Measuring productive efficiency of seabass and seabream farms in Greece

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Abstract

A stochastic Cobb-Douglas production frontier is used to provide estimates of output-oriented technical efficiency, input-oriented technical efficiency, input allocative efficiency and cost efficiency for a sample of seabass and seabream farms in Greece. Mean output-oriented technical efficiency is estimated at 78.5%, input-oriented technical efficiency at 73.6%, input allocative efficiency at 79.2%, and cost efficiency at 58.2%. Considering the sources of efficiency differentials among fish farms, it is evidence from the empirical results that large farms tend to achieve higher (technical and allocative) efficiency scores; specialization in either seabass or seabream affects positively technical and cost, but not allocative, efficiency; and utilization of skilled labor seems to have a positive impact only on technical efficiency.

Keywords: Aquaculture, seabass, seabream, cost efficiency, Greece

Introduction

Since the first half of the 1990s, Greek aquaculture has been dominated by seabass and seabream production. Output grew dramatically from 53 tons in 1985 to 17,553 tons in 1995 (Table 1) and was almost equally shared between seabass and seabream. Eventually Greece became the largest producer of seabass and seabream in Europe accounting for 55% of total European production in 1995, compared to only 25% in 1989. The growth of seabass and seabream production occurred at the expense of freshwater fish production, primarily of trout and carp (Kallifeidas 1997). The number of seabass and seabream farms almost doubled in the first half of the 1990s, but the absolute number of farms entering the industry in the 1990s decreased compared to the second half of the 1980s, when a large number of small fish farms entered the industry (Table 1).

Farm production varies considerably from small units producing up to 50 tons per year to big ones producing more than 200 tons per year. The average farm size increased significantly from 18.6 tons per year in 1990 to 109.6 tons per year in 1995 (Table 1). How-

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ever, regardless of farm size, the same type of technology is used as far as fish-cages and growing stocks are concerned (Kallifeidas 1997). The situation is entirely different with respect to hatcheries, as it is difficult for small and medium size enterprises to integrate vertically due to high establishment cost and lack of technical expertise. As a result, the number of seabass and seabream hatcheries increased at a much slower rate than the number of fish farms.

Table 1 Production, fish farms and fish hatcheries of seabass and seabream in Greece, 1985-1995

Year	Production (in tones)	Number of Fish Farms	Number of Hatcheries	Average Farm Production (tones)
1985	53	2	-	26.5
1986	89	9	1	9.9
1987	105	17	1	6.2
1988	200	27	1	7.4
1989	500	62	5	8.1
1990	1600	86	9	18.6
1991	2459	114	11	21.6
1992	4845	139	16	34.8
1993	9500	145	22	65.6
1994	13500	164	25	81.7
1995	17553	160	25	109.6

Source: Kallifeidas (1997)

The ongoing rapid development of seabass and seabream production in Greece is closely related to the competitiveness of the sector in both domestic and export markets.[1] Efficiency is one of the main factors determining competitiveness. The higher the degree of efficiency, the lower will be the unit cost of production and as a result, fish farms would be able to supply their products at lower prices. Consequently, more efficient fish farms would have better chances of surviving and prospering in the future than less efficient ones. Along these lines, an analysis of efficiency would provide information about the potential sources of inefficiency. In addition, measures of potential cost savings that can be achieved from improvements in technical and allocative efficiencies could be derived and used by fish farms as a benchmark to improve competitiveness.

The objective of this paper is to examine the extent of both technical and allocative efficiencies in seabass and seabream production in Greece based on a sample of 30 fish farms at 1994 and using the stochastic frontier approach. *First*, estimates of output-oriented technical efficiency are obtained directly from the econometric estimation of a Cobb-Douglas production frontier function. *Second*, estimates of input-oriented technical efficiency, input allocative efficiency, and cost efficiency are derived by using an indirect approach, initially proposed by Kopp & Diewert (1982) and latter extended by Bravo-Ureta & Rieger (1991) to stochastic frontier models, which relies on the derived cost frontier. *Third*, a second-stage regression approach is used to explain intra-firm variation in input-oriented technical efficiency, input allocative efficiency, and cost efficiency.

[1] The greatest portion of domestic production (around 60% in 1994) is exported, mainly to Italy and other Mediterranean countries. The portion consumed domestically has decreased over time, while that of export has increased (Kallifeidas 1997).

There are relatively few studies dealing with the measurement of efficiency in open-access fisheries and aquaculture.[2] Specifically, Kirkley *et al.* (1995; 1998) assessed technical efficiency in mid-Atlantic sea-scallop fishery; Campbell & Hand (1998) compared technical efficiency scores among domestic and distant water fishing fleets in the Solomon Islands fishing zone; and Sharma & Leung (1999) analyzed technical efficiency of longline fishery in Hawaii. On the other hand, Sharma & Leung (1998) examined the technical efficiency and its determinants for a sample of extensive and intensive fishpond farms in Nepal; Sharma (1999) measured technical efficiency of carp production in Pakistan; Iinuma *et al*. (1999) analyzed the productive performance of a sample of carp pond farms in Peninsula Malaysia; and Sharma *et al*., (1999) studied technical and allocative efficiencies for a sample of Chinese polyculture fish farms. Empirical results from these studies indicate that the factors influencing efficiency in commercial fisheries and aquaculture are dissimilar. In open access fisheries, recruitment and subsequent harvestable stocks are important in determining productive efficiency. However, these factors seem to have no influence in controlled aquaculture production. Instead, stocking rates and fish feed, along with local environmental conditions, are the most influential factors in determining fish farm output and the degree of inefficiency.

Methodological Framework

Technical efficiency reflects the ability of firms to produce as much output as possible from a given level of inputs, or to use as little input as possible to obtain a given level of output. Accordingly, two measures of technical efficiency could be defined (Kopp 1981). The first one is the output-oriented *Timmer-type* measure, which relates actual output to best practice output. It gives the maximum amount by which output can be increased for a given input vector. The second one is the input-oriented *Farrell-type* measure, reflecting the ratio of best practice input usage to actual input usage, output held constant. It gives the maximum amount by which an input vector can be decreased proportionally, while producing the same amount of output. Moreover, the input-oriented measure has an intuitive cost interpretation since one minus the degree of technical efficiency gives the percentage decrease in total cost associated with the complete removal of technical inefficiency (Kopp 1981).[3] In addition, Fare & Lovell (1978) shown that input-oriented technical efficiency is less, equal, or greater than output-oriented technical efficiency under decreasing, constant, or increasing returns to scale.[4]

Input allocative efficiency reflects the ability of using the cost-minimizing input combination given input prices and output. It determines the maximum amount by which a technically efficient input vector can be decreased proportionally in order a given output level to be produced at least cost. On the other hand, cost efficiency reflects the ability of a firm to produce a predetermined level of output at least cost. It determines the maximum amount by which an input vector can be decreased proportionally, while producing the same amount of output at the minimum cost for a given input price vector. Cost efficiency has a direct cost interpretation depicted by the ratio of minimum actual to cost of producing a given level of output (Kopp 1981), and algebraically equals the product of input-oriented technical

[2] Production function analyses in aquaculture have been limited to assess the profitability of new investment, to estimate economies of scale, and to determine optimum intensity of input use. For a comprehensive literature review see Hatch & Tai (1997).

[3] In contrast, such a cost-saving interpretation is not applicable to the output-oriented measure of technical efficiency, expect in the special case of constant returns to scale (Kopp 1981).

[4] The two measures are also equal if both equal one and thus production is technically efficient.

efficiency and input allocative efficiency (Farrell 1957). Thus a firm is economically efficient if, and only if, it is both technically and allocatively efficient.

To the extent that technical and allocative inefficiency have different causes, a determination of which of the two constitutes the main source of cost inefficiency could provide useful policy recommendations (Kumbhakar & Lovell 2000, p. 133).[5] In addition, output- and input-oriented measures of technical efficiency provide quite different information, especially from a policy point of view. The former determines by how much output supply could be increased if technical inefficiency is completely removed, while the later shows by how much cost of production could be reduced by operating with full technical efficiency. Consistency in terms of both measurement and interpretation requires these various efficiency measures to be obtained from the same model. However, from the existing literature it is evidence that firm-specific estimates of all the aforementioned efficiency measures can be obtained at once only at the cost of using self-dual production frontier functions (e.g., Cobb-Douglas), the inflexibility of which inherit the danger of biased estimates of output-oriented technical efficiency since the unmodeled complexity of production technology may appear in the composed error term.[6]

In stochastic frontier analysis, two approaches (i.e., Schmidt & Lovell 1979, 1980 and Bravo-Ureta & Rieger 1991) were developed in this direction both of which exploited the self-duality property in measuring efficiency rather than in estimating the underlying production technology. Also both approaches share a common feature in that extract estimates of output-oriented technical efficiency from the composed error term appended into the primal production frontier. They differ however in the way of measuring input-oriented technical efficiency and input allocative efficiency. Schmidt & Lovell (1979, 1980) used the analytical solutions for the cost frontier and the input demand functions, both defined in terms of the estimated parameters obtained from a system of equations consisting of the primal self-dual (Cobb-Douglas) frontier and the first-order conditions for cost minimization. Bravo-Ureta & Rieger (1991), on the other hand, used Shephard's lemma, the first-order conditions for cost minimization, and the analytical solutions for the cost frontier defined in terms of the estimated parameters obtained from a single-equation estimation of the primal self-dual (Cobb-Douglas) frontier.

The main advantage of Bravo-Ureta & Rieger (1991) approach is that allows decomposition of economic efficiency with a single-equation model, namely the primal self-dual frontier.[7] It is expected that by moving from a single-equation (Bravo-Ureta & Rieger) to a simultaneous-equation model (Schmidt & Lovell) involves a more complicated estimation problem and requires more data (i.e., input prices). Even though input price data are also needed in Bravo-Ureta & Rieger's (1991) approach, they involve only in the measurement of input-oriented technical efficiency and input allocative efficiency and not directly in the estimation of the model as in Schmidt & Lovell (1979, 1980). Moreover,

[5] It may also be possible that technical and allocative efficiency are interrelated (see Schmidt & Lovell 1980). For example, Kalirajan & Shand (1992) found that the existence of technical inefficiency influence the degree of allocative efficiency, but the opposite was not true.

[6] Attempts to model technology in a more flexible way, by using for example a translog function, restrict the number of the above mentioned efficiency measures that could be obtained at once. For example, with cross-section data, a translog cost frontier and a simultaneous equation model Kumbhakar (1997) was able to derive estimates of input-oriented technical efficiency and input allocative efficiency but not of output-oriented technical efficiency. Reinhard *et al.* (1999), on the other hand, by combining stochastic frontier analysis with shadow price models, were able to obtain at once estimates of input- and output-oriented technical efficiency from a translog production frontier.

[7] Single-equation estimation of production frontiers is theoretically consistent with the assumption of expected profit maximization under output price uncertainty (Zellner *et al.* 1966). But in such a case, expected profit maximization implies cost minimization for risk neutral producers (Batra & Ullah 1974). This enables us to go back and forth between the stochastic production and cost frontiers in a theoretically consistent way.

given that both input-oriented technical efficiency and input allocative efficiency are independent of input price scaling (Kopp 1981), adequate firm-specific efficiency estimates could be obtained by using either regional or even national input price data.[8]

To proceed consider the following stochastic production frontier function:

$$y_i = f(x_j; \beta_j)\exp(v_i - u_i) \tag{1}$$

where y_i is the observed output produced by the i^{th} firm, x_{ji} is the quantity of the j^{th} input used by the i^{th} firm, β*'s* are parameters to be estimated, v_i is a symmetric and normally distributed error term (i.e., statistical noise with $v \sim N(0, \sigma_v^2)$) that represents those factors that cannot be controlled by the firm, and u_i is an one-sided, non-negative error term representing technical inefficiency in production which is assumed as in Stevenson (1980) to follow a truncated normal distribution, i.e., $u \sim N(\mu, \sigma_u^2)$.[9] It is further assumed that v_i and u_i are independently distributed from each other. Then, firm-specific estimates of output-oriented technical efficiency are obtained by applying Battese & Coelli (1988) predictor to the following relation:

$$TE_i^O = exp(-u_i) \tag{2}$$

and confidence intervals for TE_i^O are calculated by using Horrace & Schmidt (1996) formulas. TE_i^O is by definition bounded between zero and one.

Following Bravo-Ureta & Rieger (1991), to obtain firm-specific estimates of the input-oriented measure of technical efficiency, computation of technically efficient input vector x_{ji}^T is required. This is derived by solving simultaneously the system of equation

$$y_i^* = f(x_j; \beta_j)\exp(-u_i) = y_i \exp(-v_i) \tag{3}$$

and the input ratios $x_{1i} / x_{ji} = k_{ji}$ (j>1) for each firm, where y_i^* is the maximum output that can be produced by the i^{th} firm given its production technology and input use (which is also equal to its observed output adjusted for the statistical noise, v_i), and k_{ji} is the ratio of

[8] Scaling all factor prices will have no effect on the input-oriented measure of technical efficiency because only relative prices matter. This property of input-oriented measures of efficiency is due to their radial nature.

[9] Equation (1) implies that the frontier is a neutral shift of the conventional production function in a sense that different methods of applying various inputs influence output equally. On the other hand, Kalirajan & Obwona (1994) and Huang & Liu (1994) proposed alternative non-neutral specifications, which incorporate the diversity of individual decision making behavior. However, there are some problems by applying either of these models in Bravo-Ureta & Rieger's (1991) approach. By applying the stochastic varying coefficients frontier approach there is no guarantee that the resulting cost frontier will satisfy the linear homogeneity property because the primal frontier is derived by using the highest of each estimated response coefficient and the intercept term. Whenever the resulting cost frontier is not linear homogeneous in input prices, inadequate estimates of cost efficiency would be obtained. In addition, as pointed out by one referee, the variables included in the technical inefficiency effect model of Huang & Liu (1994) cannot be ignored in deriving the resulting cost frontier; this however complicates extremely its derivation. For these reasons we proceed by using the standard error component model (1).

observed inputs x_{1i} and x_{ji} at y_i^*.[10] Then, firm-specific estimates of input-oriented technical efficiency are obtained as (Kopp 1981):

$$TE_i^I = \frac{\sum_{j=1}^{k} w_{ji} x_{ji}^T}{\sum_{j=1}^{k} w_{ji} x_{ji}} \tag{4}$$

where w_{ji} is the factor price of the j^{th} input for the i^{th} firm and $0 \leq TE_i^I \leq 1$.

Firm-specific estimates of cost efficiency are obtained by using the derived cost frontier, evaluated at y_i^*. Assuming that the production frontier in (1) is self-dual (e.g., Cobb-Douglas), a closed-form solution can be obtained for the dual cost frontier as:

$$c_i = g\left(w_{ji}, y_i^*; \alpha_j\right) \tag{5}$$

where c_i is the minimum cost of the i^{th} firm associated with output y_i^* and α_j are the corresponding parameters. The cost efficient input vector, x_{ji}^E, is obtained by applying Shephard's lemma to (5) and by substituting input prices and (3) into the derived system of factor demand equations. Then, cost efficiency is given as (Kopp 1981):

$$EE_i^I = \frac{\sum_{j=1}^{k} w_{ji} x_{ji}^E}{\sum_{j=1}^{k} w_{ji} x_{ji}} \tag{6}$$

where $0 \leq EE_i^E \leq 1$. Finally, firm-specific estimates of input allocative efficiency are obtained by utilizing Farrell's (1957) decomposition, i.e.,

$$AE_i^I = \frac{EE_i^I}{TE_i^I} = \frac{\sum_{j=1}^{k} w_{ji} x_{ji}^E}{\sum_{j=1}^{k} w_{ji} x_{ji}^T} \tag{7}$$

As with the other two input-oriented measures $0 \leq AE_i^I \leq 1$.

[10] Specification (3) ensures the stochastic nature of (1) and distinguishes Bravo-Ureta & Rieger's (1991) approach from Kopp & 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 is based on a dual (cost) frontier. As a result, the input-based measure of allocative efficiency is obtained residually in the former case by using Farrell's (1957) decomposition, while the input-based measure of technical efficiency is calculated residually in the latter case.

After computing the above efficiency measures, it is common to attempt an explanation of intra-firm variations in efficiency by using a second-stage regression approach. This involves specification of a regression model relating efficiency scores (dependent variable) with a set of explanatory variables that are expected to influence efficiency differentials among firms. In Bravo-Ureta & Rieger's (1991) model, this approach can appropriately be used in explaining input-oriented technical efficiency, input allocative efficiency and cost efficiency but not in explaining output-oriented technical efficiency. The reason is that using output-oriented technical efficiency as a dependent variable in the second-stage regression is inconsistent with the assumption of an identically and independently distributed one-sided error term in (1) (Kumbhakar *et al.* 1991; Reifschneider & Stevenson 1991). Thus, the general form of the second-stage regression is specified as follows:

$$EFF_i^I = h\left(z_{ji};\delta\right) + \omega_i \tag{8}$$

where $EFF_i^I = \left\{TE_i^I, AE_i^I, EE_i^I\right\}$, z_{ji} are variables used to explain efficiency differentials among firms, δ*'s* are parameters to be estimated, and ω_i is an identically and independently distributed random variable capturing the impact of unobserved explanatory variables, measurement errors and other sources of statistical noise.

Empirical Procedures

Data and Variables

The data used in this study were collected through questionnaires filed with the Greek Ministry of Agriculture, Department of Fishery, by 140 seabass and seabream farms at 1994. From these, 30 were selected randomly for the purposes of the present study.[11] This sample corresponds to almost 23% of fish farms producing seabass and seabream in Greece at 1994 and they accounted for approximately 30% of total national production. They were diverse in size producing from a low of 45 tons/year to a high of 451 tons/year of seabass and seabream with a mean production level of 145 tons/year and a relatively high standard deviation of 83 tons/year (Table 2). They were also diverse in inputs used especially in that some of fish farms included in the sample were not employing skilled labor (scientists and technicians).

For each fish farm, there is available information about production of seabass and seabream, annual sales, outlays on and quantities of stocking rate and fish feed, and the number of workers employed. Output (y) is consisting of annual seabass and seabream production measured in tons. Output quantity 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 sample mean. Aggregation of seabass and seabream quantity indices was conducted using Divisia indices, where revenue shares were used as weights.

Stocking rate (x_1), fish feed (x_2) and labor (x_3) are the primary inputs.[12] Stocking rate is measured by the number of juveniles utilized while the quantity of fish feed is measured in tons. Both these quantity series were converted into indices by using the representative fish

[11] Current policy of the Ministry of Agriculture regarding confidential information restricted accessibility to data on all 140 fish farms included in the original sample. Due to this, a sample consisting of 25% of the fish farms included in the original data set were selected via a random process. Unfortunately, for five of them there were missing values for one or more of the variables included in the empirical model. Thus, we end up with a total of 30 fish farms included in our sample.

[12] There were no available data on capital and for this reason it is not included as an input variable in the production function.

farm as a base of normalization. Aggregation of seabass and seabream stocking rates was conducted using Divisia indices, where cost shares were used as weights. Labor input was measured by the number of workers. Besides having information about the number of skilled and unskilled workers we did not have separate data on their total annual cost. Both kinds of labor (skilled and unskilled) were aggregated into a single variable using Divisia indices. In constructing the relevant cost shares for aggregating labor, it was assumed that skilled labor was paid one and a half time more than unskilled labor.[13]

Table 2 Summary statistics of the variables involved in the analysis.

	Mean	**Min**	**Max**	**Standard Deviation**
Output				
Seabass and Seabream Production (tons)	145	45	451	83
Input Quantities				
Stocking Rate (ths.)	259	14	462	127
Fish Feed (tons)	328	85	1144	204
Unskilled Labor (No of workers)	8	2	29	5.4
Skilled Labor (No of workers)	2	0	7	1.7
Input Prices				
Stocking Rate (Drs)	96.1	52.2	113.4	12.6
Fish Feed (Drs)	2,000	2,000	2,000	0.0
Wage (ths Drs)	5.4	4.5	5.5	2.8

Input prices needed to measure the total cost of production for each fish farm in the sample were obtained by dividing total outlays with the corresponding quantity used. They are defined as follows: w_1 represents the price of stocking rate in drachmas ($1 U.S.=242 drachmas at 1994), w_2 is the per tone price of fish feed in thousand drachmas, and w_3 is the annual payment to unskilled labor in thousand drachmas based on the number of equivalent unskilled workers. A summary of statistics of input prices is given in Table 2 from where it can be seen that all farms in the sample face the same unit price for fish feed, indicating a fairly competitive market for this input.

The farm-specific variables aimed to explain efficiency variation among fish farms were: *first*, the size of producing units expressed as the volume of their total (seabass and seabream) output (z_1). *Second*, the degree of specialization in either seabass or seabream production, which is depicted by two dummy variables (z_2 and z_3). These specialization dummy variables were constructed as the ratios of seabass and seabream production to total production (measured in tons). If these ratios were greater than 75%, a value of one was assigned in the dummy variable indicating specialization on seabass or seabream production; otherwise it was zero. Thus, fish farms were considered as specialized if the share of either seabass or seabream output is more than 75% of its total production. *Third*, the total number of skilled labor units employed by each fish farm (z_4).

Empirical Model

The stochastic production frontier function used to analyze the underlying technology of the Greek fish farms is specified to be of a Cobb-Douglas form, i.e.,

[13] This ratio was based on skilled and unskilled labor salaries in food industry. A sensitivity analysis within 1-2 range has shown no significant changes in the econometric results.

$$ln\, y_i = \beta_0 + \sum_{j=1}^{3} \beta_j\, ln\, x_{ji} + v_i - u_i \tag{9}$$

The dual cost frontier corresponding to (9) is given as:

$$ln\, c_i(w,y) = \alpha_0 + \sum_{j=1}^{3} \alpha_j\, ln\, w_{ji} + \alpha_4\, ln\, y_i^* \tag{10}$$

where $\alpha_0 = ln\left(\sum_{j=1}^{3}\beta_j\right) - \left(1/\sum_{j=1}^{3}\beta_j\right)\left(\beta_0 + \sum_{j=1}^{3}\beta_j\, ln\, \beta_j\right)$, $\alpha_j = \beta_j \Big/ \sum_{j=1}^{3}\beta_j$, $j = 1, 2, 3$

and $\alpha_4 = 1\Big/\sum_{j=1}^{3}\beta_j$. On the other hand, the second-stage regression equation (8) is specified in a log-linear form as follows:

$$ln\, EFF_i^I = \delta_0 + \sum_{j=1}^{4} \delta_j\, ln\, z_{ji} + \omega_i \tag{11}$$

and since the dependent variables, which lie between 0 and 1, have been transformed it can be estimated with OLS (Kumbhakar & Lovell 2000, p. 264).

The parameters of the stochastic production frontier (9) are estimated using maximum likelihood (ML) and the Frontier (Version 4.1) 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. 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 log-likelihood function under the null (H_0) and the alternative (H_1) hypothesis, respectively.[14] *First*, if $\gamma = \mu = 0$, each fish farm in the sample is operating on the technically efficient frontier and the model reduces to the average response function.[15] *Second*, if $\mu = 0$ the model reduces to the Aigner *et al*. (1977) formulation, with technical efficiency following a half-normal distribution.

Empirical Results

ML Estimates and Hypotheses Testing

The estimated parameters of the Cobb-Douglas average and frontier production functions are presented in Table 3. It can be seen that there are significant differences with respect to the

[14] 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 assumptotic distribution of λ is a mixed χ^2 (Coelli 1995) and the appropriate critical values are taken from Kodde & Palm (1986).

[15] The value of μ determines the point where the truncation of the distribution of the one-sided error term takes place.

estimated variance of the error term and marginal factor productivities, except that of labor which is found to be insignificant under both specifications. In the stochastic frontier model, the estimated variance of the one-sided error term is found to be $\sigma_u^2 = 0.034$ and that of the statistical noise $\sigma_v^2 = 0.047$. Given the estimated parameters of the Cobb-Douglas frontier production function in Table 3 and by using (11), the dual cost frontier is given as:

$$ln\, c_i = 4.560 + 0.479\, ln\, w_{1i} + 0.406\, ln\, w_{2i} + 0.115\, ln\, w_{3i} + 1.248\, ln\, y_i \qquad (12)$$

Hypotheses testing concerning model representation are reported in Table 4. It is evident that the traditional average production function does not represent adequately the data of fish farms in the sample as the null hypothesis that $\gamma = \mu = 0$ is rejected at the 5% level of significance. This is also depicted by the statistical significance of the $\gamma -$parameter (Table 3). Moreover, Aigner *et al.* (1977) specification is not an adequate representation for the particular sample of fish farms as the null hypothesis that $\mu = 0$ is also rejected at the 5% level of significance.

Production Structure

According to the estimated Cobb-Douglas frontier production function, stocking rate and fish feed are the foremost important factors of production for seabass and seabream farms (Table 3). As it is indicated from the relevant estimates of output elasticities, 1% increase in stocking rate and fish feed results in, *ceteris paribus*, 0.39% and 0.33% increase in total output, respectively. Labor, on the other hand, exhibits a considerably lower output elasticity (0.092), which is also statistically insignificant at the 5% level of significance.

Table 3: Parameter estimates of average production function and stochastic production frontier

Variable		**Average Function** *Estimate*	**Stochastic Frontier** *Estimate*
Constant	β_0	0.316 (0.083)*	0.685 (0.067)*
Stocking Rate	β_1	0.424 (0.114)*	0.384 (0.087)*
Fish Feed	β_2	0.484 (0.127)*	0.325 (0.083)*
Labor	β_3	0.031 (0.114)	0.092 (0.131)
$\sigma^2 \equiv \sigma_v^2 + \sigma_u^2$		0.055 (0.025)**	0.081 (0.034)**
$\gamma \equiv \sigma_u^2 / \sigma^2$		- -	0.421 (0.018)*
μ		- -	0.192 (0.027)*
Ln(θ)		-12.813	-4.602
RTS		0.939	0.801

In parentheses are the corresponding standard errors.
* Significant at the 1% level; ** significant at the 5% level.

The second feature of the structure of production is concerned with returns to scale. The hypothesis of constant returns to scale is rejected at the 5% level of significance (Table 4). Returns to scale can be measured directly through the estimated parameters of the Cobb-Douglas frontier production function by the sum of output elasticities, or through the corresponding cost frontier (12) by the reciprocal of the output-related derived parameter. Returns to scale are found to be decreasing and on average to be 0.801. This implies that an equiproportional increase in all inputs by 1% results in a 0.801% increase in total output. It also implies that a 1% increase in total output is associated with 1.248% increase in total cost.

Decreasing returns to scale are more likely associated with the restricted number of cages that can be placed in each sheltered bay due to environmental regulations.

Table 4 Hypotheses Tests

Hypothesis	λ **– statistic**	**Critical Value (α=0.05)**
$H_0 : \gamma = \mu = 0$	14.42	$\chi_2^2 = 5.14^*$
$H_0 : \mu = 0$	7.45	$\chi_1^2 = 3.84$
$H_0 : \sum_{j=1}^{3} \beta_j = 1$ (CRTS)	16.32	$\chi_1^2 = 3.84$

* Critical values are obtained from Kodde and Palm (1986).

The derived dual cost frontier (12) may be used to obtain estimates of factor demand elasticities, which are defined as $e_{jj} = \partial \ln x_j / \partial \ln w_j$. Our empirical results indicate that all factor inputs considered have inelastic demands with that of labor being the less price sensitive.[16] In particular, the estimated demand elasticities are found to be -0.479 for stocking rate, -0.406 for fish feed, and -0.115 for labor.

Efficiency Measurement

Estimates of input-oriented technical efficiency, output-oriented technical efficiency, input allocative efficiency and cost efficiency for the sample farms are reported in Tables 5 and their frequency distributions are depicted in Table 6. In addition, confidence intervals for the estimates of output-oriented technical efficiency are presented in Table 5. These intervals are found to vary widely among the sample farms. The difference between the lower and the upper efficiency intervals is within 2.3% to 14.2% limits. In general, confidence intervals are not too wide and the majority (70.0%) of fish farms is within 2% to 8% limits.

The estimated mean output-oriented technical efficiency is found to be 78.5%, which means that 21.5% increase in production is possible with the present state of technology and unchanged input uses, if technical inefficiency is eliminated (Table 5). On the other hand, the estimated mean input-oriented technical efficiency is found to be 73.6%, which implies that by operating at full technical efficiently 26.4% decrease in total cost of production can be achieved without altering technology and the volume of output produced (Table 5). Estimated input-oriented technical inefficiency measure is lower than the corresponding output-oriented measure due to decreasing returns to scale. This holds for all fish farms in the sample. Output-oriented technical efficiency scores varied from 52.5% to 99.6%, while input-oriented technical efficiency scores varied from 41.0% to 94.5% (Table 5). However, both measures show that almost 67% of sample farms achieved technical efficiency greater than 70% (Table 6).

Table 5 Output- and Input-Oriented Technical Efficiency, Allocative Efficiency and Economic Efficiency by Fish Farm

Fish	TE_i^O				TE_i^I	AE_i^I	EE_i^I
Farm	MV	LB	UB	RG			
1	67.4	66.4	72.4	6.1	64.4	67.5	43.5

[16] Cross-price demand elasticities are zero for Cobb-Douglas technologies and the corresponding Allen-Uzawa partial elasticities of substitution are equal to one. On the other hand, the Morishima elasticties of substitution are zero.

2	85.7	82.3	89.7	7.4	81.2	77.9	63.3
3	83.3	80.1	87.1	7.0	80.3	79.6	64.0
4	65.7	62.3	68.5	6.2	57.7	82.6	47.7
5	66.3	63.1	69.5	6.4	64.7	82.7	53.6
6	67.9	65.4	69.9	4.5	62.4	86.2	53.8
7	87.4	86.6	89.7	3.1	83.3	65.6	54.6
8	65.6	64.5	66.9	2.3	59.2	88.4	52.3
9	99.5	97.2	100.0	2.8	93.5	90.4	84.5
10	75.9	72.3	81.0	8.6	69.0	74.7	51.6
11	78.4	75.3	80.4	5.1	73.5	72.5	53.2
12	99.4	95.6	100.0	4.4	94.5	96.5	91.2
13	86.9	85.4	88.0	2.5	82.3	69.3	57.0
14	77.7	72.3	81.2	8.9	72.2	96.1	69.5
15	78.3	75.7	80.5	4.8	73.5	86.5	63.6
16	79.6	74.5	82.8	8.2	75.7	56.2	42.5
17	58.8	54.2	61.2	7.0	51.2	67.1	34.4
18	59.3	52.3	66.5	14.2	55.7	89.4	49.8
19	97.1	94.3	99.9	5.7	93.6	94.7	88.6
20	75.3	71.2	79.4	8.2	72.9	67.1	48.9
21	98.2	96.6	100.0	3.4	93.5	78.3	73.2
22	89.3	81.3	94.3	13.0	84.4	75.1	63.3
23	87.6	83.5	91.2	7.8	83.5	93.3	77.9
24	82.3	77.4	84.6	7.2	79.5	81.8	65.0
25	75.8	71.2	79.4	8.1	71.2	73.8	52.6
26	98.7	92.5	100.0	7.5	89.4	73.2	65.5
27	85.6	80.3	89.4	9.1	83.5	47.8	39.9
28	57.6	55.6	59.3	3.7	48.7	84.9	41.3
29	58.6	53.2	62.7	9.5	51.2	86.5	44.3
30	65.9	61.2	70.2	9.0	62.3	89.1	55.6
Mean	78.5	74.8	81.5	6.7	73.6	79.2	58.3

Note: LB: lower bound; MV: mean value; UB: upper bound; RG: range.

The degree of technical efficiency indicates that the majority of fish farms in the sample operate below the efficient frontier. This may be due to the infant stage of the industry, which started its operation in the middle of the 1980s, and still more of the fish farms receive gains from learning-by-doing economies by using the existing state of technology. Although there has been no major breakthrough on the technology used, it seems that farmers are still adjusting themselves into the new cultural practices and techniques. Fish farms in the industry may gain a lot in terms of technical efficiency by reducing juveniles damages, improving know-how associated with growing conditions, and investing in new fish-cages.

Mean input allocative efficiency was found to be 79.2%, ranging from 47.8% to 96.5% (Table 5). In addition, the frequency distribution results show that around 73% of the sample farms achieved more than 77% of input allocative efficiency (Table 6). These results indicate that sample farms have achieved a relatively good allocation of existing resources and on average were reacting satisfactory to market price signals. Nevertheless, a 20.8% decrease in total cost of production is still feasible by a further reallocation of inputs for any given level of output and input prices. On the other hand, mean input allocative efficiency is by 5.6% higher than corresponding point estimate of input-oriented technical efficiency implying that on average fish farms did better in allocating existing resources than in achieving the maximum attainable output for given resources.[17]

Table 6 Frequency Distribution of Technical (Output- and Input-oriented), Input Allocative and Cost Efficiencies

Range (%)	TE_i^O	TE_i^I	AE_i^I	EE_i^I
<30	0	0	0	0
30-40	0	0	0	2
40-50	0	1	1	7
50-60	4	5	1	9
60-70	6	5	5	7
70-80	7	7	8	2
80-90	8	8	10	2
90-100	5	4	5	1
Mean	78.5	73.6	79.2	58.3
Minimum	52.5	41.0	47.8	33.4
Maximum	99.6	94.5	96.5	91.2
Std Deviation	13.1	13.6	11.8	14.3

Based on the input-oriented technical efficiency and input allocative efficiency estimates, mean cost efficiency is found to be around 58.3% (Tables 5). This figure represents the ratio of minimum to actual cost of production. It implies that significant cost savings (41.7%) may be achieved by eliminating both technical and allocative inefficiencies. From the above results it is clear that the largest portion of economic inefficiency is due to technical inefficiency. Cost efficiency of fish farms in the sample ranges from 33.4% to 91.2% (Table 5). The frequency distribution results show that only 17% of fish farms in the sample achieved more than 70% of economic efficiency (Table 6).

Potential cost savings at full economic efficiency by farm size are presented in Table 7.[18] According to our results, large farms (>200 tons) would be able to reduce their actual costs by 39.7%, medium sized farms (100-200 tons) by 41.8% and small farms (<100 tons) by 46.3% by operating at full technical and allocative efficiency levels. On average potential total cost savings are estimated to be 60.8 million drachmas per year, ranging from 44.4 to 102.7 million drachmas for small and large farms. However, potential total cost savings would in relative terms be greater for small (46.3%) rather than large farms (39.7%) indicating that large farms achieved higher efficiency scores. But in absolute terms potential total cost savings are much greater for large farms due to substantially higher production cost. Moreover, given that the degree of technical inefficiency found to be greater than that of allocative inefficiency (Table 5), operating at the full technical efficiency level accounts for a larger percentage of total cost reduction. These percentage figures are similar for small and medium farms but differ substantially for large farms.

Table 7 Potential Cost Savings for Fish Farms by Size

Farm Size	Actual	Potential Cost Reduction[1]

[17] Theoretically, only the comparison of input-oriented measures of technical and allocative efficiency is compatible. Any comparison between output-oriented technical efficiency and input-oriented allocative efficiency is meaningless.

[18] These estimates are obtained by multiplying actual cost by $(1-EE_i^I)$ and $(1-TE_i^I)$, and calculating residually the potential cost savings arising from eliminating input allocative inefficiency.

	Cost[1]	TE^I	AE^I	Total
Small (<100 tons)	96	23.8 (53.6)	20.6 (46.4)	44.4
Medium (100-200 tons)	152	33.2 (52.2)	30.4 (47.8)	63.6
Large (>200 tons)	259	65.2 (63.5)	37.4 (36.5)	102.7
All Farms	146	35.3 (58.1)	25.5 (41.9)	60.8

[1] in million drachmas.
In parentheses are the corresponding percentage values of total cost reduction.

Determinants of Efficiency Variation

Empirical results concerning the potential sources of efficiency differentials among sample farms are presented in Table 8. Farm size has a positive and significant effect on efficiency levels, which suggests that, on average, large farms operated at higher efficiency levels than small farms. In the presence of decreasing returns to scale, this suggests that large farms achieved higher efficiency scores through better monitoring of labor and to improved feeding and health management of juveniles. Specialization in either seabass or seabream production affects positively technical and cost efficiency but it does not seem to affect input allocative inefficiency as the related estimated parameters found to be statistically insignificant at the 5% level of significance. This in turn implies the dominance of efficiency over scope economies. On the other hand, utilization of skilled labor (scientists and technicians) does not seem to affect the input allocative and cost inefficiency in a statistically significant way. In contrast, skilled labor affects positively technical efficiency implying that know-how is dependent on workers' skill endowment.

Table 8 Parameter Estimates of the Second-Stage Regression of Input-Oriented Technical, Allocative and Economic Efficiencies on Farm-Specific Characteristics

Variable		TE_i^I	AE_i^I	EE_i^I
Constant	δ_0	4.543 (0.345)*	0.564 (0.099)*	2.321 (0.234)*
Farm Size	δ_1	0.088 (0.035)*	0.150 (0.066)**	0.104 (0.046)**
Specialization in Seabass	δ_2	0.098 (0.037)*	0.123 (0.148)	0.316 (0.101)*
» in Seabream	δ_3	0.134 (0.058)**	0.084 (0.071)	0.229 (0.088)*
Skilled labor units	δ_4	0.235 (0.134)**	0.342 (0.259)	0.144 (0.129)
$\overline{R}^2$		0.255	0.298	0.302

In parentheses are the corresponding standard errors.
* Significant at the 1% level; ** significant at the 5% level.

Concluding Remarks

The growth in supply of seabass and seabream has led to considerable decrease in market price since 1989 and producers have seen their profit margins declining even though average production cost has also been reduced. This is expected to continue, as supply will increase steadily to meet demand requirements. Thus gains in seabass and seabream production or potential cost savings stemming from improvements in efficiency would be important for the Greek industry in the light of increasing competition. The results of the present study suggest that there are still considerable cost savings that may be realized by improving efficiency; these are estimated to be around 42% on average and in relative terms are expected to be greater for small farms. Moreover, by eliminating technical inefficiency production may on average increase by 21.5% without altering the state of technology and inputs use. Thus there is still room for suppressing average cost to maintain previous profit margins.

According to our results, technical inefficiency seems to be the main source of inefficiency. Thus the larger portion of cost saving would be realized by improving existing know-how. This may be achieved by lowering food conversion ratio and by improving fish ongrowing conditions. The former is related to appropriate husbandry practices and adequate feeding methods (e.g., use of demand feeders). Improving fish ongrowing conditions, on the other hand, result in better surviving rate and in increased production. Surviving rate depends on fry quality, fish-cages and health management. Even though a lot of progress has been done in fry production by the establishment of domestic hatcheries and in fish-cages by the progressive replacement of exposed site cages with offshore cages, disease problems have significantly increased in recent years and still more effort is required on finding solutions to bacterial problems.

Our second-stage regression analysis identifies two main sources of improving technical inefficiency, namely specialization and utilization of skilled labor (i.e., scientists and technicians). The former implies that cost savings associated with product diversification tend to be outweighed by cost saving arising from removing inefficiencies. As a result farms specialized in either seabass or seabream production achieved higher efficiency scores and apparently have a larger margin to squeeze average cost. On the other hand, employing skilled instead of unskilled labor will in general result in better production management and consequently, in higher technical efficiency. Eventually the resulting extra labor cost would well be covered by increased revenue. The above results could be used (with some caution however due to data limitation problems) as a benchmark for improving competitiveness of Greek seabass and seabream farms.

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