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Distance vs. Ray Functions: An Application to the Inshore Fishery of Greece

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Abstract *The objective of this paper is to compare the empirical results from two alternative representations of a stochastic multi-output technology using trip-level data of the inshore fleet in Greece. The comparisons involve technical efficiency scores, structure of the underlying technology, and technical efficiency determinants. The stochastic multi-output distance function and the stochastic ray production function indicate the same technology structure, which is non-separable in inputs and outputs, non-homothetic in inputs, and exhibits increasing returns to scale. The relative rankings of efficiency scores are very similar. The distributions of efficiency scores, however, are different, and the ray production frontier yields systematically lower technical inefficiency levels than the multi-output distance function.*

Key words Distance function, ray production function, fisheries.

JEL Classification Codes D24, C13.

Introduction

Until recently, econometric studies of technical efficiency (TE) for multi-output technologies have either: (*a*) aggregated outputs into a single index (*e.g.*, Pascoe, Andersen, and de Wilde 2001; Sharma and Leung 1999) or (*b*) modeled the technology through a dual function (*e.g.*, Resti 2000; Bauer 1990). Both approaches have certain limitations. Aggregation of outputs assumes implicitly input-output separability that is not always compatible with the real-world data. Estimation of a dual (profit, cost, or revenue) frontier requires detailed information on output and/or input prices, as well as a behavioral postulate that is not necessarily valid.

Lovell *et al*. (1994) developed a multi-output generalization of the primal approach to measuring TE which involves direct estimation of a multi-output distance function. Lothgren (1997) and (2000a) proposed an alternative approach which relies on a Ray production function. The empirical applications of those recently developed tools are very few. Coelli and Perelman (2000) obtained TE estimates for European railways using a deterministic multi-output distance function. Morrison, Johnston, and Frengley (2000) applied a stochastic multi-output distance function to New Zealand sheep and beef farming sectors, while Lothgren (2000a) studied TE in Swedish hospitals through a stochastic ray production frontier.

The objective of this paper is to compare the empirical results from stochastic distance and stochastic ray production frontiers on a panel of observations/trips of

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inshore fishing vessels in Greece. Comparison of efficiency scores (absolute levels, distributions, and relative rankings) from different methods has been the topic of a number of works during the ’90s (*e.g.*, Sharma, Leung, and Zaleski 1997; Hjalmarsson, Kumbhakar, and Heshmati 1995; Neff, Garcia, and Nelson 1993). Earlier works compared efficiency estimates from approaches involving different estimation procedures (parametric vs. non parametric) and different assumptions about the frontier (deterministic vs. stochastic).[1] The present work is concerned with two parametric approaches under stochastic output variations. The only difference between the distance function and the ray production function approach lies in the way each econometrically handles the presence of multiple outputs. It would be certainly useful to find out whether this difference has an impact on the resulting technical efficiency estimates. Comparisons here include, in addition, the implied technology structures (input-output separability, homotheticity) and the implied technical efficiency determinants.

Multi-output generalizations of the primal approach are promising for empirical research on TE in fisheries. As pointed out by several authors (*e.g.*, Sharma and Leung 1999; Kirkley and Strand 1988; Wilen 1981; Carlson 1973) the economic behavior of fishermen is not well understood (there is no generally accepted microtheory decisionmaking by the fishing firm). Fishermen may harvest in accordance with different strategies, or they may be optimizing over several objectives. Things are further complicated by harvests of incidental species (bycatch). It is not very surprising, therefore, that most works that relied on revenue or profit maximization led to empirical results such as negative own-price supply elasticities, which are in striking contrast with the behavioral postulates (*e.g.*, Squires and Kirkley 1991; Dupont 1991; Kirkley and Strand 1988).

It is well recognized that the sustainable management of stocks and the efficient use of production inputs are both prerequisites for the maximization of the social benefits from the fishing industry. However, despite the methodological developments and the widespread use of alternative frontier approaches in assessing technical efficiency in many industries, the application of these methods to commercial fisheries is rather limited. This must be largely attributed to the fact that management authorities are typically more concerned with the biological aspects of fisheries resources rather than with the economic performance of fishermen. For example, while the fisheries management objectives in the EU involve resource conservation, maintenance of employment in the sector and the associated coastal communities, and improvement of economic performance, the last generally receives lower priority relative to the first two objectives (Holden 1994; Pascoe, Andersen, and de Wilde 2001). There are no previous studies on efficiency for the fisheries sector in Greece. Also, it appears that there are no published works on efficiency for the fishing fleets of other Mediterranean countries.

The paper is organized as follows: The second section contains the theoretical framework (stochastic distance and stochastic ray production functions), while the third section describes the data and the empirical models. The fourth section presents the empirical results. Conclusions and certain policy implications are offered in the final section. Full sets of parameter estimates are presented in the Appendix.

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[1] Multi-output parametric frontiers have not been considered in the relevant literature. Several authors have compared parametric single-output models with non-parametric (DEA) multi-output ones. The DEA method, however, is not appropriate for TE analysis in fisheries because it assumes a deterministic frontier. This misspecification results in a negative bias in TE scores which, as shown by Lothgren (2000b), carries over to the average efficiency estimates obtained by bootstrap.

Theoretical Framework

The Stochastic Distance Function Approach

Let y be a Mx1 vector of outputs, x a Kx1 vector of inputs, and $P(x)$ the output set describing the output combinations that are feasible for each $x \in R_+^K$. The output-oriented distance function, defined as:

$$D_o(x, y) = \min_{\mu} \{\mu : y/\mu \in P(x)\} \quad (1)$$

gives the minimum amount by which an output vector can be deflated and still remain producible with a given input vector. $D_0(x,y)$ is non-decreasing, positively linearly homogeneous and convex in y, and decreasing in x. It takes a value less than or equal to one for any output vector belonging to $P(x)$. In particular, it takes a value of one when y is located on the outer boundary of $P(x)$ (that is, when there is no technical inefficiency in production).[2]

The stochastic multi-output distance function model maybe written as:

$$1 = D_o(y_i, x_i) \cdot \exp(u_i - v_i) \quad (2)$$

where i stands for a firm, v_i are i.i.d $N(0, \sigma_v^2)$ distributed random errors, and $u_i \geq 0$ are the corresponding one-sided errors representing technical inefficiency (Kumbhakar and Lovell 2000; Morrison, Johnston, and Frengley 2000).

Relation (2) must be converted into an estimable regression model. This can be accomplished by exploiting the linear homogeneity property of D_0 according to which:

$$1 = y_{mi} D_o\left(\frac{y_i}{y_{mi}}, x_i\right) \exp(u_i - v_i) \Rightarrow \frac{1}{y_{mi}} = D_o\left(\frac{y_i}{y_{mi}}, x_i\right) \exp(u_i - v_i) \Rightarrow \quad (3)$$

$$\ln y_{mi} = -\ln D_0 + v_i - u_i$$

with $m \in M$.

The Stochastic Ray Production Function Approach

Key to the multi-output generalization of a single-output production function is the representation of the output vector in the polar-coordinate form:

$$y = \|y\| \omega(\theta), \quad (4)$$

where $||y||$ stands for the Euclidean norm of the output vector [defined as $||y|| = (\sum_{m=1}^{M} y_m^2)^{1/2}$], and $\omega(\theta)$ is a Mx1 vector:

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[2] A distance function may be specified with an input orientation as well. This study employs an output distance function because the main objective is to make comparisons with a ray production function that is output oriented. Relationships between output- and input-oriented distance functions are discussed in Kumbhakar and Lovell (2000) and Coelli, Prasada Rao, and Battese (1998). An output-oriented distance function has been employed by Grosskopf, Margaritis, and Valdmanis (1995) to estimate output substitutability in hospital services.

$$\omega_m(\theta) = \cos\theta_m \prod_{j=0}^{m-1} \sin\theta_j, \quad m = 1, 2, \ldots, M \tag{5}$$

that transforms the polar-coordinate angle vector $\theta \in [0, \pi/2]^{M-1}$ to the output mix vector $\omega(\theta) = y/\|y\|$ (Mardia, Kent, and Bibby 1979). The polar-coordinate angles, in turn, may be obtained recursively from the inverse transformation $\omega^{-1}(\theta)$ as:

$$\theta_m(y) = \cos^{-1}\left(\frac{y_m}{\|y\| \prod_{j=0}^{m-1} \sin\theta_j} \right), \quad m = 1, 2, \ldots, M. \tag{6}$$

The ray production function, denoted as $f(x_i, \theta_i)$, offers the maximum norm of the attainable outputs, given the inputs x and the polar-coordinate angles θ. The output-oriented distance function and the ray production function are related as:

$$D_o(y_i, x_i) = \frac{\|y_i\|}{f(x_i, \theta_i)} \tag{7}$$

from which follows:

$$\|y_i\| \leq f(x_i, \theta_i) \Leftrightarrow D_o(y_i, x_i) \leq 1. \tag{8}$$

The partial derivatives of the ray production function with respect to the polar-coordinate angles describe the response of the output norm when the output mix is changed along the production frontier, given the level of inputs. For a three-output technology, θ_1 represents the angle from the y_1 axis towards the plane spanned by the y_2 and y_3 axes, while θ_2 represents the angle between y_2 and y_3 in the $y_2 - y_3$ plane. Thus, the derivative $(\partial f/\partial\theta_1)$ represents changes in the output norm for changes in the output mix with fixed proportions between y_2 and y_3. In the same way, the derivative $(\partial f/\partial\theta_2)$ represents changes in the output norm due to changes in the output mix, with the level of y_1 held constant.

The stochastic ray production function may be written as:

$$\|y_i\| = f(x_i, \theta_i) \cdot \exp(v_i - u_i) \Leftrightarrow \ln\|y_i\| = \ln f(x_i, \theta_i) + (v_i - u_i). \tag{9}$$

The Data and Empirical Models

The inshore fleet consists of small, family-operated vessels making short trips close to the coasts of the mainland and of the islands of Greece. It contributes 43% of the volume and 51% of the harvest values and accounts for 70% of the total employment in the country's commercial fisheries (National Statistical Service of Greece 1998). The fleet vessels operate mainly as trammel netters, and to a lesser extent, small ring netters, long-liners, and gill netters. The present study relies on information from 690 trips of 44 vessels during May 2000 to April 2001. All sample vessels have home ports along the coasts of Northeastern Greece. The information was collected through in-person interviews with skippers.[3] In several cases, either the vessel did not go fishing at the time of the interview or the skipper was not available to respond. Hence, the resulting data set is unbalanced. This, however, poses no problem in TE analysis with a stochastic frontier (Battese and Coelli 1988, 1992). Unbalanced data sets have been used in all earlier empirical studies on TE in fisheries that relied on panel data.

The inshore fishery of Greece is a classic example of a multi-species one. As a matter of fact, harvests of more than 120 individual species were recorded during the survey period. For practical reasons (feasibility of estimation) and following the standard classification of harvests by the National Statistical Services of Greece, the individual species are aggregated into fish, crustaceans, and cephalopods.

Output possibilities frontiers in fisheries are generally depicted as functions of fishing effort and stock abundance (Cunninghum and Whitmarsh 1980; Hannesson 1983). In theory, fishing effort encapsulates all physical inputs used for harvesting (Conrad and Clark 1987). In empirical works, it is typically specified as a function of certain easily measurable production inputs. These, in this study, are fishing time, crew size, gear, and vessel size. The amount of gear deployed (length and altitude of the nets) and its characteristics (mesh size) are important determinants of potential yields and they vary from trip to trip, depending on the species targeted. As in Squires (1987) and Dupont (1991), gear is approximated by the market value of the nets deployed in each individual trip. Potential influence of the gear type on output is captured by including a dummy variable (trammel vs. other net) in the frontier. Vessel size reflects fishing capacity and constraints the areas and seasons of vessel operation. As in Pascoe and Robinson (1998) and Squires and Kirkley (1999), it is approximated by the deck area (the product of length and breadth). Stock abundance varies with time and poses a technological constraint which affects the relationship between fishing effort and harvests. As in Squires and Kirkley (1991, 1999), Segerson and Squires (1993), and Pascoe and Robinson (1998), the effects of changes in resource stocks over the year are captured by including three seasonal (quarterly) dummies as explanatory variables. The fourth quarterly dummy is dropped to avoid perfect collinearity. The use of seasonal dummies implies that stock dimension changes between seasons, but not during a season. An initial experimentation with monthly dummies yielded a number of dummy-related parameters which were not significant at conventional levels. The seasonal dummies in this case provide a more parsimonious representation of stock effects. Given that the two models involve exactly the same specification of the stocks effects, the comparison of the empirical results will not be affected.[4]

To allow for technical inefficiency effects, the one-sided error, u_i, is specified as a function of vessel and skipper characteristics. In particular,

$$u_i = \Phi(z_i) + w_i, \tag{10}$$

where z_i is a RX1 vector of factors affecting TE levels, and w_i are i.i.d random variables defined by the truncation of the normal distribution with mean zero and variance σ_w^2, so that at the point of truncation $w_i \geq -\Phi(z_i)$. The latter is consistent with u_i being a non-negative truncation of the $N(u_i, \sigma_w^2)$ distribution, with $\mu_i = \Phi(z_i)$.

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[3] A potential problem with in-person interviews is misreporting of catches and revenues. The inshore fishermen in Greece do not face output quotas, and their incentive for misreporting is limited. The interviews were conducted by marine biologists of the Fisheries Institute (located in Northeastern Greece). The fishermen in the sample have known the interviewers for several years. They trust them, and their responses are reliable.

[4] Kirkley, Squires, and Strand (1995, 1998) and Pascoe, Andersen, and de Wilde (2001) developed indexes of stock abundance from information collected through independent routine resource monitoring programs. Similar information is not available for the multi-species inshore fishery of Greece.

The present study considers four potential TE determinants. These are the age and the formal education of the skipper, and the HP and the GRT of the vessel. Since the inshore vessels in Greece use static gear, their propulsion power is not directly related to their fishing capacity. Larger HP, however, enables vessels to steam more safely and at higher speeds to (and between) the fishing grounds and, thus, it may influence their performance. As noted by Pascoe and Robinson (1998) the GRT, which provides an indication of the enclosed area on a boat, is a measure of vessel size alternative to that of the deck area (employed already as an argument in the production frontier).[5] The age and the formal education of the skipper are included to capture potential skipper-skill effects on TE.[6] Table 1 provides definitions and descriptive statistics of the variables used for the analysis.

Both the distance function and the ray production function are specified in the translog form which is flexible and accommodates easily the inclusion of the one-sided error to estimate TE for every trip/observation. The stochastic distance function with three outputs, four inputs, and three seasonal dummies(s) is:

$$0 = a_0 + \sum_{m=1}^{3} a_m \ln y_{mi} + 0.5\sum_{m=1}^{3}\sum_{l=1}^{3} a_{ml} \ln y_{mi} \ln y_{li} + \sum_{k=1}^{4} \beta_k \ln x_{ki} \tag{11}$$

$$+ 0.5\sum_{k=1}^{4}\sum_{g=1}^{4} \beta_{kg} \ln x_{ki} \ln x_{gi} + \sum_{k=1}^{4}\sum_{m=1}^{3} \delta_{km} \ln x_{ki} \ln y_{mi} + \sum_{p=1}^{3} \gamma_p s_p + \phi D + u_i - v_i$$

with the regularity conditions:

$$\sum_{m=1}^{3} a_m = 1, \ \sum_{l=1}^{3} a_{ml} = 0 \ (m = 1, 2, 3), \ \sum_{m=1}^{3} \delta_{km} = 0 \ (k = 1, 2, 3, 4) \tag{12α}$$

(homogeneity of degree + 1 in outputs), and

$$a_{ml} = a_{lm}(m, l = 1, 2, 3) \quad \text{and} \quad \beta_{kg} = \beta_{gk}(k, g = 1, 2, 3, 4) \tag{12β}$$

(symmetry).

Using the linear homogeneity condition, normalizing with y_1 and rearranging leads to:

$$\ln y_1 = -\left(a_0 + \sum_{m=2}^{3} a_m \ln y^*_{mi} + 0.5 * \sum_{m=2}^{3}\sum_{l=2}^{3} a_{ml} \ln y^*_{mi} \ln y^*_{li} + \sum_{k=1}^{4} \beta_k \ln x_{ki} \right. \tag{13}$$

$$\left. + \sum_{k=1}^{4}\sum_{g=1}^{4} \beta_{kg} \ln x_{ki} \ln x_{gi} + \sum_{k=1}^{4}\sum_{m=2}^{3} \delta_{km} \ln x_{ki} \ln y^*_{mi} + \sum_{p=1}^{3} \gamma_p s_p + \phi D \right) + v_i - u_i,$$

where $y^*_{mi} = y_m/y_1$ ($m = 2, 3$).

The general translog multi-output distance function encompasses a number of alternative technologies as special cases. A technology exhibits weak input-output

[5] The correlation coefficient between GRT and deck area in the sample is 0.83.

[6] As noted by Squires and Kirkley (1999) and Kirkley, Squires, and Strand (1998), "skipper skill" is a rather complex concept which relates to information gathering and utilization, managing and supervising the crew, responding to changes in weather conditions and resource abundance, and minimizing risk and uncertainty. Because of its complexity, it can only be partially measured in terms of basic personal characteristics.

Table 1
Definitions and Descriptive Statistics of the Variables Used for the Analysis

Variables	Description	Statistics Mean	SD
Stochastic Distance Function and Stochastic Ray Production Function			
Outputs			
Fish (y_1)	In kg	18.255	39.368
Cephalopods (y_2)	In kg	9.14	24.374
Crustaceans (y_3)	In kg	2.736	6.554
Eucledian norm of outputs ($\|y\|$)	In kg	27.003	43.377
Production Inputs			
Fishing time (x_1)	In hours	13.991	10.472
Crew size (x_2)	In number of persons	1.875	0.873
Gear (x_3)	In 1,000 Greek drachmas*	1,179.3	1,393.8
Vessel size (deck area) (x_4)	In m^2	30.583	15.116
Polar Coordinate Angles			
y_1 towards the plane $y_2 - y_3$ (θ_1)	In radians	0.676	0.676
Betw. y_2 and y_3 in the plane $y_2 - y_3$ (θ_2)	In radians	0.715	0.621
Seasonal Dummies (s_1, s_2, s_3)	Dichotomous		
Gear Type (D)	Dichotomous, with value 1 when trammel nets are used, and 0 otherwise	0.764	na
Inefficiency Model			
HP (z_1)	In kw	96.089	73.058
GRT (z_2)	In metric tons	5.572	4.783
Skipper Formal Education (z_3)	Dichotomous, with value 1 when skipper has either primary or some secondary education, and 0 otherwise	0.783	na
Skipper Age (z_4)	In years	47.588	11.042

Note: *1 EURO = 340.75 Greek drachmas

separability when the marginal rates of technical substitution between (outputs) inputs are independent of input (output) levels.[7] The existence of weak separability allows aggregation of inputs into a single index (fishing effort), since under this technology structure one may meaningfully rank alternative effort levels (represented by

[7] Strong separability is a more restrictive form and requires the marginal rates of substitution between variables of different groups be independent of the levels of variables in any other group. Here, there are only two groups (inputs and outputs); thus, weak separability is equivalent to strong separability.

isoquants) without knowing the levels and the mixes of the individual species harvested. In the same way, it allows aggregation of outputs into a single index (total harvest), since one may meaningfully rank alternative total harvest levels without knowing the levels and the mixes of individual inputs. For the multi-output distance function, weak input-output separability requires:

$$\delta_{km} = 0 \ (k = 1, 2, 3, 4) \quad \text{and} \quad (m = 2, 3). \tag{14}$$

A technology is input homothetic when the expansion paths of inputs are rays emanating from the origin. Homotheticity requires:

$$\sum_{g=1}^{4} \beta_{kg} = 0 \ (k = 1, 2, 3, 4). \tag{15}$$

Input-output separability along with input homotheticity implies the existence of consistent quantity and price indexes so that the product of the aggregate price and quantity equals the total cost of the components of effort (or the total revenue of the components of harvests). Linear homogeneity in inputs (homogeneity of degree –1) requires, in addition to equation (15),

$$\sum_{k=1}^{4} \beta_k = -1 \quad \text{and} \quad \sum_{k=1}^{4} \delta_{km} = 0 \ (m = 2, 3). \tag{16}$$

The *k*th production elasticity is defined as:

$$E_k = -\partial \ln D / \partial \ln x_k \tag{17}$$

and because of equation (13) it becomes:

$$E_k = \beta_k + \sum_{g=1}^{4} \beta_{kg} \ln x_{gi} + \sum_{m=2}^{3} \delta_{km} y^*_{mi}. \tag{18}$$

It is the proportional increase in y_1 due to 1% increase in x_k. However, for the calculation of E_k, output mixes are held constant. Therefore, the production elasticity is the proportional increase in all outputs caused by 1% increase in the *k*th input (Morrison, Johnston, and Frengley 2000). The scale elasticity is the sum of the individual production elasticities.

The translog stochastic ray production frontier is:

$$\ln\|y_i\| = \beta_0 + \sum_{k=1}^{4} \beta_k \ln x_{ki} + \sum_{m=1}^{2} b_m \theta_{mi} + 0.5 \sum_{k=1}^{4} \sum_{l=1}^{4} \beta_{kl} \ln x_{ki} \ln x_{li} \tag{19}$$

$$+ \sum_{k=1}^{4} \sum_{m=1}^{2} \rho_{km} \ln x_{ki} \theta_{mi} + 0.5 \sum_{m=1}^{2} \sum_{n=1}^{2} \omega_{mn} \theta_{mi} \theta_{ni} + \sum_{p=1}^{3} \gamma_p s_p + \phi D + v_i - u_i$$

with the symmetry restrictions $\beta_{kl} = \beta_{lk}$ $(k,l = 1,2,3,4)$ and $\omega_{mn} = \omega_{nm}$ $(m,n = 1,2)$.

Since the polar-coordinate angles depend on output mixes, weak input-output separability for equation (19) requires:

$$\rho_{km} = 0 \quad (k = 1, 2, 3, 4) \quad \text{and} \quad (m = 1,\ 2). \tag{20}$$

Homotheticity requires:

$$\sum_{l=1}^{4} \beta_{kl} = 0 \quad (k = 1, 2, 3, 4), \tag{21}$$

while linear homogeneity requires [in addition to equation (21)]

$$\sum_{k=1}^{4} \beta_k = 1 \quad \text{and} \quad \sum_{k=1}^{4} \rho_{km} = 0\ (m = 1, 2). \tag{22}$$

The production elasticity with respect to *k*th input is:

$$E_k = \partial \ln\left(\|y\|\right) / \partial \ln x_k \tag{23}$$

and gives the proportional increase in all outputs induced by a 1% increase in that input.

The distance function and the ray production function have been estimated along with the inefficiency model:

$$u_i = \delta_0 + \sum_{r=1}^{4} \delta_r z_{ir} + w_i \tag{24}$$

by maximum likelihood in one-stage using the econometric package FRONTIER 4.1 (Coelli 1996). Prior to estimation, all variables (expect dichotomous) are normalized around the sample mean to define the point of technology approximation (Huang and Liu 1994). In several observations (trips), the harvested quantities of one or two species are zero. To make logarithmic transformations feasible, those zeros have been replaced by the very small positive number 0.0001.[8]

Empirical Results

Appendix tables A.1 and A.2 provide parameter estimates. A barrage of Generalized Likelihood Ration Tests (LRT) follows to shed some light on the structure of production technology and the nature of technical inefficiency as implied by the two models.[9] Table 2 presents the LRT results on technology structure for the distance and ray functions. The null hypothesis of weak input-output separability is rejected in both cases. Therefore, the two alternative models suggest that it is not possible to

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[8] This practice is very common in fisheries analysis with trip level data (*e.g.*, Squires 1987; Kirkley and Strand 1988).

[9] The test statistic $\lambda = -2[\ln L(H_0) - L(H_1)]$, where $L(H_1)$ and $L(H_0)$ are the log-likelihood values under the alternative and the null hypothesis, respectively, follows the chi-squared distribution with degrees of freedom equal to the number of restrictions imposed.

Table 2
Tests on Technology Structure

Null Hypothesis	Distance Function Test Statistic	Ray Function Test Statistic	Degrees of Freedom	Theoretical Value (5% level)
Weak input-output separability	44.642	59.752	8	15.507
Linear homogeneity	63.986	74.632	7	14.067
Homotheticity	10.714	19.774	4	9.486

construct composite indexes for harvests and effort. The null hypothesis of input homotheticity is also rejected in both cases, implying that input mixes change with the level of harvests. So is the null hypothesis of homogeneity of degree –1 in inputs, suggesting that returns to scale in the fleet of inshore vessels in Greece are not constant. Indeed, the scale elasticities at the point of technology approximation (these are the sums of the first order input coefficients) are substantially higher than unity (1.86 for the distance function and 2.03 for the ray production function). According to the empirical results, therefore, vessels in the fleet operate under increasing returns to scale.

To the best of my knowledge, there has been only one empirical study on input-output separability in fisheries. That was by Squires (1987) for otter trawlers in New England, where input-output separability was not rejected. That earlier evidence, however, should be interpreted with caution, since the technology in Squire's study turned out to be of a Cobb-Douglas form (implying that all interaction terms are zero). It is well known (*e.g.*, Coelli and Perelman 2000) that a Cobb-Douglas technology is not acceptable for multi-product firms operating in pure competitive industries (like fisheries) because it fails to satisfy the requirement of concavity in the output dimensions.[10]

Scale elasticities that were substantially higher than unity have been reported in Kirkley, Squires, and Strand (1995, 1998), Pascoe and Robinson (1998), Pascoe, Andersen, and de Wilde (2001), Sharma and Leung (1999), and Squires and Kirkley (1999). The economic theory suggests that operation in a sub-optimal (increasing returns) or super-optimal scale (decreasing returns) gives rise to scale inefficiency which manifests itself in the form of low productivity levels.[11] The empirical finding of increasing returns, therefore, implies that the inshore vessels in Greece may experience short-run productivity gains by increasing the levels of inputs and harvests. This appears to be quite reasonable, given that the fleet consists of rather small vessels (table 1). In the longer-run, however, these productivity gains may disappear because of the negative impact of additional harvests on resource stocks.

Although the two alternative models agree on the general technology structure (separability, homotheticity, and homogeneity), they exhibit certain differences with regard to individual parameters. For example, the production elasticity with respect to fishing time for the distance function is 0.4, while for the ray production function

[10] Here, the Cobb-Douglas form (element-wise separability) is strongly rejected for both models. The empirical values of the LRT statistics are 520.412 and 141.326 for the distance and the ray production function, respectively, which exceeded, by far, the theoretical value of 32.671 (with 21 degrees of freedom at the 5% level).

[11] The productivity of all inputs taken together is maximized where constant returns to scale prevail (Cooper, Seiford, and Tone 2000).

model it is 0.73. Similar differences can be observed for the remaining inputs as well. The limiting factor (that is, the factor with the highest production elasticity) for the distance function is gear, while for the ray production function, it is fishing time. The differences in production elasticities are certainly important for designing policies aimed at reducing harvests through individual input controls.

Turning now to the nature of technical inefficiency, three hypotheses are relevant: first, technical inefficiency is absent; second, technical inefficiency is not stochastic; and third, technical inefficiency does not depend on vessel and skipper characteristics. The first hypothesis requires $\gamma = \delta_0 = \delta_1 = \delta_2 = \delta_3 = \delta_4$, where:

$$\gamma = \frac{\sigma_u^2}{\sigma_w^2 + \sigma_u^2} = \frac{\sigma_u^2}{\sigma^2}$$

is the proportion of the total output variability attributed to technical inefficiency. The second hypothesis requires $\gamma = 0$, while the third $\delta_1 = \delta_2 = \delta_3 = \delta_4 = 0$.

Table 3 presents LRT tests on the nature of inefficiency. Both models agree that stochastic technical inefficiency is present and that the skipper and vessel characteristics considered in the present study do influence TE levels. On the basis of the distance function, variations in TE explain 20% of output variations, while on the basis of the ray production function, they explain only 0.8%. Despite the difference in this respect, both models suggest that stochastic output variability is dominated by uncontrollable random shocks (*e.g.*, those related to resource abundance or weather conditions) rather than by stochastic variations in TE.

In an empirical analysis, the relative importance of the two sources of stochastic output variability is likely to depend on the data used. Aggregation of data over a monthly or yearly time period may smooth out some of the day-to-day random fluctuations and, as a result, increase the relative importance of stochastic variations in TE. Pascoe, Andersen, and de Wilde (2001) and Sharma and Leung (1999) employed aggregated data and found that stochastic variations in TE were more important than uncontrollable random shocks. Kirkley, Squires, and Strand (1995, 1998) employed trip-level data and reached the same conclusion. They, however, noted that their result was quite surprising, since in a fishery the uncontrollable random shocks are *a priori* expected to dominate stochastic variations in TE.

The coefficients of the *z* variables in the inefficiency model have the same signs and, in most cases, are significant at similar levels. Positive (negative) signs of parameters in the inefficiency model imply negative (positive) effects of the respective

Table 3
Tests on the Nature of Technical Inefficiency

Null Hypothesis	Distance Function Test Statistic	Ray Function Test Statistic	Degrees of Freedom	Theoretical Value (5% level)
Technical inefficiency is absent	19.700	25.647	6	11.911
Technical inefficiency is deterministic	8.612	9.462	2	5.138
Skipper and vessel characteristics do not affect TE	15.690	18.352	4	9.486

Note: Because in the first and the second hypotheses γ lies at the boundary of the parameter space, the relevant theoretical values come from Kodde and Palm (1986).

factors on TE. It appears that higher propulsion power raises TE. The GRT (proxy for size), however, has a negative impact. In Sharma and Leung (1999), size was proxied by vessel length and found to have a positive impact. So it was found in Pascoe, Andersen, and de Wilde (2001), where size was proxied by the number of crew members. Using Kruskal-Wallis tests on equality of means, Kirkley, Squires, and Strand (1995) could not reject the null hypothesis that TE is invariant to crew size. Kirkley, Squires, and Strand (1995) argue (without offering empirical evidence) that there may be a negative relationship between TE and production inputs which are difficult to adjust. Such a least adjustable input is the GRT, which remains the same from trip to trip and for low and high harvests.[12] Younger skippers with higher formal education appear to attain higher levels of TE than older with lower formal education.

The multi-output distance function model and the ray production function model are used to obtain technical efficiency estimates per trip. Figure 1 presents the distributions of the efficiency scores. Regarding the multi-output distance function, the TE estimates are distributed with a mean 0.806, a standard deviation of 0.12, a median of 0.839, a maximum of 0.946, and a minimum of 0.347. In 16.3% of the trips, the TE scores are less than or equal to 0.7. In 63.3%, they lie in the interval (0.7-0.9), while in 20.1%, they are above 0.9. Regarding the ray production function, the TE estimates are distributed with a mean of 0.853, a standard deviation of 0.123, a median of 0.855, a maximum of 1, and a minimum 0.552. In 14.2% of the trips, the TE scores are less than or equal to 0.7. In 41.3%, they lie in the interval (0.7-0.9), while in 44.6%, they are above 0.9. The Pearson and Spearman rank correlation coefficients are very high (0.865 and 0.902, respectively) and statistically significant at any reasonable level, suggesting that the two models lead to very similar relative efficiency rankings.

Given that for the ray production function the efficiency score exceeds 0.9 in nearly one out of two trips, while for the distance function this occurs in only one out of five trips, it is interesting to test formally whether the scores suggested by the two alternative models come from the same distribution. To this end, the present study utilizes the non-parametric Rank-Sum test statistic (Cooper, Seiford, and Tone 2000):

$$T = \frac{R_D - n(2n+1)/2}{\sqrt{n^2(2n+1)/12}} \tag{25}$$

that follows approximately the standard normal distribution, with R_D being the sum of rankings corresponding to the distance function model. The empirical value of the test statistic is –17.77, implying that the efficiency scores come from different distributions and, in particular, that the scores of the distance function model are systematically lower that those from the ray production function model.

As mentioned in the Introduction, the two approaches differ only in the way each econometrically handles the presence of multiple inputs. Therefore, the observed differences in the results must be attributed exclusively to specification; that is, to the fact that the dependent variables and a subset of the independent variables (those related to the output mix) in the two models are not the same.

The average rates of TE suggested by the two models are very similar to 0.85 reported by Sharma and Leung (1999) for the long-line fishery in Hawaii, but they are higher than 0.75 obtained by Kirkley, Squires, and Strand (1995, 1998) for the

[12] The same result is obtained if deck is used in place of GRT.

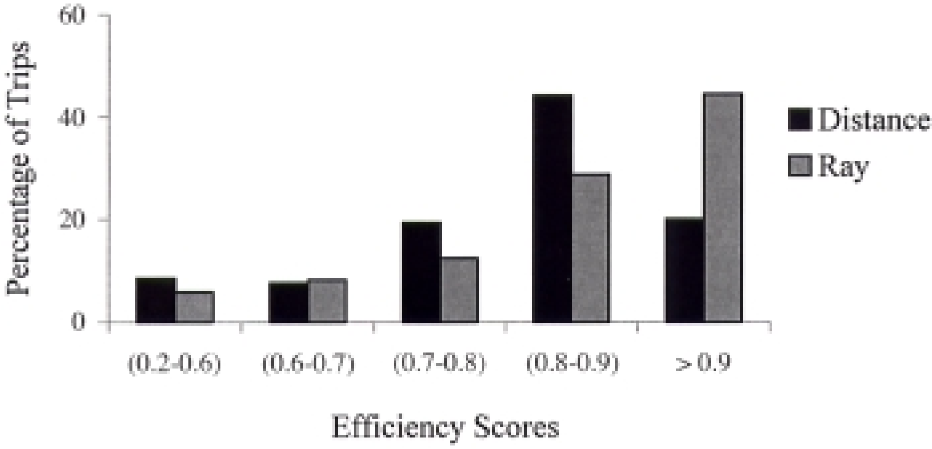

Figure 1. Distributions of Efficiency Scores per Trip from the two Models

mid-Atlantic sea scallop fishery. Pascoe, Andersen, and de Wilde (2001) report TE scores in the range 0.65 to 0.82 for Dutch trawlers.

Conclusions

Comparisons of efficiency scores obtained from different approaches have been an important research topic during the last ten years. None of the earlier works, however, considered multi-output parametric frontiers that are the most relevant for fisheries economics research. In this paper, a stochastic multi-output distance function and a stochastic ray production function are applied to trip-level data from the inshore fleet of Greece. According to the empirical results:

(*a*) Both models suggest that the assumptions of weak input-output separability, input homotheticity, and constant returns to scale are not compatible with the real-world data. Rejection of weak input-output separability, in particular, indicates that public regulation relying on concepts, such as total catch and total effort, is likely to be ineffective.

(*b*) Although the two models agree on the general technology structure, they disagree on the magnitudes of certain parameters (mainly production elasticities), which are relevant for policies aiming at reduction of harvests through individual input controls.

(*c*) The multi-output distance function and the ray production function lead to similar relative rankings of the efficiency scores. The distributions of efficiency scores, however, are different since the ray production function yields systematically lower inefficiency levels than the distance function.

(*d*) The formal education of skippers has a positive impact on TE, while age has a negative impact. Greece (in the context of the 3rd Community Support Framework-

CSF) is contemplating an early retirement program for fishermen over 55 years old. It appears that such a program is likely raise technical efficiency for inshore vessels. Its effect will be stronger if the older fishermen are succeeded by younger ones who have typically higher levels of formal education.

(*e*) Propulsion power has a positive impact on TE. Since 1986, the structural policy of the EU with respect to the fisheries sector has been implemented through the Multi-Annual Guidance Programs (MAGPs). Early MAGPs provided financial assistance for renovation/reconstruction of inshore vessels in Greece, without placing restrictions on propulsion power. It appears, therefore, that the inshore fleet has benefited from those policies. The 4th MAGP places restrictions on HP and GRT and provides incentives for withdrawal/decommissioning of inshore vessels of 12 meters or more in length. Vessel size (measured here in terms of GRT) appears to be negatively related to TE. This, however, does not necessarily imply that restrictions on vessel size will enhance the fleet's performance. The reason is that any positive impact of such policy on TE will be, at least partially, offset by additional scale inefficiency (the vessels already too small). Moreover, with vessel size restricted, the only way fishing effort can be increased is through employing higher quantities of the remaining inputs. The latter may give rise to economic inefficiency by inducing non-optimal input mixes, thus deteriorating the economic performance of the fleet (Squires 1987).

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Appendix

Table A.1
Stochastic Distance Function

Parameter	Estimate	Standard Error	Parameter	Estimate	Standard Error
a_0	0.766	0.190	a_{22}	–0.059	0.003
β_1	0.398	0.121	a_{23}	0.013	0.002
β_2	0.269	0.145	a_{33}	–0.059	0.003
β_3	0.805	0.115	δ_{12}	0.062	0.017
β_4	0.382	0.174	δ_{13}	–0.035	0.013
a_2	–0.297	0.012	δ_{22}	–0.057	0.022
a_3	–0.299	0.012	δ_{23}	–0.081	0.024
β_{11}	–0.037	0.084	δ_{32}	0.022	0.017
β_{12}	0.099	0.152	δ_{33}	0.032	0.015
β_{13}	0.121	0.075	δ_{42}	0.01	0.025
β_{14}	0.013	0.137	δ_{43}	0.031	0.022
β_{22}	1.698	0.668	γ_1	–0.012	0.133
β_{23}	–0.313	0.244	γ_2	–0.381	0.141
β_{24}	–0.398	0.468	γ_3	–0.181	0.134
β_{33}	–0.147	0.163	ϕ	0.152	0.130
β_{34}	0.355	0.219	σ^2	1.113	0.085
β_{44}	0.533	0.516	γ	0.207	0.074
Inefficiency Model					
δ_0	–4.411	1.165	δ_3	0.806	0.366
δ_1	–1.955	0.728	δ_4	2.915	1.009
δ_2	1.811	0.644			

Table A.2

Stochastic Ray Production Function

Parameter	Estimate	Standard Error	Parameter	Estimate	Standard Error
β_0	–0.535	0.127	ρ_{11}	0.067	0.014
β_1	0.727	0.112	ρ_{12}	0.072	0.014
β_2	0.539	0.121	ρ_{21}	–0.021	0.024
β_3	0.535	0.092	ρ_{22}	–0.0004	0.021
β_4	0.232	0.181	ρ_{31}	0.042	0.016
b_1	0.056	0.038	ρ_{32}	0.026	0.015
b_2	0.245	0.039	ρ_{41}	–0.018	0.026
β_{11}	0.032	0.061	ρ_{42}	0.01	0.022
β_{12}	0.138	0.112	ω_{11}	0.029	0.008
β_{13}	0.097	0.054	ω_{12}	0.038	0.008
β_{14}	0.043	0.103	ω_{22}	0.072	0.008
β_{22}	0.616	0.422	γ_1	–0.286	0.097
β_{23}	–0.328	0.173	γ_2	–0.466	0.102
β_{24}	0.098	0.312	γ_3	–0.291	0.099
β_{33}	0.021	0.114	ϕ	–0.003	0.096
β_{34}	0.175	0.154	σ^2	0.462	0.026
β_{44}	0.573	0.396	γ	0.0084	0.0025
Inefficiency Model					
δ_0	–0.795	0.092	δ_3	0.346	0.063
δ_1	–0.337	0.089	δ_4	0.574	0.175
δ_2	0.386	0.071			