distance functions with respect to input and output quantities. The variance parameters, σ^2 and γ, are statistical significant at the 5% level. Moreover, the ratio parameter γ is estimated at 0.9038 indicating that the technical inefficiency is likely to have a significant role in explaining output variability among fish farms in the sample.

Several hypotheses concerning model representation were examined using the likelihood ratio test (see Table 3). First, the "average" input distance function does not represent adequately the structure of technology for Greek fish farms. The null hypothesis that $\gamma = \mu = \xi_i = 0$ for all i is rejected at the 5% level of significance indicating that the technical inefficiency effects are in fact stochastic. This finding is also depicted from the statistical significance of the γ-parameter. In addition, the estimated frontier model cannot be reduced to Aigner, Lovell and Schmidt (1977) specification as the null hypothesis that $\mu = 0$ is rejected at the 5% level of significance. This is also true for the time-pattern of inefficiency as the hypothesis that this is common among fish farms, i.e., $\xi_i = \theta$, is rejected at the 5% significance level. Thus, the estimated frontier model cannot be reduced to Battese and Coelli (1992) specification.

The next set of hypotheses testing is related to the structure of production and the sources of productivity changes. The first of these hypotheses concerns with technical change. Specifically, the hypothesis that there is no technical change, i.e., $TC=1$ and thus its contribution to productivity is null, is rejected at the 5% level of significance (see Table 3). Notice that this hypothesis requires that each of the *TCM*, *OB* and *IB* is equal to one. Thus the next hypothesis concerns with the individual components of the technical change effect. In particular, the hypotheses that each of the *TCM*, *OB* and *IB* is individually equal to one are rejected at the 5% level of significance.[16] In turn this implies that both neutral and biased elements are presented in determining the technical change effect.

The hypothesis that technical inefficiency is time-invariant, i.e., $\xi_i = 0$ for all *i*, is also rejected at the 5% level of significance (see Table 3). During the period 1995-99, technical efficiency tended to increase over time for the most of the fish farms in the sample, as the estimated ξ_i parameters reported in Table 2 indicate. Specifically of the 14 farms in the sample only two seem to worsen the use of their resources, and only one of the estimated parameters is not statistically different than zero at the 5% level of significance level (this implies that technical efficiency may have been time invariant for that particular fish farm). In addition, the hypothesis of constant returns to scale is rejected at the 5% level of significance. This implies that scale inefficiency should be considered as an additional reason for not achieving the maximum output, and that the "overall" scale effect should be taken into account in measuring productivity changes.

The frequency distribution of input-oriented technical and scale efficiency are presented in Table 4. The vast majority of fish farms in the sample have consistently achieved scores of technical efficiency between 65 and 75% during the period 1995-99, but there are no fish farms that achieved technical efficiency scores greater than 90%. The estimated mean technical efficiency was found to be 70.8% during the period 1995-99 ranging from a minimum of 53.9% to a maximum of 83.7%. However, the variation of technical efficiency ratings is not significant as the average standard deviation is only 5.6%. Thus, on average, a 29.2% decrease in total cost could have been achieved without altering the total volume of output, the production technology and the levels of inputs used. These estimates are comparable with those reported by Karagiannis, Katranidis and Tzouvelekas (2000, 2002) for 1994.

On the other hand, scale efficiency was found to be considerably higher than technical efficiency. Specifically, the average input-oriented scale efficiency over farms and time was found to be 85.3%, namely 15% higher than the average technical efficiency. The variation of scale efficiency estimates is also moderated but higher than that of technical efficiency (the average standard deviation is 7.5%). In particular, mean scale efficiency ranges from a minimum of 67.4% to maximum of 97.1%. However, the vast majority of fish farms in the sample have achieved scale efficiency scores between 85 and 100%. This means that Greek fish farms could considerably improve their resource use by operating at optimal scale wherein their ray average productivities are maximal. The vast majority of the farms in the sample is found to operate under sub-optimal scale, thus with decreasing returns to scale. There is only one farm that consistently operated with the most productive scale size.

Estimates of the Malmquist productivity index as well as its sources of growth are reported in Table 5.[17] According to these estimates, during the period 1995-1999, productivity increased with an average annual rate of 1.9%. However, the annual growth rate was sufficiently lower during the period 1995-1997. Concerning its sources of growth, it can be seen from Table 5 that technical change and the input-mix effect have contributed positively to productivity growth, whereas the temporal changes of technical and scale efficiency have been sources of deterioration. In particular, the estimated annual rate of technical change is on average 0.4%. This rather slow rate of change is due to the input and the output bias indices, which counteracted with the magnitude index and eventually tended to outweigh its impact. Without accounting for the biased components, the estimated annual rate of technical change could have been in the order of 3.3%.

The input-mix effect was the most important source of productivity growth during the period examined. The average value of the input-mix effect indicates that scale efficiency associated with the input combinations used in two successive periods - conditional on the same output-mix - increases at an annual rate of 6.6%. On the other hand, the average value of the SEC component indicates that the radial scale efficiency associated with the output combinations produced in two successive periods - conditional on the same input-mix – decreases at an annual rate of 4.5%. However, the input-mix effect was strong enough to outweigh the negative effect of the scale efficiency changes on productivity. Hence the "scale effect", that is, the combined contribution of radial scale efficiency changes and scale efficiency changes associated with temporal changes in the input mix raised productivity by 1.8%.

On the other hand, the temporal changes of technical efficiency had virtually no impact on productivity growth. Hence, the absence of technical efficiency improvements and the low rate of technical change made the TFP growth of the fish farms to be determined mostly by the scale effect, and more precisely by the input mix-part of this effect.

6. Concluding Remarks

The paper demonstrates how the generalized decomposition of the Malmquist productivity index suggested by Balk (2001) can be implemented in an input-oriented analytical framework using the parametric approach, a tranlog specification for the distance function of the underlying production technology, and discrete-form data. In assembling the various components of the index we explore further its technical change-component by decomposing it into a neutral part, an input bias and an output bias. Thus, we specify an input-oriented Malmquist productivity index which allows for technical efficiency change; scale efficiency change; an input-mix effect; and, technical change further decomposed into neutral, output-induced and input-induced shifts of the technology frontier over time. In addition, we show how the statistical significance of the assembling parts of technical change can be formally tested via parameter restrictions and LR-tests.

The detailed decomposition of technical change we suggest offers additional insights as it tests formally, and illuminates the *nature* of the overall technical change that shapes up the Malmquist TFP index. Moreover, we show how this Malmquist index may become operational in the case of a tranlog input distance function by deriving computable expressions for all its assembling parts. The expressions we derive are obtained via a discrete changes-approach. This is an additional gain because economic data do not come in continuous form and therefore the use of time derivatives in estimating productivity growth indices may well be misleading (e.g., Coelli *et al.* 1998, p.233-234).

We offer an application of the suggested Malmquist index specification by measuring and decomposing the TFP of a sample of Greek, seabass and seabream-producing farms during the period 1995-99. Findings indicate that the TFP of the

Greek fish farms increased over the period examined at a moderate rate of about two percent, and it was shaped up primarily by the input mix-effect and technical change. Specifically, the fish farms in the sample show considerable technical inefficiency which remained stable over time; thus, the contribution of technical efficiency in productivity growth was null. Scale inefficiency also appears to be present among the fish farms examined although at a lower degree than technical inefficiency. Moreover, the observed scale inefficiency shows temporal variation and contributes negatively to the farms' TFP growth. This implies that by adjusting their scale of production fish farms could improve their productivity.

In contrast to the technical and scale efficiency, technical change and the impact of the input mix used seem to be the driving forces behind the TFP growth of the fish farms. Overall, technical change appears to contribute positively to TFP growth; however, the input and output bias parts of the technical change moderate the neutral shifts of the technology frontier over time. The input mix effect turns out to be the major factor in shaping up the TFP growth of the fish farms. This implies that during the period examined, the input-mix used by the fish farms in successive time periods tends to increase scale efficiency, conditional on the output mix.

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Table 1: Descriptive Statistics of the Variables

Variable	Mean	Max	Min	Standard Deviation
Outputs:				
Seabass (tonnes)	99	390	11	75.3
Seabream (tonnes)	93	312	2	72.0
Inputs:				
Labour (No of workers)	14	75	3	12.8
Stocking rate (ths)	846	2,600	139	558.2
Fish Feed (tonnes)	210	729	41	123.8
Cages (m^2)	3,214	7,561	934	1,797.1

Table 2: Parameter Estimates of the Translog Input-Distance Function and Technical Ineffciency Model.

Parameter	Estimate	StdError	Parameter	Estimate	StdError
Stochastic Input Distance					
α_0	0.1709	(0.0690)**	δ_{BrF}	-0.0189	(0.1255)
α_{Bs}	-0.5677	(0.0976)*	δ_{BrC}	-0.2058	
α_{Br}	-0.4960	(0.0962)*	ζ_{Bs}	-0.2165	(0.0810)**
β_L	0.2993	(0.1231)**	ζ_{Br}	0.0882	(0.0384)**
β_S	0.3425	(0.0977)*	β_{LS}	-0.0266	(0.0774)
β_F	0.1129	(0.0481)**	β_{LF}	0.1544	(0.0392)*
β_C	0.2453		β_{LC}	0.0345	
γ_1	0.0529	(0.0142)*	β_{LL}	-0.1623	(0.0539)*
γ_2	-0.0388	(0.0175)**	β_{SF}	-0.0042	(0.0891)
α_{BsBr}	0.0904	(0.0348)**	β_{SC}	-0.0467	
α_{BsBs}	-0.0566	(0.0884)	β_{SS}	0.0774	(0.0918)
α_{BrBr}	-0.1634	(0.0592)**	β_{FC}	0.0052	
δ_{BsL}	-0.2761	(0.0762)*	β_{FF}	-0.1554	(0.0593)**
δ_{BsS}	0.0444	(0.0921)	β_{CC}	0.0070	
δ_{BsF}	0.1379	(0.0491)*	θ_L	-0.0181	(0.0929)
δ_{BsC}	0.0938		θ_S	-0.1762	(0.0595)*
δ_{BrL}	0.0764	(0.0327)**	θ_F	0.1035	(0.0359)*
δ_{BrS}	0.1482	(0.0394)*	θ_C	0.0907	
Technical Inefficiency Model					
ξ_1	-1.7216	(0.1412)*	ξ_8	-0.3195	(0.2008)
ξ_2	4.0733	(0.1691)*	ξ_9	2.8831	(0.1229)*
ξ_3	1.9842	(0.0981)*	ξ_{10}	1.3071	(0.1374)*
ξ_4	0.1211	(0.1850)	ξ_{11}	1.5264	(0.1736)*
ξ_5	2.4571	(0.1042)*	ξ_{12}	2.1358	(0.1903)*
ξ_6	0.9373	(0.1997)*	ξ_{13}	2.3382	(0.1539)*
ξ_7	3.5985	(0.1003)*	ξ_{14}	2.0194	(0.1625)*
γ	0.9038	(0.1058)*	σ^2	0.1126	(0.0092)*
μ	-2.1836	(0.0171)*	$Ln(\theta)$	-25.369	

Where **Bs** stands for Sea-Bass, **Br** for Sea-Bream, **L** for Labour, **S** for stocking rate, **F** for feeding staff and **C** for cages. * (**) indicate statistical significance at the 1 (5)% level.

Table 3: Model Specification Tests

Hypothesis	LR-test	Critical Value (α=0.05)
No technical inefficiency	75.69	$\chi^2_{16} = 26.30$
Aigner *et al.* (1997) model	14.95	$\chi^2_{1} = 3.84$
Time-varying technical inefficiency with common pattern	49.85	$\chi^2_{14} = 23.68$
Zero technical change	33.52	$\chi^2_{7} = 14.07$
Input Hicks neutral technical change	21.23	$\chi^2_{4} = 9.49$
Output Hicks neutral technical change and CRS	39.02	$\chi^2_{7} = 14.07$
Input and output Hicks neutral technical change and CRS	24.98	$\chi^2_{13} = 22.36$
Time-invariant technical inefficiency	52.14	$\chi^2_{14} = 23.68$
Constant returns to scale	35.98	$\chi^2_{7} = 14.07$
Cobb-Douglas and Hicks neutral technical change	56.75	$\chi^2_{20} = 31.4$
Ray-homogeneity	6.85	$\chi^2_{1} = 3.84$
Input-output separability	16.04	$\chi^2_{6} = 12.59$

Table 4: Frequency Distribution of Input-Oriented Technical and Scale Efficiency

Efficiency (%)	1995	1996	1997	1998	1999	1995-99
Technical Efficiency						
50-55	0	0	1	1	1	1
55-60	1	1	0	0	0	0
60-65	1	1	1	1	1	1
65-70	3	3	4	3	4	4
70-75	5	5	5	5	4	4
75-80	2	2	2	2	2	2
80-85	1	1	1	1	1	1
85-90	1	1	0	1	1	1
90-95	0	0	0	0	0	0
95-100	0	0	0	0	0	0
Mean	71.4	70.9	71.2	70.6	70.1	70.8
StDev	5.4	6.0	5.8	6.3	5.9	5.6
Maximum	85.8	86.3	84.2	87.9	86.3	83.7
Minimum	57.3	56.7	54.2	53.5	51.2	53.9
Scale Efficiency						
55-60	0	0	0	1	1	0
60-65	1	0	1	0	0	0
65-70	1	1	1	1	0	1
70-75	1	1	1	1	1	0
75-80	1	1	1	1	1	2
80-85	2	2	2	1	2	1
85-90	3	4	3	3	4	5
90-95	2	3	3	3	3	3
95-100	3	2	2	2	2	2
Mean	86.4	90.3	86.5	83.2	80.1	85.3
StDev	9.2	9.6	9.1	8.6	7.4	7.5
Maximum	100	100	100	100	100	95.4
Minimum	62.3	66.9	60.2	58.6	57.4	67.4

Table 5: Decomposition of Malmquist Productivity Index (1995-1999)

	95-96	96-97	97-98	98-99	Mean
Total Factor Productivity	1.014	1.012	1.028	1.028	1.019
Technical Change	0.885	1.076	1.042	1.024	1.004
Technical Change Index	1.011	1.090	1.012	1.020	1.033
Output Bias Index	0.922	0.999	1.043	0.988	0.987
Input Bias Index	0.950	0.988	0.986	1.016	0.985
Techn. Efficiency Change	0.998	0.998	0.999	0.999	0.998
Scale Efficiency Change	1.093	0.901	0.909	0.929	0.955
Input Mix Effect	1.050	1.045	1.088	1.082	1.066

Endnotes

[1] Another difference between the non-parametric and the parametric approach, when the latter is based on stochastic frontiers, is that we are unable to estimate directly the Malmquist productivity index (Fuentes, Grifell-Tatje and Perelman, 2001). Instead it should be computed indirectly through its components. The reason is that dealing with stochastic frontiers it is not possible to estimate the conditional expectation resulting in the predicted value of the distance function by combining the technology and the data of two different periods. This problem does not however arise when a deterministic frontier is employed.

[2] The main disadvantages of the parametric approach are: *first*, a particular function form should be used to approximate the underlying production technology; *second*, it cannot function in cases with insufficient degrees of freedom; and *third*, it cannot provide precise estimates when there is extreme invariability in the data.

[3] It is also possible to test whether technical change is implicit Hicks input and output biased or neutral.

[4] A backward-looking approach is employed for the construction of the Malmquist productivity index by using period t technology as a reference point. Alternatively, either a forward-looking approach or a geometric mean of the two could have been used.

[5] For technical change, as well as all other assembling parts of (1), values equal to one indicate no contribution to productivity changes.

[6] Since the same technology is used in both the numerator and the denominator of (6), *SEC* is independent of technical change (Balk, 2001).

[7] Also notice that in the single-input case ME_I^t is identically equal to one.

[8] Actually speaking this is the reciprocal of the input-oriented Malmquist productivity index used by Fare *et al*. (1992). It has however an appealing interpretation common to productivity literature since progress (regress) is depicted by values greater (less) than one.

[9] The separability property implies that the productivity index can be interpreted as a relationship between an aggregated output and an aggregated input (Orea, 2002). This property is related to a separability restriction on production technology, which in a parametric framework can be tested statistically.

[10] A general concern with estimation of (13) is that the normalized inputs appearing, as regressors may not be exogenous. According to Coelli and Perelman (1999, 2000), however, the transformed input variables in (13) are measures of input mix, which are more likely to be exogenous in an expected profit maximization framework.

[11] In the case of unbalanced panels, t includes a subset of integers representing the periods for which observations on individual producers are obtained.

[12] Notice that both the hypotheses of common temporal pattern and of time invariant technical efficiency can be tested statistically.

[13] Another advantage of the fitted value procedure is that, in the case of global CRS, the Malmquist productivity index can directly be computed through (9), regardless of whether a stochastic or a deterministic frontier is used.

[14] Actually, the procedure used in the non-parametric approach cannot be applied because there is nothing to ensure that the CRS distance function necessarily envelops the corresponding VRS distance function when the parametric approach is used (Orea, 2002).

[15] CRS and joint input and output Hicks neutrality imply that $A(\bullet)$ and $B(\bullet)$ in (28) depend only on t and they are equal to each other (Fare and Grosskopf, 1996, pp. 86-91). Moreover, in this case the Malmquist productivity index satisfies the circular test, which means that both productivity and technical change are path independent.

[16] In addition, the hypothesis of joint CRS and input and output Hicks neutrality is rejected at the 5% level of significance (see Table 3). This implies that the estimated Malmquist productivity index does not satisfy the circular test and consequently, both productivity and technical change are path dependent.

[17] Since the separability between inputs and outputs in the estimated distance function is rejected at the 5% level of significance (see Table 3), the estimated productivity index cannot be interpreted as a relationship between an aggregated output and an aggregated input.