Marine Resource Economics, Volume 20, pp. 163–184
Printed in the U.S.A. All rights reserved

0738-1360/00 $3.00 + .00

The Inclusion of Stocks in Multi-species Fisheries: The Case of Danish Seiners

JESPER LEVRING ANDERSEN
Food and Resource Economics Institute

Abstract *Efficiency analysis in fisheries has become an area of increased research. However, setting up models to perform such analyses is complicated and several important modeling issues, including choice of inputs and outputs, level of aggregation and inclusion of stock indices, have only briefly been addressed in the literature. The latter issue is addressed in this paper, using data on Danish seiners and Data Envelopment Analysis (DEA) to estimate efficiency. Production in fisheries is obviously dependent on the fish stocks, and comparing vessel efficiency, therefore, needs to account for stock developments. Three methods to include fish stocks are analyzed. It is shown that estimations based on the Catch Per Unit Effort (CPUE) stock measure differ from the estimations based on independent stock measures, and are independent of the choice of time horizon and choice of input/output measures.*

Key words Data Envelopment Analysis, fish stock, multi-species fisheries, technical efficiency.

JEL Classification Code Q22.

Introduction

Traditionally, estimated production functions only include controllable (discretionary) input factors; *i.e.*, factors that the producers can influence directly through their behavior (Alvarez 2001). For some sectors in the economy, however, it is necessary to include non-controllable factors as well. In particular, this is the case where there are considerable variations in the conditions experienced by the producers across time, space, and production unit. The fishing industry is one such sector.

The early seminal articles within fisheries economics recognized the importance of considering fish stocks (Gordon 1954; Schaefer 1957; and Clark 1973a,b). Fishermen's catches are highly dependent on the availability of fish in the respective fishing areas. If the stocks are low, a given effort will result in a lower catch in contrast to a situation with high fish stocks. Excluding fish stocks from production and efficiency analysis will, therefore, provide misleading results.

Different methods to include fish stocks in production functions have been suggested. However, there is no consensus about which method to use. This is due to several reasons. One is the type of fishery analyzed; *e.g.*, single- or multi-species

Jesper Levring Andersen is an assistant professor at the Food and Resource Economics Institute, Rolighedsvej 25, 1958 Frederiksberg C, Copenhagen, Denmark, email: jla@foi.dk.

The research was supported by the Centre of Fisheries and Aquaculture, Management and Economics (FAME) financed by the Danish Ministry for Food, Agriculture, and Fisheries and the Danish Agricultural and Veterinary Research Council. Comments by professor Peter Bogetoft and Erik Lindebo from the Danish Research Institute of Food Economics, affiliated to the Danish Royal Veterinary and Agricultural University, and three anonymous referees are gratefully appreciated.

fishery. Another is describing the state of the fish stock; *e.g.*, are independent stock measures available or not?

It is important to investigate whether different methods of stock inclusion give different results, because the analysis can have a significant influence on management recommendations. For example, if a "wrong" instead of a "right" method for stock inclusion is used, the choice of regulation may be inappropriate and give rise to social losses. Webster, Kennedy, and Johnson (1998, p. 3) recommend with reference to Valdmanis (1992) and Nunamaker (1985) to "*run a number of different models from each dataset and evaluate the sensitivity of the results to changes in model specification.*"

The purpose of this paper is to analyze methods which include fish stock measures when estimating technical efficiency. The three methods investigated are: (*i*) inclusion of a stock index for each primary species based on Catch Per Unit Effort (CPUE); (*ii*) inclusion of one stock index obtained from independent stock assessments for each of the primary species; and (*iii*) inclusion of one composite stock index for each observation based on the independent stock measures and the relative importance of the primary species.

The analysis is based on data for Danish seiners between 18 and 24 meters in length for the years 1995 to 1999. The results of using different measures will be tested for consistency, and whether the conclusions depend on the time horizon being short or long run will be analyzed. The three consistency tests presented in Bauer *et al.* (1998) are adopted. These tests investigate the following questions: (*i*) Are similar means and standard deviations observed? (*ii*) Do the vessels obtain the same ranking? and (*iii*) Are the same vessels classified as "best" and "worst"?

The paper is organized as follows: The first section discusses different methods for including stocks in fisheries production analysis. The following section briefly introduces the utilized estimation method. Based upon the two previous sections, three methods for stock inclusion are identified, and each method is presented in the third section, which also includes a general formulation of the programming problem to be estimated. The data used in the analysis are described in the fourth section, and the results are presented in the fifth section. The paper closes with a conclusion and a discussion of topics for future research.

Inclusion of Fish Stocks in Production Analysis

When a fishery is characterized as operating under changing or unequal resource conditions, it is necessary to consider this when performing production analysis (Morrison 2000). In such situations, the lack of including stock measures in the analysis will assign any resource effects to inefficiency and give a wrong impression of the level of technical efficiency. The consequence can, for instance, be that management decisions are made on an incorrect basis, leading to the regulation of a specific fishery that is not optimal.

Reasons for considering variations in resource conditions can be due to changes over time, between fishing areas, and/or between vessels. Changing resource conditions over time and/or fishing areas may be relevant in both single-species and multi-species fisheries. In these situations, inclusion of fish stock measures are important to ensure that vessels fishing in periods or areas with low fish stocks are not disfavored when compared to vessels fishing in another period or area with higher fish stocks.

It is generally not necessary to consider changing resource conditions between vessels if the analysis is performed on cross-sectional data for a single-species fishery, because the resource conditions are equal for all vessels. An example is Bjørndal (1989), who estimates production functions for the North Sea herring fishery. However, if the analyzed fishery is characterized by multi-species with vessels targeting different species, it is important to account for different resource conditions between the vessels.[1] In this situation, the species caught may have a different relative importance for each vessel. If the technical efficiency scores between the included vessels are to be compared, it is necessary to account for this by including some measure of fish stock in the estimations. This applies whether cross-sectional or panel data for a multi-species fishery are used.

During the last decades, several methods have been used to include fish stock measures in production analysis. The optimal situation would be to have an independent stock measure for each vessel for every period and area. However, such measures are almost impossible to obtain at reasonable costs. Other methods have been used in the literature, and these will briefly be presented and discussed. An important aspect in choosing a method is the accessibility of possible independent stock measures.[2] If such estimates are available in the form of biological assessments of fish stocks, these can often be applied.

Consider first a fishery without the availability of independent fish stock measures. Technical efficiency analysis of such fisheries is possible despite this lack of information. Several methods have been suggested in the literature to account for this.

One method is to use dummy variables as a method to consider stock fluctuations. For instance, Pascoe and Robinson (1998) and Coglan, Pascoe, and Mardle (1998) analyzed the multi-species fishery in the English Channel using dummy variables for years, months, and métiers (area) to account for any stock effects. Campbell and Hand (1998) also use this approach to analyze the Solomon Islands pole-and-line fishery. A dataset covering two years is used to analyze the New England otter trawl fleet by Squires (1987), and stock changes are accounted for by including one dummy variable in the analysis. Kompas and Nhu (2002) do not apply available independent stock measures, and argue that weather dummies can account for important stock variations in the Australian northern prawn fishery. However, the inclusion of dummies to account for stock effects is not without problems, because it can result in a significant loss of degrees of freedom.[3] This depends on the number of fishing areas, time periods, and fishing vessels.

There are also examples of analyses where CPUE is used as a measure of fish availability. Comitini and Huang (1967) use "catch per skate" as a measure of stock density in the North Pacific halibut fishery. Eggert (2001) analyses the Swedish trawl fishery for Norway lobster and uses the overall average landings value as a proxy of stock availability. Analyzing demersal trawlers in the English Channel, Pascoe and Coglan (2002) use average catch value per hour fished. However, the use of CPUE as a measure of stock abundance is not straightforward. It depends on other inputs used in the production, as mentioned by Sharma and Leung (1998). The

---

[1] If vessels target only one species in a multi-species fishery with bycatch of other less important species, the analysis can be treated as a single-species fishery, depending on the specific fishery. However, if comparison across time or areas is required, it is still necessary to include a stock index for the target species.

[2] Stock measures can be considered independent if they are calculated without being directly related to the analysed fishery.

[3] The loss of freedom is especially important when SPF is used. DEA can be performed with dummy variables by dividing data into groups using categorical DMUs (see Cooper, Seiford, and Tone [2000]). This approach, however, demands an ability to compare every area and period in order to make a hierarchy.

measure can also reflect a change in vessel composition of the specific place and point in time.

Richards and Schnute (1986) test whether there is any correlation between CPUE and availability of fish. They find that this measure is not preferable when based on data from commercial fishery statistics, at least not when analyzing the inshore rockfish fishery in the Strait of Georgia in British Columbia. Based on data from the International Council for the Exploration of the Sea (ICES), Harley, Myers, and Dunn (2001) compare CPUE with independent stock abundance data. They find that there does not seem to be proportionality between stock and CPUE for three groups of fish; *i.e.*, cod, flatfish, and gadiformes. Hilborn and Walters (1992) discuss why different aspects of fishermen's behavior will cause CPUE not to be proportional to abundance. As mentioned by Pascoe and Herrero (2004), a problem of using the CPUE approach is that an implicit assumption is made about constant returns to scale between fish stock and effort.

If independent stock measures are available, the fish stock can be considered as natural capital in line with man-made capital in classic production theory. Several types of stock estimates have been applied in the literature, and some collect these for the specific analysis. Others seek to estimate these and some use stock information obtained from organizations delivering biological assessments. ICES and the Inter-American Tropical Tuna Commission (IATTC) are examples of such organizations.

Kirkley, Squires, and Strand (1995, 1998) analyze the single-species sea scallop fishery in the Mid-Atlantic. As a measure of abundance, supposedly bias-free samples are obtained using the last tow of approximately 50 vessels. This method is based on individually collected data. Pascoe and Herrero (2004) estimate abundance indicators for the Spanish octopus fishery in the South Atlantic region and use them to modify the dependent variable.

Several articles use independent stock estimates published by biological institutions. Hanneson (1983) uses ICES biomass assessments to estimate production functions in the Norwegian Lofoten fishery. Eide *et al.* (1998) use the same approach when analyzing the Norwegian bottom trawlers fishing for northeast Arctic cod, using total yearly biomass. An independent measure of tuna stock abundance is also used by Cabrera-Muro (2002) in an analysis of the Mexican tuna fishery from 1992 to 1995. Grafton, Squires, and Fox (2000) look at the British Colombia halibut fishery. They obtain yearly data on the weight of the total available halibut stock from an independent biological survey.

Pascoe, Andersen, and de Wilde (2001) estimate technical efficiency for Dutch beam trawlers. They include a composite Fisher quantity index based on biomass for sole and plaice and the related overall prices for these species. Data on biomass was obtained from the Netherlands Institute for Fisheries Research. The prices were used as weights when aggregating the two stocks into one.

Several methods have been applied in order to account for stock effects in production analysis. The choice of method is dependent upon the type of fishery to be analyzed, the type of analysis to be performed, and the availability of independent stock measures.

Only one of the reviewed articles applies Data Envelopment Analysis (DEA) to estimate technical efficiency (Pascoe and Coglan 2002), while the rest primarily uses the Stochastic Production Frontier approach. However, Pascoe and Coglan (2002) did not have independent stock measures, and instead used year, month, and métier as categorical variables to estimate technical efficiency separately for each category. Hence, this excludes the possibility of comparison between vessels in different years, months, and métiers.

The Theory of Data Envelopment Analysis

Measuring the level of efficiency for different Decision Making Units (DMUs) has received increasing attention among scientists, managers, and regulators.[4] The questions asked include: Why do some DMUs have higher efficiency levels than others? How can DMUs with low levels of efficiency improve? And how does regulation influence the observed efficiency levels?

Efficiency is not one single concept. From an economist's point of view, the primary objective is to obtain economic efficiency, which refers to a situation where the DMUs are maximizing their profits. However, economic efficiency can be decomposed into allocative and technical efficiency, respectively. Allocative efficiency measures whether the input mix used by the DMUs minimizes cost, given the input prices.

The interpretation of the technical efficiency measure depends on the orientation used. In an output orientation, the objective is to maximize the output level given the observed input level. Here, technical efficiency is a measure of the relative change (increase) in output that can be obtained keeping the inputs unchanged. The input orientation, on the contrary, aims to minimize the use of inputs for a given output level. Hence, technical efficiency measures the possible decrease in input use while keeping the output level constant. In the following, the Farrell (1957) efficiency measure of maximal radial expansion (contraction) in outputs (inputs) that are feasible for the DMU is used.[5] Technical efficiency can furthermore be subdivided into other efficiency measures (Webster, Kennedy, and Johnson 1998).

Estimation of technical efficiency hinges on the estimation of production frontiers that compare observed production with maximal production. Traditionally, production functions have been estimated as average production functions. However, the classic notation of a production function is as a frontier giving the maximal possible output for a given input (Quirk 1987). The awareness of this discrepancy has increased, and today there are several methods for estimating production frontiers. These methods are gathered under the term "distance functions," which measure the distance between actual production and the best-practice production. The two most prominent methods are the parametric Stochastic Production Frontier (SPF) method and the non-parametric DEA method.

Both methods have their advantages and disadvantages. SPF is advantageous when data are highly influenced by idiosyncratic randomness. In the SPF method, it is also possible, through statistical tests, to evaluate the results obtained. However, SPF assumes specific functional forms for the production function,[6] and furthermore the handling of several outputs is not straightforward.[7] DEA avoids the two disadvantages of SPF. However, DEA does not deal with stochasticity,[8] and all deviations from the production frontier are considered to be due to pure inefficiencies and not noise. Several articles compare the results obtained by using SPF and DEA, respectively. Among these are Lee and Holland (2000) and Coglan, Pascoe, and Mardle (1998), but their comparisons do not produce any solid conclusion about which method to use.

---

[4] The term Decision Making Unit is used instead of firm, because DEA is also well suited to analyse other types of units, such as government services and non-profit organisations (see Steering Committee for the Review of Commonwealth/State Service Provision [1997]).

[5] Other non-radial measures of technical efficiency are also available. See Färe and Lovell (1978) and Russell (1985).

[6] Webster, Kennedy, and Johnson (1998) consider this to be an advantage because it enables one to perform solid tests of the results.

[7] Coelli and Perelman (1996, 1999, 2000) use parametric distance functions to analyse a multi-output situation for European railways.

[8] DEA has been modified to consider stochasticity (see Grosskopf [1996] for a survey of the different methods).

In this paper, DEA has been chosen as the method to perform the estimations of technical efficiency. It can be argued that when analyzing a fishery, it is necessary to consider stochasticity. However, Coglan, Pascoe, and Mardle (1998) point out that if monthly or longer time period data are used, the trip-related stochasticity is reduced, and the necessity for dealing with stochasticity is not as important. Because the forthcoming analysis is based on individual monthly data, DEA without stochasticity is considered a valid method.

The following review of the DEA theory is intended to give the reader the basic knowledge needed to understand the method.[9] The review will be input-oriented due to the fact that the vessels being analyzed are restricted by catch limitations in the form of quotas. Combined with the biological circumstances, it seems irrelevant to use an output-oriented approach, where the fishermen are assumed to maximize their output given the current input use.

DEA is a technique using mathematical programming methods[10] to find the frontier that envelops the data observed and thus reflect the best practice. The relative efficiency of each observation is then measured relative to this frontier, as observations on the frontier are considered fully efficient. The technique has been used to analyze the structures of many different industries. Besides fisheries, examples include hospitals (Dervaux, Kerstens, and Leleu 2000), schools (Arnold *et al.* 1996), banks (Sherman and Gold 1985), and farms (Battese 1991).[11]

DEA can be conducted with a short-run or long-run time horizon. In the long run, all inputs that the DMU can directly influence are considered variable or discretionary, and thus changeable at a minimum cost. In the short run, some inputs may be fixed or non-discretionary, and a distinction between variable and fixed inputs is necessary. However, under both time horizons, some important inputs can be directly uncontrollable for the DMU. An example is fish stocks. Although these inputs cannot be changed by the DMUs, they are still important when estimating the level of technical efficiency, and inclusion is, therefore, relevant (Golany and Roll 1993).

The input-oriented DEA with only discretionary inputs seeks to identify the radial reduction in all inputs that will make the DMU technically efficient. However, with non-discretionary inputs in the production structure, these cannot be altered, and the efficiency measure only indicates the necessary radial reductions in the discretionary inputs, leaving the non-discretionary inputs unchanged. Following Charnes, Cooper, and Rhodes (1978) and Banker and Morey (1986),[12] the problem for DMU *o* of the J DMUs can, assuming variable returns to scale, formally be written as:

$$\mathrm{Min}_{\theta,\lambda} \quad \theta_o \tag{1}$$

$$\text{subject to} \quad -y_{ok} + \sum_{j=1}^{J} \lambda_{oj} \; y_{jk} \geq 0 \qquad k = 1,\ldots,K \tag{2}$$

$$\theta_o \; x_{ol}^{D} - \sum_{j=1}^{J} \lambda_{oj} \; x_{jl}^{D} \geq 0 \qquad l = 1,\ldots,L \tag{3}$$

---

[9] Readers with special interest in DEA are encouraged to read Charnes *et al.* (1994) and Cooper, Seiford, and Tone (2000). Coelli, Rao, and Battese (1999) also discuss SPF and productivity measurement.
[10] The parametric SPF method uses econometric theory to estimate the frontier.
[11] An extensive reference list can be found on www.deazone.com.
[12] Golany and Roll (1993) modify the DEA problem with respect to two aspects. One is to allow for the simultaneous presence of non-discretionary inputs and outputs. Another is the presence of only partially discretionary input and outputs.

$$x_{oi}^{ND} - \sum_{j=1}^{J} \lambda_{oj} \quad x_{ji}^{ND} \geq 0 \qquad i = 1,\ldots,I \tag{4}$$

$$\lambda_{oj} \geq 0, \sum_{j=1}^{J} \lambda_{oj} = 1 \qquad j = 1,\ldots,J, \tag{5}$$

where j is the number of DMUs or observations ($j = 1,\ldots,J$), k is the number of outputs y ($k = 1,\ldots,K$), l is the number of discretionary inputs x^D ($l = 1,\ldots,L$), and i is the number of non-discretionary inputs x^{ND} ($i = 1,\ldots,I$). The radial reduction in the discretionary inputs necessary to make DMU j fully efficient is measured by the scalar θ, which is constrained to be equal or below one in an input-oriented approach.[13] It can be seen that no reductions are imposed in the non-discretionary input observed for DMU j. λ is a vector of j intensity variables identifying the extent observation j is used to construct the piecewise linear frontier approximation that envelops the data. Constant returns to scale is assumed if no restriction is imposed on the sum of λ.

Restrictions (2) to (4) secure that the DMU is within the production possibility set for the industry, while reducing the discretionary inputs x^D. The production possibility set for the industry is based on the assumption that it is impossible to produce more than any of the observed outputs, or linear combinations of these (ensured by restriction (2)), using less than any of the observed inputs or linear combinations of these (ensured by restrictions (3) and (4)).

Three Methods for Stock Inclusion

An array of approaches for including fish stocks into production analysis was reviewed in the first section. To my knowledge, no comparative studies analyzing the consequences of choosing a specific approach to biomass inclusion has been performed. It is thus difficult to prefer one approach to another. As mentioned in the introduction, the primary purpose of this paper is to perform such a comparison. It is also the intention to provide insight into the practical importance of these methods in order to recommend the use of a common method.

In this section, the stock inclusion methods to be analyzed will be identified and discussed. Furthermore, the programming problem related to each of these methods will be formulated using the DEA theory presented in the previous section. Three methods have been chosen. In one method, the stock index is derived from the catch data, while the two other methods are based on independent fish stock measures, and the methods are as follows:

1. CPUE stock indices.
2. Separate stock indices.
3. A composite stock measure.

Method 1, *CPUE stock indices*, includes one stock index for each of the primary species. The stock index for each species is calculated on a monthly basis by dividing the catch/landings with the number of days at sea conducted by the relevant

---

[13] This measure is exactly equal to the inverse of the input distance function, which is constrained to be equal to or above one. See Coelli, Rao, and Battese (1999) for further insights.

vessel, and is the same for all vessels participating in a given month. It follows along the lines of Comitini and Huang (1967), Eggert (2001), Pascoe and Coglan (2002).

The formula for calculating the fish stock measure in Method 1, $\hat{s}$, is:

$$\hat{s}_{km} = \sum_{j=1}^{J} \frac{y_{jkm}}{x_{jm}^{D}} \geq 0 \qquad j = 1,\ldots,J, \tag{6}$$

where the notation is as used previously, but with m indicating the time period ($m = 1,\ldots,M$); *i.e.*, month. Observe that the discretionary input in this formula is the number of days at sea.

Method 2, *separate stock indices*, simply includes one stock index, $\bar{s}$, for each of the primary species, as also done by Eide *et al.* (1998) and Hanneson (1983). In Method 2, the stock indices are on a yearly basis, because the available biological fish stock measures are only calculated yearly.

Method 3, *a composite stock measure*, considers the relative importance when including fish stocks in the technical efficiency analysis in line with Pascoe, Andersen, and de Wilde (2001). None of the two previous methods consider the relative importance of each primary species. For instance, even though all vessels catch the primary species, these may make up different relative amounts of the catch for different reasons. Method 3 accounts for this by calculating a monthly individual composite stock index, $\tilde{s}$, by using the following formula:

$$\tilde{s}_{jm} = \sum_{k=1}^{K} \bar{s}_{k} \frac{y_{jkm}}{\sum_{k=1}^{K} y_{jkm}} \geq 0 \qquad j = 1,\ldots,J, \tag{7}$$

where $\bar{s}$ is the independent stock index for each of the primary species used in Method 2.

With the presented stock indices in mind, it is possible to point to some advantages and disadvantages of each method. Method 1 does not require the availability of independent fish stock measures, which may be the case in many fisheries. However, as discussed previously, some analyses have shown that the correlation between stock and CPUE is problematic. Method 2 is, on the other hand, based on independent measures, but does not consider the relative importance of the primary species for each vessel. Method 3 remedies this by calculating a stock index using the independent stock indices and the available catch data. However, a stock index based on the output measures could give rise to some theoretical considerations about consistency, as was also the case for Method 1.

With the above methods in mind, the following programming problem must be solved in order to calculate the level of technical efficiency for vessel o in month m:

$$\text{Min}_{\theta,\lambda} \ \theta_{om} \tag{8}$$

$$\text{subject to} \qquad -y_{okm} + \sum_{j=1}^{J} \lambda_{jm} \ y_{jkm} \geq 0 \qquad k = 1,\ldots,K \tag{9}$$

$$\theta_{om} \ x_{olm}^{D} - \sum_{j=1}^{J} \lambda_{jm} \ x_{jlm}^{D} \geq 0 \qquad l = 1,\ldots,L \tag{10}$$

$$x_{oim}^{ND} - \sum_{j=1}^{J} \lambda_{jm} \quad x_{jim}^{ND} \geq 0 \qquad\qquad i = 1,\ldots,I \qquad (11)$$

$$s_{okm}^{ND} - \sum_{j=1}^{J} \lambda_{jm} \quad s_{okm}^{ND} \geq 0 \qquad\qquad m = 1,\ldots,M \qquad (12)$$

$$\sum_{j=1}^{J} \lambda_{jm} = 1, \lambda_{jm} \geq 0 \qquad\qquad j = 1,\ldots,J. \qquad (13)$$

Observe that the dimensions of the non-discretionary stock index differ between the methods, cf. $\hat{s}_{km}$, $\bar{s}_k$ and $\tilde{s}_{jm}$. Also observe that in Methods 1 and 3, the stock index is on a monthly basis, while Method 2 uses a yearly index, and that the number of stocks differ from the number of outputs in Methods 1 and 2; *i.e.*, only stocks for species in $K' \quad K$ are included.

In the programming problem, it has been assumed that variable returns to scale apply, cf. restriction 12. In this paper, both short-run and long-run analysis is performed. Grosskopf and Valdmanis (1987) argue that, contrary to long-run analysis, short-run analysis does not presuppose constant returns to scale. Instead, they suggest the use of variable returns to scale in the short run. Because the objectives of this paper are not to evaluate the consequences of different scale assumptions, variable returns to scale is assumed for both time horizons.

Description of the Data

Having defined the methods to be analyzed and the programming problem to be solved, the utilized dataset will be described. The dataset was extracted from the databases hosted by the Danish Directorate of Fisheries. The dataset covers the Danish seiners between 18 and 24 meters fishing in the period from 1995 to 1999 in the North Sea, Skagerrak, Kattegat, and/or the Baltic Sea. However, only those vessels that were registered in the Danish Vessel Register by the end of 1999 were included.

By the end of 1999, 43 Danish seiners were active compared to 36 in 1995. These Danish seiners had a varied behavioral fishing pattern with respect to the choice of location, considering that they fished in all four of the primary Danish fishing waters mentioned above. The number of observations available for each separate area is shown in table 1. Considering that there are too few observations available in Kattegat and the Baltic Sea, these areas are excluded in the analysis.

The fishing effort of vessels can be decomposed into two separate measures in

Table 1
Number of Observations Available for the Danish Seiners

	1995	1996	1997	1998	1999	Total
The North Sea	243	246	268	276	267	1,300
Skagerrak	126	125	133	134	118	636
Kattegat	16	16	6	10	7	55
The Baltic Sea	35	42	59	65	88	289

the form of fishing power and fishing time (Segura 1973). The former measures the amount of capital and labor used, while the latter measures the amount of time it is active. Andersen (1999) discusses this topic in more detail.

Several physical measures are available for the Danish seiners. Based on the coefficient of variation, which is a relative measure calculated as the standard deviation divided by the average value, length and engine power have the lowest relative dispersion, and these are used in the following analysis. Their characteristics are presented in table 2.

Besides fishing power measures of the Danish seiners, it is also important to get an impression of their fishing time. This can be measured as the time in which the gear is active or as the length of a fishing trip. Here the latter is used, because it includes all the time where an economic activity is conducted. Table 3 shows the number of days at sea per month in each of the analyzed fishing areas.

The Danish seiners use a technology invented by the Dane Jens Væver in 1848. The technology generates a relatively 'clean' fishery with little bycatch and high-quality fish. The two primary species are cod and plaice, measured in terms of catch weight and revenue. Table 4 shows the catch weight composition for the two areas.

From table 4, a trend towards a higher catch proportion of plaice can be ob-

Table 2
Descriptive Statistics for Fishing Power Measures, Average 1995–99

	Average Value	Standard Deviation	Minimum	Maximum
Length (meters)	19.19	0.91	18.00	22.00
Engine power (horsepower)	196.91	69.17	121.36	444.24

Table 3
Descriptive Statistics for Fishing Time Measure, Average 1995–99

	Average Number of Days at Sea	Standard Deviation	Minimum	Maximum
The North Sea	14.57	6.92	1.00	31.00
Skagerrak	12.58	7.26	1.00	31.00

Table 4
Average Catch Composition for Different Fishing Areas, Weight (%)

		1995	1996	1997	1998	1999
The North Sea	Plaice	30	38	53	42	55
	Cod	53	46	36	47	31
	Other species	18	16	11	11	14
Skagerrak	Cod	41	38	42	45	37
	Plaice	35	33	31	27	36
	Other species	24	29	27	28	27

served. This development is, to a high degree, in line with the developments in cod and plaice stock indices.[14] Table 5 shows a decrease in cod stocks compared to an unchanged/minor increase in plaice stocks. The availability of fish and the following management initiatives; *i.e.*, gear and catch restrictions, may be the primary reason for the reduced importance of cod in the catch composition for the Danish seiners.

Turning attention to catches measured in weight and deflated revenue, the most important fishing area for the Danish seiners is the North Sea (table 6). Here, approximately 65% of the catches are caught. Skagerrak is the second most important area with approximately 30%. In these two areas, total catches were at their highest in 1997, while average catches peaked in 1998.

Data are generally considered reliable. However, the output measures (weight) are based on landings and not actual catch. This implies that discards are not included, thus underestimating the actual production. For the specific fishery, the

Table 5
Development in Stock Indices for Different Fishing Areas, 1995–99 (1995=100)

	Cod	Plaice	
	The North Sea and Skagerrak	The North Sea	Skagerrak
1995	100	100	100
1996	108	90	100
1997	115	82	107
1998	104	101	108
1999	92	101	103

Source: International Council for the Exploration of the Sea (ICES).

Table 6
Yearly Catches for Different Fishing Areas (tonnes and 1,000 DKK)

		1995	1996	1997	1998	1999
The North Sea	Total catch weight	3,852	3,422	4,731	4,444	4,277
	Total catch deflated revenue	56,787	50,771	70,934	67,869	64,839
	Average catch weight	133	114	135	135	116
	Average catch revenue	1,958	1,692	2,027	2,057	1,752
Skagerrak	Total catch weight	1,681	1,633	2,364	2,167	1,611
	Total catch revenue	24,254	24,116	35,988	31,830	25,912
	Average catch weight	62	74	95	108	64
	Average catch revenue	898	1,096	1,440	1,591	1,036
Total	Total catch weight	5,533	5,056	7,095	6,611	5,888
	Total catch revenue	81,041	74,887	106,922	99,699	90,750
	Average catch weight	154	140	177	165	140
	Average catch revenue	2,251	2,080	2,673	2,492	2,161

[14] The stock assessments made by ICES, besides commercial landings data, are primarily based on survey data from research vessels and discard samplings.

discards are estimated to be around 15% and 13% in the North Sea and Skagerrak, respectively (Krog 2003), but no information on specific vessels is obtainable, and the output figures are therefore not corrected to take this into account. Technical efficiency can thus be underestimated for some vessels.

Analysis of the Danish Seiners

Estimated Models

Several models are estimated in order to pursue the objectives of this paper and to test the robustness of the results. This sub-section will briefly describe these models. In total, 48 models are estimated, 24 models for each of the two fishing areas used by the Danish seiners between 18 and 24 meters. With reference to the taxonomy in figure 1, the three-step procedure for understanding the taxonomy of the estimated models will be explained.

Firstly, a choice has to be made about the way to measure outputs. Two choices are available in the dataset: catches in weight or deflated revenue. The use of revenue as an output measure is discussed. Traditional production theory uses the physical units to measure outputs. However, practical analysis often tends to use monetary units instead. This is despite the fact that "*the specified frontier is not truly a production function*" (Sharma and Leung 1998, p. 273). There can be different motives for choosing revenue instead of weight. For example, if production is characterized by being multi-product, prices can be used to aggregate these outputs into one or several groups of output. Price variation is often considered a problem when using revenue, and hence the use of deflated catch revenues is recommended.

The former section showed that the Danish seiners fishing in the North Sea and Skagerrak primarily fish for cod and plaice. Hence, the number of outputs included in the mathematical programming problems is cod, plaice, and other species.

Secondly, the fishing effort measures have to be defined. These measures are dependent on the time horizon, because this determines whether measures are changeable. In the short run, all included fishing power measures are non-discretionary, while they are discretionary in the long run. The measure of fishing time is, on the other hand, discretionary in both the short and long run.

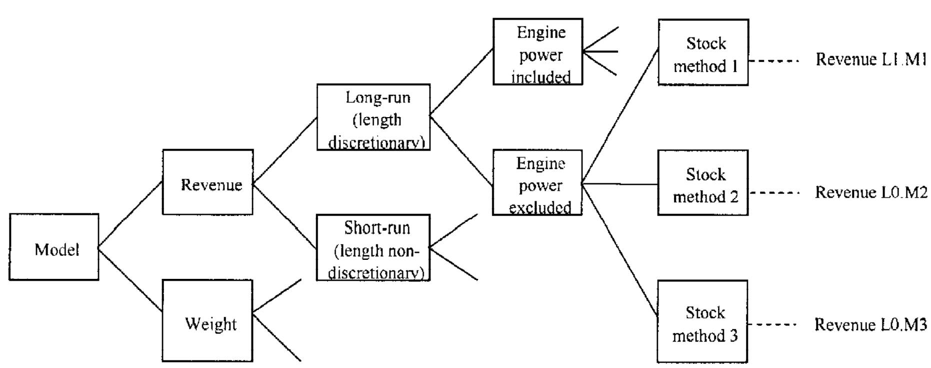

Figure 1. Taxonomy of the Estimated Models

In practice, two fishing power measures are used; *i.e.*, length and engine power. Length is included in all of the estimated models as being either non-discretionary or discretionary, depending on the time horizon. Engine power is, on the other hand, only included in some of the models and has, if it is included, the same attribute as length; *i.e.*, non-discretionary in the short run and discretionary in the long run. The measure of fishing time in form of the number of days at sea is included in all of the estimated models and assumed discretionary.

Finally, the method for including fish stocks in the models is chosen. As explained previously, the different methods are used to investigate the inclusion of fish stocks in efficiency analysis of the Danish seiners. However, irrespective of the method and time horizon, the fish stock measure is always considered to be non-discretionary.

Considering the large number of models to be estimated, acronyms have been given to each model for convenience. Each acronym is formulated from the basic rule *Model te.m* and consists of three parts. *Model* can be replaced with either revenue or weight, depending on the choice of output measure. t specifies the time horizon chosen and can be either S for short run or L for long run; thus, t $\{S,L\}$. e denotes whether engine power is included or not. If included, e equals 1, otherwise it equals 0; thus, e $\{0,1\}$. Finally, m represents the stock method used. It can have a value of M1, M2, or M3, cf. the methods presented in the second section; thus, m $\{M1,M2,M3\}$.

In figure 1, an example of an associated acronym is given. *Revenue L1.M1* is the acronym for a long-run model with revenue as output measure; engine power is included, and Stock Method 1 used to account for stock conditions. In Appendix 1, an overview of all variables in the estimated models is available, including the acronyms used.

Choice of Method for Fish Stock Inclusion

With the taxonomy in mind, programming problems have been estimated using the General Algebraic Modeling System (GAMS), assuming variable returns to scale and strong disposability (Brooke *et al.* 1998). Given that data are on a monthly basis, a total of 1,300 and 636 programming problems were solved for the North Sea and Skagerrak, respectively, in all 48 models.

Based upon these estimations of technical efficiency using DEA, the three methods for including fish stocks will now be compared. To compare the estimations and evaluate the level of consistency between these, Bauer *et al.* (1998) mention several conditions that need to be fulfilled. Three of these are related to investigating whether the methods give the same results (Pardina, Rossi, and Ruzzier 1999), and will, therefore, be used in the following. They are:

1. Similar means and standard deviations should be observed.
2. The DMUs should obtain the same rank.
3. The same DMUs should be classified as "best" and "worst."

The fulfillment of these conditions is considered for the analyzed data in relation to the objectives of this paper. The comparisons are made between the monthly score for each observation; not between the scores of each month, and the methods used for testing these relationships will follow along the lines found in Pardina, Rossi, and Ruzzier (1999).

The first condition is considered using the means and standard deviations obtained from the estimations. The second condition is approached by using three tests, cf. below, and the third condition is considered using the upper and lower quartiles; *i.e.*, the 75% and 25% quartiles.

The tests used to investigate the second condition are the: (*i*) Spearman rank correlation test; (*ii*) Friedman test; and (*iii*) Wilcoxon test. The first evaluates the strength of association between two variables, or in this case, the estimated models. The second and third tests determine whether the distribution in each of the estimated models can be considered similar. The Friedman test is used when comparing more than two groups of data, and the Wilcoxon test is used when comparing two groups of data. The three tests are all non-parametric, implying that they do not *a priori* require any knowledge of the distribution of the obtained scores. The advantage is that an assumption of normally distributed scores is not necessary, and the tests are so-called "distribution free." Further insight into the theoretical foundation of the three tests can be found in Sigel and Castellan (1998) and Conover (1999).[15]

The average efficiencies and standard deviations for the estimated models are presented in table 7 for the North Sea and Skagerrak, respectively.

As expected, the level of technical efficiency increases with increasing flexibility in the choice of non-discretionary input variables. In the least flexible model; *i.e.*, Model S0.m, technical efficiency varies between 0.41 and 0.49 in the North Sea and between 0.47 and 0.57 in Skagerrak. In the most flexible model; *i.e.*, Model L1.m, technical efficiency is around 0.95 in both areas. However, the two long-run

Table 7
Average Technical Efficiencies for Danish Seiners

	Model S0.m		Model S1.m		Model L0.m		Model L1.m	
	Average	Standard Deviation	Average	Standard Deviation	Average	Standard Deviation	Average	Standard Deviation
North Sea								
Weight te.M1	0.47	0.24	0.53	0.27	0.95	0.04	0.96	0.04
Revenue te.M1	0.49	0.24	0.56	0.27	0.95	0.04	0.95	0.04
Weight te.M2	0.46	0.24	0.53	0.26	0.95	0.04	0.96	0.04
Revenue te.M2	0.47	0.25	0.53	0.27	0.95	0.04	0.95	0.04
Weight te.M3	0.41	0.23	0.46	0.25	0.95	0.04	0.95	0.05
Revenue te.M3	0.41	0.23	0.47	0.26	0.95	0.04	0.95	0.04
Skagerrak								
Weight te.M1	0.57	0.27	0.61	0.28	0.96	0.04	0.96	0.04
Revenue te.M1	0.55	0.26	0.59	0.26	0.96	0.04	0.96	0.04
Weight te.M2	0.53	0.25	0.57	0.26	0.95	0.04	0.95	0.04
Revenue te.M2	0.53	0.24	0.56	0.26	0.95	0.04	0.95	0.04
Weight te.M3	0.47	0.25	0.50	0.25	0.95	0.04	0.95	0.04
Revenue te.M3	0.47	0.23	0.50	0.26	0.95	0.04	0.95	0.04

Notes: Model {Revenue,Weight}, *t* {S,L}, *e* {0,1}, *m* {M1,M2,M3}.

[15] All tests were performed by using an add-in for Microsoft Excel called Analyse-it. The programme can be downloaded from www.analyse-it.com.

models do not reflect this difference. This indicates that vessel length generally restricts the possibilities for adaptation.[16]

Comparing the short-run and long-run models, a high similarity is observed in the average means between Model te.M1 and Model te.M2, and they generally seem to estimate higher values of technical efficiency compared to Model te.M3. The standard deviations, on the other hand, are rather similar in the three methods. This does not seem to be influenced by the choice of fishing area or output measure.

High and significant correlations are observed between the different inclusions of fish stocks within each of the three models; again, irrespective of which fishing area is analyzed. However, there seems to be a tendency for higher correlations between Model te.M2 and Model te.M3 (table 8). Generally, the estimated technical efficiencies in the three models seem to vary in similar ways, no matter which fish stock measure is applied.

Tests for statistical significant differences in the distributions between the methods are then undertaken. Firstly, the Friedman test is applied. However, the null hypothesis is rejected in all models. Therefore, despite the high correlations between the efficiency estimates in the three models, these models do not seem to have identical distributions. The highest Spearman correlations are observed between Model te.M2 and Model te.M3. In order to test whether the distributions observed in Model te.M2 and Model te.M3 are identical, a Wilcoxon test is applied. The hypothesis of equal distribution is, however, rejected for these two models.

The last condition for consistency is to identify whether the same DMUs are categorized as the "best" and "worst" between the three different methods. Using the upper and lower quartiles, this hypothesis can be accepted if the percentage of DMUs that are simultaneously present in the quartiles is high. The percentages in the two quartiles are given in table 9.

The percentage of DMUs simultaneously present in the upper and lower quartile varies considerably when comparing the different models. The highest percentages are found when comparing Model te.M2 and Model te.M3. This is most evident in the long-run models, where the percentage in some situations is above 90%. The lowest percentages are generally observed when comparing all three models, while comparing Model te.M1 with Model te.M2 and Model te.M1 with Model te.M3 gives approximately the same percentages. There seems to be a general tendency towards lower percentages of DMUs simultaneously present in the respective quartiles in Skagerrak compared to the North Sea, but the trends are the same as above.

A mixed conclusion can be drawn about consistency based on the above investigation of the three conditions. Comparing the three methods with respect to "similar means and standard deviations," they all seem to perform well. However, with respect to "the DMUs should obtain the same ranks," Methods 2 and 3 seem to perform well with respect to high and significant correlations between the models, but perform poorly with respect to obtaining identical distributions. Finally, Methods 2 and 3 perform well with respect to the condition that "the same DMUs should be classified as best and worse." Method 1 only seems to perform well in obtaining "similar means and standard deviations," when being compared to the two other methods. Regarding the two other consistency conditions, Method 1 generally performs poorly.

---

[16] The dataset includes an implicit assumption which influences the estimations. Looking at the North Sea, the maximum length is 22 meters, while the minimum is 18 meters. This implies that θ cannot be lower than 0.82, and this conclusion is not altered when including engine power. In the short run, the number of days at sea imposes the restriction, and here θ cannot be lower than 0.03. The larger difference in the average technical efficiencies in the short-run models is due to the increased ability to distinguish the DMUs from each other.

Table 8
Spearman Rank Correlations between Technical Efficiency Estimations

	Weight te.M1	Weight te.M2	Weight te.M3	Revenue te.M1	Revenue te.M2	Revenue te.M3
North Sea						
Model S0.M1	1.00			1.00		
Model S0.M2	0.85	1.00		0.83	1.00	
Model S0.M3	0.90	0.92	1.00	0.87	0.93	1.00
Model S1.M1	1.00			1.00		
Model S1.M2	0.82	1.00		0.80	1.00	
Model S1.M3	0.87	0.89	1.00	0.83	0.89	1.00
Model L0.M1	1.00			1.00		
Model L0.M2	0.90	1.00		0.91	1.00	
Model L0.M3	0.91	0.95	1.00	0.90	0.96	1.00
Model L1.M1	1.00			1.00		
Model L1.M2	0.87	1.00		0.79	1.00	
Model L1.M3	0.89	0.93	1.00	0.80	0.94	1.00
Skagerrak						
Model S0.M1	1.00			1.00		
Model S0.M2	0.71	1.00		0.72	1.00	
Model S0.M3	0.70	0.89	1.00	0.70	0.89	1.00
Model S1.M1	1.00			1.00		
Model S1.M2	0.71	1.00		0.71	1.00	
Model S1.M3	0.72	0.89	1.00	0.72	0.89	1.00
Model L0.M1	1.00			1.00		
Model L0.M2	0.77	1.00		0.80	1.00	
Model L0.M3	0.73	0.94	1.00	0.82	0.94	1.00
Model L1.M1	1.00			1.00		
Model L1.M2	0.77	1.00		0.79	1.00	
Model L1.M3	0.76	0.94	1.00	0.81	0.94	1.00

Notes: Model {Revenue,Weight}, t {S,L}, e {0,1}, m {M1,M2,M3}.
All correlations were tested to be significantly different from zero at the 1% level.

Based on the three conditions for consistency, it can be concluded that Methods 2 and 3 obtain approximately the same technical efficiency levels for the DMUs. Method 1 obtains the same average scores as Methods 2 and 3, but is not identical when comparing the individual DMUs. This conclusion is valid irrespective of the choice of time horizon, input measures, and output measures. This indicates that the conclusions are robust and not dependent on model specification.

Concern of whether the stock indices are binding restrictions in the estimations may arise and can result in the influence of these not appearing in the results. This can be investigated by performing additional estimations for some of the models. In these estimations, the previously non-discretionary inputs were assumed discretionary, while the previously discretionary inputs were reduced to the efficient level and assumed non-discretionary. Hereby, it becomes possible to estimate an efficiency level with respect to the stock indices; *i.e.*, a slack value. The results show that the efficiency levels are high and very often equal to one, thus indicating that the stock indices are binding restrictions in the performed estimations.

Table 9
Percentage of DMUs Simultaneously Present in Upper or Lower Quartile

	Model S0.m		Model S1.m		Model L0.m		Model L1.m	
	Q75	Q25	Q75	Q25	Q75	Q25	Q75	Q25
North Sea								
Weight te.M1/te.M2/te.M3	55.77	64.92	54.03	61.93	59.57	85.79	51.46	75.54
Weight te.M1/te.M2	59.69	70.21	57.43	71.12	60.54	86.81	59.24	85.16
Weight te.M1/te.M3	65.97	71.12	63.92	67.54	61.41	87.36	54.50	78.77
Weight te.M2/te.M3	77.40	86.05	78.65	80.79	95.09	97.25	79.76	86.19
Revenue te.M1/te.M2/te.M3	57.56	55.67	48.86	52.17	69.57	87.29	44.55	70.16
Revenue te.M1/te.M2	64.77	63.27	53.62	60.80	73.99	89.94	47.62	70.53
Revenue te.M1/te.M3	63.92	60.80	56.65	60.00	70.33	87.85	47.62	71.43
Revenue te.M2/te.M3	79.66	82.86	77.65	77.78	91.93	96.69	85.96	97.56
Skagerrak								
Weight te.M1/te.M2/te.M3	37.19	45.09	50.61	51.75	35.96	59.72	37.83	57.89
Weight te.M1/te.M2	47.91	57.84	45.21	53.11	39.65	61.76	44.39	59.90
Weight te.M1/te.M3	41.96	55.56	39.47	54.59	39.62	63.81	42.86	62.80
Weight te.M2/te.M3	67.37	64.95	64.77	58.42	83.23	91.06	77.91	89.83
Revenue te.M1/te.M2/te.M3	39.09	45.91	37.92	54.50	58.08	77.61	44.34	59.81
Revenue te.M1/te.M2	49.30	58.42	50.00	57.64	48.60	64.95	49.76	62.25
Revenue te.M1/te.M3	47.22	56.10	42.60	55.34	49.30	65.50	48.54	63.46
Revenue te.M2/te.M3	62.24	66.67	66.49	60.80	71.89	89.14	80.00	91.28

Notes: Model {Revenue,Weight}, *t* {S,L}, *e* {0,1}, *m* {M1,M2,M3}.

Conclusion

Estimation of technical efficiency has increased significantly since M.J. Farrell's thoughts on efficiency in 1957. In order to perform a reliable analysis, many aspects have to be addressed. However, in fisheries one of the most important aspects is the inclusion of fish stocks in order to account for fish stock developments.

Several methods have been used in the fisheries literature, but with no discussion as to which one is preferable. This paper has, therefore, addressed this problem. In total, three methods have been considered. Method 1 used CPUE data from the included vessels to derive a stock index, which, on a monthly level, was the same for all the analyzed vessels. The two other methods were based on independent biological fish stock assessments. Method 2 simply included, on a yearly basis, a fish stock for each of the primary species without distinguishing between vessels. Method 3 considered a composite fish stock measure for each individual vessel based on the relative importance of the primary species for the vessel and the independent stock measures.

Several techniques have been suggested as ways of performing estimations of technical efficiency. In this paper, DEA was used. This technique uses mathematical programming to estimate the frontier of the analyzed dataset. Afterwards, the production of each decision-making unit is compared with this frontier to find the level of technical efficiency. Danish seiners between 18 and 24 meters were used to analyze this issue. Both short- and long-run models were included with different output and input measures. This was done in order to test the robustness of the obtained results. However, fish stocks were assumed non-discretionary in all of the estimations.

In order to compare the estimations, the approach considered in Bauer *et al.*

(1998) was used. This approach is based on three consistency conditions, namely the: (*i*) efficiency levels and standard deviations; (*ii*) obtained rankings; and (*iii*) simultaneous identification of the same "best" and "worst" vessels.

Based on the chosen approach, it can be concluded that when comparing Methods 2 and 3, conditions 1 and 3 were satisfied, while condition 2 was partly satisfied. Thus, these methods were considered to obtain approximately similar results. Method 1, on the other hand, only performed well with condition 1, when being compared to Methods 2 and 3. These conclusions were robust to changes in choice of time horizon and output and input measures. It is important to note whether the included fish stock measure is based on independent stock assessment data or not. However, when using indices based on independent stock measures, it does not seem to matter how these are included.

The comparison of different approaches to include fish stocks in the analysis of technical efficiency is considered a necessary first step to determine the best way to do this. A logical next step would be to test which stock inclusion method actually gives the correct answers. This can be analyzed using three other consistency conditions mentioned by Bauer *et al.* (1998), which as mentioned by Rossi and Ruzzier (1999), focus on whether the answers are correct; not whether they are the same. The three conditions are as follows: (*i*) measures should be consistent with other performance measures; (*ii*) the efficiency measure for a DMU should be stable over time; and (*iii*) the results should agree with prior expectation. On the current basis, it has not been possible to investigate these conditions more thoroughly.

Several other topics could also be investigated in future research. The conclusions in this paper have been based on the analysis of Danish seiners, which only have two important species. A next step would be to investigate whether the conclusions change for fisheries with more than two important species. For example, including a large number of separate fish stocks may make the vessels more distinct from each other. This implies a higher technical efficiency score, because a larger fraction of the vessels is used to envelope the dataset.

A further step could be to investigate whether the application of statistical tests changes the derived conclusions. The literature on using statistical tests in relation to DEA is evolving. Kittelsen (1999, p. 3) points to the fact that more simulations are necessary to "*draw clear conclusions about the usefulness of the suggested approximate hypothesis tests*." However, Banker (1993, 1996) and Simar and Wilson (1995, 2002) have investigated this topic.

References

Alvarez, A. 2001. Some Issues in the Estimation of Technical Efficiency in a Fishery. *Efficiency Series Paper* 2/2001. University of Oviedo, Spain.

Andersen, J.L. 1999. *A Review of the Basic Biological and Economic Approaches to Fishing Effort*. Working Paper 12/1999. Copenhagen, Denmark: Danish Research Institute of Food Economics.

Arnold, V.L., I.R. Bradhan, W.W. Cooper, and S.C. Kumbhakar. 1996. New Uses of DEA and Statistical Regressions for Efficiency Evaluation and Estimation—With an Illustrative Application to Public Secondary Schools in Texas. *Annals of Operations Research* 66:255–77.

Banker, R.D. 1993. Maximum Likelihood, Consistency and Data Envelopment Analysis: A Statistical Foundation. *Management Science* 39(10):1265–73.

___. 1996. Hypothesis Tests Using Data Envelopment Analysis. *Journal of Productivity Analysis* 7:139–59.

Banker, R.D., and R.C. Morey. 1986. Efficiency Analysis for Exogenously Fixed Inputs and Outputs. *Operations Research* 34(4):513–21.

Battese, G.E. 1991. *Frontier Production Functions and Technical Efficiency: A Survey of Empirical Applications in Agricultural Economics*. NSW, Australia: University of New England.

Bauer, P., A. Berger, G. Ferrier, and D. Humphrey. 1998. Consistency Conditions for Regulatory Analysis of Financial Institutions: A Comparison of Frontier Efficiency Methods. *Journal of Economics and Business* 50:85–114.

Bjørndal, T. 1989. Production in a Schooling Fishery: The Case of the North Sea Herring Fishery. *Land Economics* 65(1):49–56.

Brooke, A., D. Kendrick, A. Meeraus, R. Raman, and R.E. Rosenthal. 1998. *GAMS, A User's Guide*. Washington, DC: GAMS Development Corporation.

Cabrera-Muro, H.R. 2002. *Technical Efficiency of the Mexican Tuna Fishery: A Stochastic Frontier of Production Approach*. Doctoral thesis from Facultad de Ciencias Marinas FCM, Campus Ensenada B.C., Universidad Autonoma de Baja California UABC, Mexico.

Campbell, H.F., and A.J. Hand. 1998. Joint Ventures and Technology Transfer: the Solomon Islands Pole-and-Line Fishery. *Journal of Development Economics* 57:421–42.

Charnes, A., W.W. Cooper, and E. Rhodes. 1978. Measuring the Efficiency of Decision Making Units. *European Journal of Operational Research* 2:429–44.

Charnes, A., W.W. Cooper, A.Y. Levin, and L.M. Seiford. 1994. *Data Envelopment Analysis: Theory, Methodology and Application*. Boston, MA: Kluwer Academic Publishers.

Clark, C.W. 1973a. The Economics of Overexploitation. *Science* 181:630–34.

___. 1973b. Profit Maximisation and the Extinction of Animal Species. *Journal of Political Economy* 81:950–61.

Coelli, T.J., and S. Perelman. 1996. *Efficiency Measurement, Multi-output Technologies and Distance Function: With Application to European Railways*. CREPP Working Paper 96/05. Belgium: University of Liege.

___. 1999. A Comparison of Parametric and Non-Parametric Distance Functions: With Application to European Railways. *European Journal of Operational Research* 117:326–39.

___. 2000. Technical Efficiency of European Railways: A Distance Function Approach. *Applied Economics* 32:1967–76.

Coelli, T.J., D.S.P. Rao, and G.E. Battese. 1999. *An Introduction to Efficiency and Productivity Analysis*. Boston, MA: Kluwer Academic Publishers. Third printing.

Coglan, L., S. Pascoe, and S. Mardle. 1998. DEA Versus Econometric Analysis of Efficiency in Fisheries. *Proceeding of the 9th Biannual Conference of the International Institute of Fisheries Economics and Trade*. Tromsø, Norway: IIFET.

Comitini, S., and D.S. Huang. 1967. A Study of Production and Factor Shares in the Halibut Fishing Industry. *Journal of Political Economy* 75(4):366–72.

Conover W.J. 1999. *Practical Non-parametric Statistics,* Third Edition. Wiley.

Cooper, W.W., L.M. Seiford, and K. Tone. 2000. *Data Envelopment Analysis: A Comprehensive Text with Models, Applications, References and DEA-Solver Software*. Boston, MA: Kluwer Academic Publishers.

Dervaux, B., K. Kerstens, and H. Leleu. 2000. Remedying Excess Capacities in French Surgery Units by Industry Reallocations: The Scope for Short and Long Term Improvements in Plant Capacity Utilization. *Public Provision and Performance*, J.L.T. Blank, ed. Elsevier.

Eggert, H. 2001. Technical Efficiency in the Swedish Trawl Fishery for Norway Lobster. *Essays on Fisheries Economics*. Doctoral Thesis. Sweden: Gothenburg University.

Eide, A., F. Skjold, F. Olsen, and O. Flaaten. 1998. Bioeconomic Production Function in Fisheries: An Analysis of Trawl Catches in the Barents Sea. Paper presented at the 9th Biannual Conference of the International Institute of Fisheries Economics and Trade. Tromsø, Norway: IIFET

Färe, R., and C.A.K. Lovell. 1978. Measuring the Technical Efficiency of Production. *Journal of Economic Theory* 19:150–62.

Farrell, M.J. 1957. The Measurement of Productive Efficiency. *Journal of the Royal Statistical Society*, Series A, III:253–90.

Golany, J.A., and Y. Roll. 1993. Some Extensions of Techniques to Handle Non-Discretionary Factors in Data Envelopment Analysis. *Journal of Productivity Analysis* 4(4):419–32.

Gordon, H.S. 1954. The Economic Theory of a Common Property Resource: A Note. *Journal of Political Economy* 62:124–42.

Grafton, Q., D. Squires, and K. Fox. 2000. Private Property and Economic Efficiency: A Study of a Common-Pool Resource. *Journal of Law and Economics* 43:679–713.

Grosskopf, S. 1996. Statistical Inference and Nonparametric Efficiency: A Selective Survey. *The Journal of Productivity Analysis* 7:161-76.

Grosskopf, S., and V. Valdmanis. 1987. Measuring Hospital Performance. *Journal of Health Economics* 6:89–107.

Hannesson, R. 1983. Bioeconomic Production Function in Fisheries: Theoretical and Empirical Analysis. *Canadian Journal of Fisheries and Aquatic Sciences* 40:968–82.

Harley, S.J., R.A. Myers, and A. Dunn. 2001. Is Catch-Per-Unit-Effort Proportional to Abundance? *Canadian Journal of Fisheries and Aquatic Sciences* 58:1760–72.

Hilborn, R., and C.J. Walters. 1992. *Quantitative Fisheries Stock Assessment: Choice, Dynamic & Uncertainty*. Chapman & Hall, International Thomson Publishing.

International Council for the Exploration of the Seas (ICES). Stock assessment reports available at: www.ices.dk.

Kirkley, J.E., D. Squires, and I.E. Strand. 1995. Assessing Technical Efficiency in Commercial Fisheries: The Mid-Atlantic Sea Scallop Fishery. *American Journal of Agricultural Economics* 77:686–97.

___. 1998. Characterizing Managerial Skill and Technical Efficiency in a Fishery. *Journal of Productivity Analysis* 9:145–60.

Kittelsen, S.A.C. 1999. *Monte Carlo Simulations of DEA Efficiency Measures and Hypothesis Tests*. Memorandum no. 09/99. Department of Economics, University of Oslo, Norway.

Kompas, T., and C. Nhu. 2002. *Catch, Efficiency and Management: A Stochastic Production Frontier Analysis of the Australian Northern Prawn Fishery*. Economics of Development working paper. ANU, Australia: National Centre for Development Studies.

Krog, C. 2003. *Discard in Danish Fisheries*. Unpublished paper in Danish.

Lee, S.T., and D. Holland. 2000. The Impact of Noisy Catch Data on Estimates of Efficient Output Derived From DEA and Stochastic Frontier Models: A Monte Carlo Comparison. Paper presented at the 10th Biannual Conference of the International Institute of Fisheries Economics and Trade. Oregon: IIFET.

Morrison, C.J. 2000. Thoughts on Productivity, Efficiency and Capacity Utilization Measurement for Fisheries. Paper presented at the 10th Biannual Conference of the International Institute of Fisheries Economics and Trade. Oregon: IIFET.

Nunamaker, T.R. 1985. Using Data Envelopment Analysis to Measure the Efficiency of Non-Profit Organisations: A Critical Evaluation. *Managerial and Decision Economics* 13:317–22.

Pardina, M.R., M. Rossi, and C. Ruzzier. 1999. *Consistency Conditions; Efficiency Measures for the Electricity Distribution Sector in South America*. Working Paper no. 5. Centro de Estudios Económicos de la Regulación, Instituto de Economía. Universidad Argentina de la Empresa, Argentina.

Pascoe, S., and L. Coglan. 2002. The Contribution of Unmeasurable Inputs to Fisheries Production: An Analysis of Technical Efficiency of Fishing Vessels in the English Channel. *American Journal of Agricultural Economics* 84(3):585–97.

Pascoe, S., and I. Herrero. 2004. Estimation of a Composite Fish Stock Index Using Data Envelopment Analysis. *Fisheries Research* 69(1):91–105.

Pascoe, S., and C. Robinson. 1998. Input Control, Input Substitution and Profit Maximisation in The English Channel Beam Trawl Fishery. *Journal of Agricultural Economics* 49(1):16–33.

Pascoe, S., J.L. Andersen, and J.W. de Wilde. 2001. The Impact of Management Regulation on the Technical Efficiency of Vessels in the Dutch Beam Trawl Fishery. *European Review of Agricultural Economics* 28(2):187–206.

Quirk, J.P. 1987. *Intermediate Microeconomics*. Third Edition. Science Research Associates.

Richards, L.J., and J.T. Schnute. 1986. An Experimental and Statistical Approach to the Question: Is CPUE an Index of Abundance? *Canadian Journal of Fisheries and Aquatic Sciences* 43:1214–27.

Rossi, M.A., and C.A. Ruzzier. 1999. *On the Regulatory Application of Efficiency Measures*. Argentina: Asociacion Argentina de Economia Politica.

Russell, R.R. 1985. Measures of Technical Efficiency. *Journal of Economic Theory* 35:109–26.

Schaefer, M.B. 1957. Some Considerations of Population Dynamics and Economics in Relation to the Management of Marine Fisheries. *Journal of the Fisheries Research Board of Canada* 14:669–81.

Segura, E.L. 1973. Optimal Fishing Effort in the Peruvian Anchoveta Fishery. *Ocean Fishery Management: Discussions and Research*, A.A. Sokoloski, ed. NOAA Technical Report NMFS CIRC-371:57–64.

Sharma, K.R., and P.S. Leung. 1998. Technical Efficiency of the Long-line Fishery in Hawaii: An Application of a Stochastic Production Frontier. *Marine Resource Economics* 13:259–74.

Sherman, J.D., and F. Gold. 1985. Bank Branch Operating Efficiency: Evaluation with Data Envelopment Analysis. *Journal of Banking and Finance* 9:297–316.

Siegel, S., and N.J. Castellan, Jr. 1988. *Nonparametric Statistics for the Behavioral Sciences,* 2nd Edition. Singapore: McGraw-Hill International Editions, Statistical Series.

Simar, L., and P.W. Wilson. 1995. Sensitivity Analysis of Efficiency Scores: How to Bootstrap in Nonparametric Frontier Models. *Management Science* 44(1):49–61.

___. 2002. Non-Parametric Tests of Returns to Scale. *European Journal of Operational Research* 139(1):115–32.

Squires, D. 1987. Fishing Effort: Its Testing, Specification, and Internal Structure in Fisheries Economics and Management. *Journal of Environmental Economics and Management* 14:268–82.

Steering Committee for the Review of Commonwealth/State Service Provision. 1997. *Data Envelopment Analysis: A Technique for Measuring the Efficiency of Government Service Delivery*. Canberra, Australia: AGPS.

Valdmanis, V. 1992. Sensitivity Analysis for DEA Models: An Empirical Example Using Public vs. NFP Hospitals. *Journal of Public Economics* 48:185–205.

Webster, R., S. Kennedy, and L. Johnson. 1998. *Comparing Techniques for Measuring the Efficiency and Productivity of Australian Private Hospitals*. Working Papers in Econometrics and Applied Statistics, no. 98/3. Australian Bureau of Statistics.

Appendix 1

Estimated Models and their Acronyms

Model[1]	Outputs	Discretionary Inputs	Non-discretionary Inputs
Model S0.M1	1) Catch of cod 2) Catch of plaice 3) Catch of other species	1) Number of days at sea	1) Length 2) CPUE dependent cod stock index 3) CPUE dependent plaice stock index
Model S0.M2	1) Catch of cod 2) Catch of plaice 3) Catch of other species	1) Number of days at sea	1) Length 2) Independent cod stock index 3) Independent plaice stock index
Model S0.M3	1) Catch of cod 2) Catch of plaice 3) Catch of other species	1) Number of days at sea	1) Length 2) One stock index based on the relative importance of cod and plaice
Model S1.M1	1) Catch of cod 2) Catch of plaice 3) Catch of other species	1) Number of days at sea	1) Length 2) Engine power 3) CPUE dependent cod stock index 4) CPUE dependent plaice stock index
Model S1.M2	1) Catch of cod 2) Catch of plaice 3) Catch of other species	1) Number of days at sea	1) Length 2) Engine power 3) Independent cod stock index 4) Independent plaice stock index
Model S1.M3	1) Catch of cod 2) Catch of plaice 3) Catch of other species	1) Number of days at sea	1) Length 2) Engine power 3) One stock index based on the relative importance of cod and plaice
Model L0.M1	1) Catch of cod 2) Catch of plaice 3) Catch of other species	1) Number of days at sea 2) Length	1) CPUE dependent cod stock index 2) CPUE dependent plaice stock index
Model L0.M2	1) Catch of cod 2) Catch of plaice 3) Catch of other species	1) Number of days at sea 2) Length	1) Independent cod stock index 2) Independent plaice stock index
Model L0.M3	1) Catch of cod 2) Catch of plaice 3) Catch of other species	1) Number of days at sea 2) Length	1) One stock index based on the relative importance of cod and plaice
Model L1.M1	1) Catch of cod 2) Catch of plaice 3) Catch of other species	1) Number of days at sea 2) Length 3) Engine power	1) CPUE dependent cod stock index 2) CPUE dependent plaice stock index
Model L1.M2	1) Catch of cod 2) Catch of plaice 3) Catch of other species	1) Number of days at sea 2) Length 3) Engine power	1) Independent cod stock index 2) Independent plaice stock index
Model L1.M3	1) Catch of cod 2) Catch of plaice 3) Catch of other species	1) Number of days at sea 2) Length 3) Engine power	1) One stock index based on the relative importance of cod and plaice

Notes: [1] If catch weight is used to measure output, the model name is "Weight S0.M1," etc. When deflated catch revenue is used, the model name is "Revenue S0.M1," and so forth.