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Revenue-based capacity utilisation measures and decomposition: The case of Danish North Sea trawlers

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Abstract

In fisheries, capacity analysis has largely been limited to measuring physical capacity, defined as the maximum amount of output that can be produced per unit of time, given existing plant and equipment and unrestricted availability of variable inputs. An economic measure of capacity can be defined as the maximum revenue attainable for the given fixed inputs, using relevant outputs and output prices. This paper examines these two approaches to capacity by applying data envelopment analysis to physical and economic input/output data for Danish North Sea trawlers. The economic and physical measures are compared and contrasted using correlation analysis. An innovative analysis into the composition of possible revenue increments is also presented and reasons for economic inefficiency of vessels are identified.

Keywords: Data envelopment analysis; Fisheries; Economic capacity; Revenue gain

1. Introduction

Fishing capacity has become a management topic of great significance in recent years. Problems stemming from ill-defined property rights and race-for-fish behaviour include overcapitalisation of the fishing industry and consistent overexploitation of the resource base. Under the initiative of the Food and Agricultural Organisation of the United Nations (FAO) and the International Plan of Action for the Management of Fishing Capacity, the use of Data Envelopment Analysis (DEA) has been proposed as a possible tool to enable the measurement of fishing capacity worldwide. Such estimates would give fishery managers valuable information on the commensurate level of fleet capacity that should be in place, given the availability of resources and the economic status of the fishing industry.

The DEA measurement approach in fisheries has to date mostly concerned a physical measure of capacity. It is however often considered that an economic dimension should be built into this kind of analysis, since the main objective of fishers is often to maximise profits or revenues, or minimise costs, rather than physical landing weight (cf. Kirkley et al., 2002, for a discussion on behavioural assumptions). Such strategies are not captured, or

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indeed favoured, in the standard physical capacity approach, and may in fact be perceived as inefficient behaviour in a purely technical sense. Economic measures of capacity however require the application of economic data. Due to the general scarcity of such data, economic capacity analysis has yet to be seriously considered in a fisheries context. Herrero and Pascoe (2003) provide a good example where catch volume and revenue approaches to stochastic frontier production analysis are contrasted, allowing them to investigate the difference in fisher strategies in the Spanish South-Atlantic trawl fishery.

The aim of this paper is to take the first step towards an economic portrayal of capacity, as mentioned above, by investigating a revenue maximisation approach and a specific application of this. This approach can be applied when inputs can be assumed to be fixed, e.g. in the short run. It is often assumed that most fishers operate in order to maximise the value of catches, as an approximation of short-run profit, rather than the mere catch volume.

Firstly we discuss measuring technical efficiency, capacity definitions and the theoretical approaches to measuring capacity of vessels. We then consider two optimisation models by using the economic and the physical approaches to measuring capacity. Results are compared and contrasted, and are further elaborated by analysing a decomposition of the economic capacity into technical and economic factors, thus highlighting the factors that need attention in any management scheme that aims to improve efficiency.

The results of the economic capacity analysis, and the decomposition of this, are applied in an investigation of the composition of the total revenue gains possible for vessels operating at less than full economic capacity, an exercise that gives our research a further dimension. It is shown that by using the results of the economic capacity analysis the total possible revenue gains can be decomposed into a part resulting from technically optimal use of inputs, a part resulting from optimal use of variable inputs and a part resulting from landing the optimal catch composition.

2. Capacity and efficiency

2.1. Measuring technical efficiency

In the simplest terms, technical efficiency (TE) in an output-orientation is an indicator of how close actual production is to the maximal production that could be produced given the available factors of production (Farrell, 1957). Alternatively, an input-oriented TE is an indicator of the minimum levels of inputs or factors of production necessary to produce a given level of output relative to the levels of inputs actually used to produce that same level of output (Kirkley et al., 1999). Thus, this helps to estimate the proportional reduction in inputs that is possible whilst holding output levels constant.

In this paper we consider the output-oriented approach. This is regarded to be more intuitive for this analysis since, at the fishing vessel level, the choice of fixed inputs is considered more exogenous than the level of outputs. Furthermore, the capacity measurement by definition is output-oriented. Coelli et al. (1999) illustrate the output-oriented measure by considering the case where production involves two outputs (y_1 and y_2) and a single input (x). If we hold the input quantity fixed at a particular level, we can represent the technology by a production possibility frontier (PPF) in two dimensions.

In Fig. 1 we can see the PPF, i.e. the upper bound of production possibilities. Point B lies below the PPF and corresponds to an inefficient firm. Point B′, however, represents an efficient firm situated on the PPF. The distance defined by BB′ is a measure of technical inefficiency, i.e. the amount by which outputs of firm B can be increased without requiring extra input. Coelli et al. (1999) define the measure of output-oriented TE as the radial measure ratio 0B/0B′. For example, a TE score of 0.80 indicates that outputs can be increased by 25% (1/

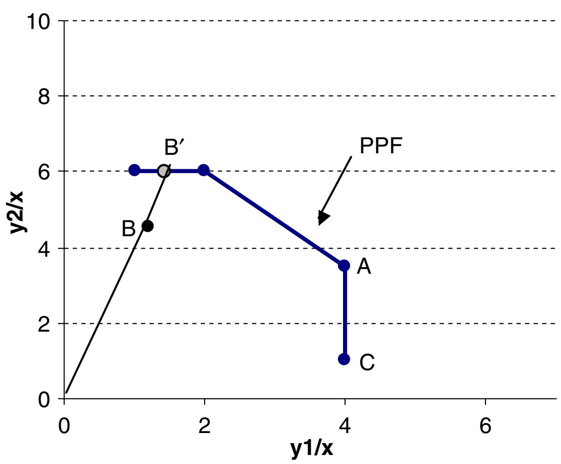

Fig. 1. Technical efficiency from an output orientation (Coelli et al., 1999).

0.8) whilst holding the current level of inputs fixed. A TE score of 1.0 represents a firm that is technically efficient and is thus on the frontier.

The returns to scale assumption is important. Under constant returns to scale (CRS) we assume that firms are of optimal scale, which is most often linked to the long-term perspective. For fisheries, this would assume that a doubling of inputs (e.g. engine power) results in a doubling of catch output, which is often not observed. Banker et al. (1984) suggest using variable returns to scale (VRS) to avoid efficiency scores being confounded by scale efficiencies, i.e. only vessels of similar scale are compared with each other.[1] VRS helps to envelope the data points more tightly (in a convex manner) than under CRS or non-increasing returns to scale (NIRS) assumptions. Hence, efficiency scores under VRS will tend to exceed scores under CRS and NIRS, given the weak assumption about the production possibility set. The choice of returns to scale should be carefully made in relation to the firms under analysis and may be assisted by undertaking regression analyses of the firms' production functions (Coelli et al., 1999).

2.2. Measuring capacity using DEA

Capacity can be defined in several ways, as examined in Coelli et al. (2002). In physical terms, Johansen (1968) defines capacity as the maximum amount that can be produced per unit of time with existing plant and equipment, provided that the availability of variable factors of production are not limited. In economic terms, Klein (1960) states that the output level associated with optimal capacity is at the tangency point between the short-run average cost (SRAC) and long-run average cost curves (LRAC). Berndt and Morrison (1981) further suggest that the minimum point of the SRAC curve should represent optimal capacity. Coelli et al. (2002) stress that the three above-mentioned capacity measures suggest that firms operate at a point where short-run profit is foregone. Hence, they suggest that the point of short-run profit maximisation be used as the preferred measure of capacity. A further concept of economic capacity can be defined as the output level that is consistent with the minimum efficient scale, or the minimum point of the LRAC curve.

[1] For fisheries, this is expected to be a reasonable assumption since licensing will tend to be limiting, which will be difficult to change in the short run.

In 1999, the Food and Agricultural Organisation of the United Nations (FAO) agreed on an International Plan of Action for the Management of Fishing Capacity. The plan calls for all member states to achieve efficient, equitable and transparent management of fishing capacity by 2005, and to provide estimates of capacity of their fishing fleets by 2001. In this regard it has been concluded that the Johansen (1968) definition of capacity, with slight modification, can be shown to provide a suitable measure of capacity. Guidelines laid down by the FAO Technical Working Group on the Management of Fishing Capacity (FAO, 1998, p. 10), hence proposed that capacity should be viewed as a physical (technical) output, where:

> Fishing capacity is the maximum amount of fish over a period of time (year, season) that can be produced by a fishing fleet if fully utilised, given the biomass and age structure of the fish stock and the present state of the technology.

An extension of the efficiency analysis by Farrell (1957) was undertaken by Charnes et al. (1978), who first applied data envelopment analysis (DEA) to multiple input, multiple output processes. Since then, DEA has been used to assess efficiency in many different areas, ranging from the public sector to the fishing industry. It has also been applied to estimate optimal input utilisation, productivity, identify strategic groups, determine benchmarks and total quality programmes, and to estimate social and private costs of regulating undesirable outputs and capacity (Kirkley et al., 2000).

Färe et al. (1989) proposed that the DEA framework could be modified in order to estimate capacity as defined by Johansen (1968). Here, the capacity estimate refers to the maximum potential or frontier level of output that could be produced given the fixed factors and full utilisation of the variable factors. Hence, this capacity approach differs from the Farrell TE approach in that the variable factors are allowed to vary. Firms that are not on the frontier are below the frontier, either because they are using inputs inefficiently or because they are using lower levels of variable inputs relative to firms on the frontier.

DEA is particularly well suited for estimating capacity in multi-species fisheries, as it can readily accommodate both multiple inputs (capital and labour) and multiple outputs (Ward, 2000). One of the drawbacks of DEA, however, is that it is unable to account for the stochastic nature of data. With

DEA, all random deviations from the frontier are deterministically attributed to inefficiency, and do not account for data noise (e.g. catch rate fluctuations) or measurement error. The position of the frontier may be impacted by this assumption, as the model assumes that the highest observed catch rates could always be duplicated (Ward, 2000).

3. Model specifications

3.1. Physical model

The estimation of capacity output can be obtained by solving a linear programming model in the General Algebraic Modelling System (GAMS) language (Brooke et al., 1998). We designate the vector of outputs by $y = (y_1, \ldots, y_m)$ and the vector of inputs by $x = (x_1, \ldots, x_n)$, with m outputs, n inputs, and J firms or observations. Capacity output and the optimum or full input utilisation values for firm j are found by solving the following problem:

$$\max_{\theta,z,\lambda} \theta_1 \tag{1}$$

subject to:

$$\sum_{i=1}^{J} z_i y_{im} \geqslant \theta_1 y_{jm} \quad \forall m, \tag{2}$$

$$\sum_{i=1}^{J} z_i x_{in} \leqslant x_{jn}, \quad n \in F_x, \tag{3}$$

$$\sum_{i=1}^{J} z_i x_{in} = \lambda_{jn} x_{jn}, \quad n \in V_x, \tag{4}$$

$$\sum_{i=1}^{J} z_i = 1, \tag{5}$$

$$z_i \geqslant 0 \quad \forall i, \qquad \lambda_{jn} \geqslant 0 \quad \forall j,n, \tag{6}$$

where θ_1 is the capacity score, y_{jm} is the amount of output m produced by firm j, x_{jn} is the quantity of input n used by firm j, λ_{jn} is the expansion/contraction factor for the n variable inputs that ensures full capacity output by firm j, and z_i is the intensity variable for firm i. θ is greater than or equal to one and is the amount by which the output must be increased to reach full capacity utilisation.

Inputs are divided into fixed factors (e.g. tonnage, engine power), defined by the set F_x, and variable factors (e.g. days at sea) defined by the set V_x. Eq. (2) represents one constraint for each output, while Eq. (3) constrains the set of fixed factors. Eq. (4) allows variable inputs to vary freely.[2] Eq. (5) imposes VRS, ensuring that inefficient firms are only compared to firms of similar scale. Further, it allows for greater flexibility in the model, an important feature for the rather heterogeneous fishing fleet under analysis. Eq. (6) is the non-negativity condition on the z and λ variables.

The model is run once for each firm in the data set. Capacity output is then determined by multiplying θ_1 by observed output. This is consistent with the Johansen (1968) definition of capacity because only fixed factors constrain production (Walden and Kirkley, 2000).

3.1.1. CU biased

Capacity utilisation (CU) can be calculated using the observed output y as follows:

$$\mathrm{CU}_{\mathrm{BIAS}} = \frac{1}{\theta_1}. \tag{7}$$

Here, biased CU ($\mathrm{CU}_{\mathrm{BIAS}}$)[3] gives the fraction that the observed output constitute of the maximum obtainable output for the same firm, measured along a ray through the origin (cf. Fig. 1). Thus the ray measure converts the multiple-output problem to a single-product problem by keeping all outputs in fixed proportions (Vestergaard et al., 2003), in line with the Farrell (1957) measure of output-oriented technical efficiency due to the radial expansion of outputs. The $\mathrm{CU}_{\mathrm{BIAS}}$ scores range from 0 to 1, with 1 representing full capacity utilisation. Values of less than 1 indicate that the firm is operating at less than full capacity given the set of fixed inputs. Using this CU approach provides us with additional information that is not obtained from a Farrell TE analysis, cf. the above discussion. However, the approaches are interrelated since CU = 1 also requires that TE = 1.

3.1.2. CU unbiased

The $\mathrm{CU}_{\mathrm{BIAS}}$ measure might be downwards biased because the observed outputs may not necessarily be produced in a technically efficient manner (Färe et al., 1994). A technically efficient measure of outputs (cf. Section 2.1) can be obtained by solv-

[2] It is clear that the presence of Eq. (4) has no influence on the solution of the problem (1)–(6). Eq. (4) provides information on the utilisation of the variable inputs, although this is not attempted in the empirical application.

[3] The reason for calling the CU measure given in (7) biased will be clarified below.

ing a problem where both the variable and fixed inputs are constrained to their current levels. This further provides additional and complementary insight into the measure of capacity analysis.

Färe et al. (1994) show that this can be determined by solving a linear programming problem, identical to the DEA VRS model for measuring capacity outlined in Section 3.1.1, but where Eq. (3) now also restricts the use of variable inputs (and Eq. (4) is removed). Using the same notation as in Eqs. (1)–(6), we thus have the following problem:

$$\max_{\theta,z} \theta_2 \tag{8}$$

subject to:

$$\sum_{i=1}^{J} z_i y_{im} \geqslant \theta_2 y_{jm} \quad \forall m, \tag{9}$$

$$\sum_{i=1}^{J} z_i x_{in} \leqslant x_{jn}, \quad n \in F_x \cup V_x, \tag{10}$$

$$\sum_{i=1}^{J} z_i = 1, \tag{11}$$

$$z_i \geqslant 0 \quad \forall i. \tag{12}$$

The result of this problem, θ_2, shows the amount by which production can be increased if the observed inputs are used in a technically efficient manner, where θ_2 is greater or equal to one. The inverse, $\mathrm{TE} = 1/\theta_2$, is the standard Farrell output-oriented technical efficiency (Färe et al., 1994; Coelli et al., 1999).

The technically efficient CU ($\mathrm{CU_{UNBI}}$) measure is then calculated as the ratio of $\mathrm{CU_{BIAS}}$ and the technical efficiency TE (Färe et al., 2000). That is:

$$\mathrm{CU_{UNBI}} = \frac{1/\theta_1}{1/\theta_2} = \frac{\mathrm{CU_{BIAS}}}{\mathrm{TE}}. \tag{13}$$

This $\mathrm{CU_{UNBI}}$ measure again ranges from 0 to 1. Values less than 1 indicate that output is less than the potential output, which can be gained if all current inputs (variable and fixed) are used efficiently. There currently remain various viewpoints of the appropriateness of the biased and unbiased approaches (cf. Coelli et al., 2002).

3.2. Economic model

As often noted in fishery economics literature, fishing is an economic activity. Hence, it may be more appropriate to assume that fishers would pursue revenue maximisation rather than maximising physical output, for example, and is relevant if costs are more or less fixed.

According to Färe et al. (2000) the capacity output models, outlined above, can be adapted to represent a revenue maximisation problem. This problem can be formulated as follows:

$$\max_{y^*_{jm},z,\lambda} \sum_m p_m y^*_{jm} \tag{14}$$

subject to:

$$\sum_{i=1}^{J} z_i y_{im} \geqslant y^*_{jm} \quad \forall m, \tag{15}$$

$$\sum_{i=1}^{J} z_i x_{in} \leqslant x_{jn}, \quad n \in F_x, \tag{16}$$

$$\sum_{i=1}^{J} z_i x_{in} = \lambda_{jn} x_{jn}, \quad n \in V_x, \tag{17}$$

$$\sum_{i=1}^{J} z_i = 1, \tag{18}$$

$$z_i \geqslant 0 \quad \forall i, \qquad \lambda_{jn} \geqslant 0 \quad \forall j, n, \tag{19}$$

where p_m is the output price for output m, and y^*_{jm} is the revenue maximising level of output m produced by firm j, given the output prices p_m and the input levels x_{jn}, and λ_{jn} is the expansion/contraction factor for the n variable inputs that ensures full capacity output by firm j.

We can then define total revenue utilisation, or economic capacity utilisation (EU), of firm j to be:

$$\mathrm{EU_{BIAS}} = \frac{\sum_m p_m y_{jm}}{\sum_m p_m y^*_{jm}}. \tag{20}$$

That is, EU is the ratio of observed revenue of firm j to maximum revenue, as calculated by the model, but given that the variable inputs are allowed to vary freely.[4] This measure is the economic equivalent of the $\mathrm{CU_{BIAS}}$ score in physical terms, as described in Section 3.1.1. The economic equivalent to $\mathrm{CU_{UNBI}}$, the $\mathrm{EU_{UNBI}}$, is defined by Färe et al. (2000), and is calculated by running the economic model where both variable and fixed inputs are restricted to their current levels and then taking the fraction between observed and technically efficient revenue as in Eq. (13). Thus:

[4] Contrary to the definition by Coelli et al. (1999), where variable inputs are kept fixed.

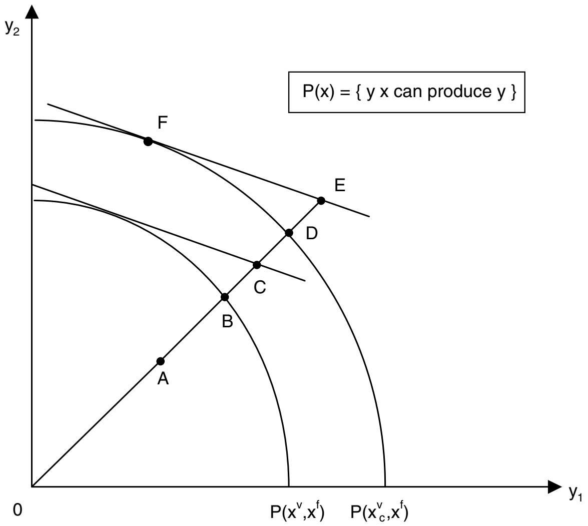

Fig. 2. Economic capacity utilisation in a 2-output case.

$$\mathrm{EU}_{\mathrm{UNBI}} = \frac{\sum_m p_m \tilde{y}^*_{jm}}{\sum_m p_m y^*_{jm}}, \tag{21}$$

where $\tilde{y}^*_{jm}$ is the economically optimal level of output m for observation j, given that the variable inputs are fixed. $\mathrm{EU}_{\mathrm{UNBI}}$ is the amount by which the revenue can be increased by varying the variable inputs, given that the input utilisation and the output composition are economically optimal before altering the variable inputs.

The economic capacity measures defined by Eqs. (20) and (21) are illustrated in Fig. 2. Firm A is economically inefficient when the variable inputs are kept fixed and is thus also inefficient when the variable inputs are allowed to vary freely. The $\mathrm{EU}_{\mathrm{BIAS}}$ score defined above (Eq. (20)) is equal to 0A/0E, while the $\mathrm{EU}_{\mathrm{UNBI}}$ score is equal to 0C/0E.

It is clear from the above that a vessel can operate at full physical capacity but not operate at full economic capacity, i.e. have $\mathrm{CU}_{\mathrm{BIAS}} = 1$ but $\mathrm{EU}_{\mathrm{BIAS}} < 1$, because the vessel does not produce the economically optimal output mix. In Fig. 2, firm D is operating at full physical capacity but at less than full economic capacity. In order to evaluate how far a vessel at full physical capacity is from being at full economic capacity, an allocative capacity utilisation (ACU) measure has been defined along the lines of the well-known definition of allocative efficiency:

$$\mathrm{ACU} = \frac{\mathrm{EU}_{\mathrm{BIAS}}}{\mathrm{CU}_{\mathrm{BIAS}}} \Longleftrightarrow \mathrm{EU}_{\mathrm{BIAS}} = \mathrm{ACU} \cdot \mathrm{CU}_{\mathrm{BIAS}}. \tag{22}$$

1/ACU is the ratio by which the revenue of a vessel on the capacity frontier (the frontier containing firm D in Fig. 2) can be increased further by allocating the output mix of the vessel. In Fig. 2 the ACU of firm D is 0D/0E. Given Eq. (13) it is seen that Eq. (22) may be further decomposed by:

$$\mathrm{EU}_{\mathrm{BIAS}} = \mathrm{ACU} \cdot \mathrm{CU}_{\mathrm{UNBI}} \cdot \mathrm{TE}. \tag{23}$$

This decomposition of the total economic capacity utilisation is useful for management, as it highlights the factors that need attention in any management scheme that aims to improve capacity utilisation. The decomposition is illustrated in Fig. 2, as $\mathrm{EU}_{\mathrm{BIAS}} = 0\mathrm{A}/0\mathrm{E} = (0\mathrm{D}/0\mathrm{E})(0\mathrm{B}/0\mathrm{D})(0\mathrm{A}/0\mathrm{B}) \equiv \mathrm{ACU} \cdot \mathrm{CU}_{\mathrm{UNBI}} \cdot \mathrm{TE}$.

In Fig. 2, $P(x^{\mathrm{v}}, x^{\mathrm{f}})$ refers to the situation where both variable and fixed inputs are held fixed. In the $P(x^{\mathrm{v}}_c, x^{\mathrm{f}})$ situation, variable inputs are allowed to vary (consistent with our capacity approach).

4. Data

The dataset comprises 97 side/stern trawling vessels fishing consumption species in the North Sea in 1999, exhibiting only minor catches of fish for reduction species (representing less than 5% of total catch value of each vessel). Trawl is the most used gear in Danish fisheries. In 1999 the trawling fleet segment fishing the North Sea had landings of 855 thousand tonnes in Danish ports, representing revenues of about €150 million (FD, 2002).

The dataset used is held in the Danish Research Institute of Food Economics (FOI) account statistics database and includes annual 1999 data on fixed inputs (tonnage, engine power and length), variable inputs (crew and days at sea), outputs (six species groups) and related output prices (cf. Tables 1 and 2). The species groups include crustacea, codfish, flatfish, herring/mackerel, fish for reduction, and other consumption species. Given the relative heterogeneous and seasonal nature of fishing activities and catch outputs, a prevailing characteristic of the Danish trawling fleet, we have opted for variable returns to scale to allow for greater flexibility in the model. Here it is thus noted that CU and EU scores obtained will tend to be higher than those obtained under other scale assumptions. Vessel output per day at sea is used in order to remove unnecessary stochastic noise from the dataset.

Average output prices for each of the six species groups have been calculated for 1999. Here, average price, referred to 'Fleet average' in Table 2, has been

Table 1
Average vessel inputs and outputs (1999)

Inputs/outputs	Units	Average	SD
Tonnage	GT/GRT	90.0	86.9
Engine power	Kilowatts	344	250
Length	Metres	21.4	7.4
Days at sea	Days	82.8	55.8
Crustacea	Kilograms	2112	3882
Codfish	Kilograms	40,103	57,866
Flatfish	Kilograms	744	4331
Herring/mackerel	Kilograms	47,748	67,400
Fish for reduction	Kilograms	28,088	100,320
Other	Kilograms	1257	1960

Table 2
Average fish prices, Danish kroner (1999)

	Crustacea	Codfish	Flatfish	Herring/mackerel	Fish for reduction	Other
Fleet – average	57.66	14.31	15.90	1.52	0.64	14.21
Vessel – average	57.06	14.93	15.75	3.66	0.64	17.12
Median	58.57	14.49	14.99	2.33	0.60	13.44
SD	10.25	2.82	4.14	3.92	0.10	10.64
25%	54.28	13.05	13.35	1.50	0.58	9.22
75%	63.54	16.39	17.09	3.39	0.68	23.40
5%	38.79	11.29	12.39	1.00	0.55	5.64
95%	66.84	19.92	20.81	10.13	0.82	37.41
Observations	46	97	97	16	11	97

calculated as the total revenue obtained by all vessels for a certain species group divided by the catch volume. This has helped to remove outliers that will be more influential if an average of all vessels' individual average price is used ('Vessel average'), which are most noticeable for some vessels catching herring/mackerel and other species. In Table 2 we can observe the distribution of prices among vessels in the dataset, noting that the 'Fleet average' prices have been used in the model of our analysis.

Table 3
CU and EU scores

	Biased		Unbiased	
	CU	EU	CU	EU
Mean	0.81	0.61	0.94	0.93
Median	0.88	0.62	1.00	1.00
SD	0.21	0.21	0.12	0.12
25%	0.63	0.43	0.92	0.91
75%	1.00	0.75	1.00	1.00

5. Results

A summary of CU and EU scores and statistical interpretations can be viewed in Table 3 and Fig. 3.

The results indicate that EU_{BIAS} scores are systematically lower than CU_{BIAS} scores. This is to be expected, as it is clearly possible to be physically efficient without being economically efficient, cf. Fig. 2 and the discussion of allocative economic capacity utilisation above. Given the decomposition of EU_{BIAS} (Eq. (24)), Table 4 and Fig. 4 show basic statistical characteristics of the ACU and TE measures, which together with CU_{UNBI} (Table 3) compose the total capacity utilisation measure.

A comparison of Table 4 and Fig. 4 (where CU_{UNBI} is included for comparative purposes) with Table 3 and Fig. 3 indicates that it is especially the ACU score that contributes to the EU_{BIAS} score, as ACU is mostly skewed away from unity, when compared with CU_{UNBI} and TE. Correspondingly, EU_{BIAS} has an approximately normal distribution with a rather low mean of 0.61. TE also seems to have some influence on EU_{BIAS} while CU_{UNBI} seems to be of less importance.

The Spearman rank correlation coefficient between EU_{BIAS} and CU_{BIAS} is 0.74, which is significant, indicating that a vessel with high CU_{BIAS} will also have a high EU_{BIAS}, and vice versa, even

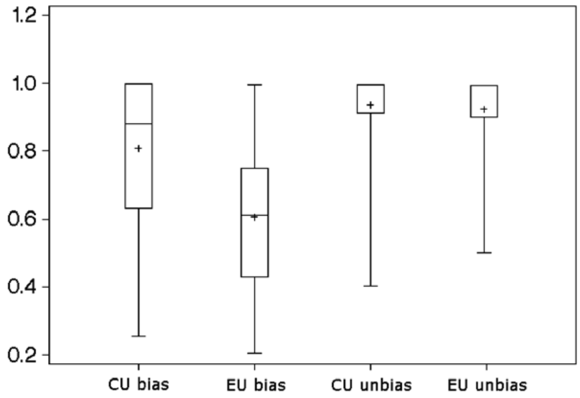

Fig. 3. Box plots of CU and EU scores.

Table 4
Basic statistics of ACU and TE scores

	ACU	TE
Mean	0.76	0.86
Median	0.77	0.99
SD	0.16	0.19
25%	0.68	0.75
75%	0.87	1.00

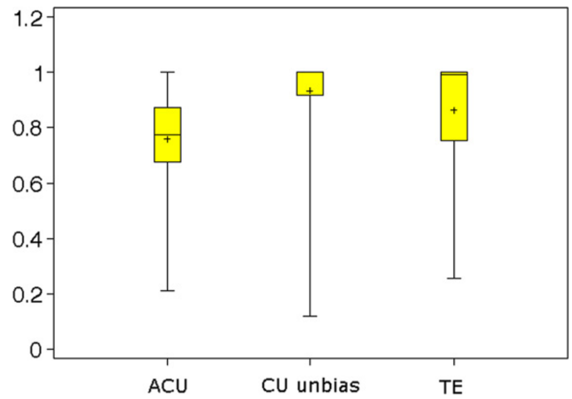

Fig. 4. Box plots of the distributions of ACU, CU_{UNBI} and TE scores.

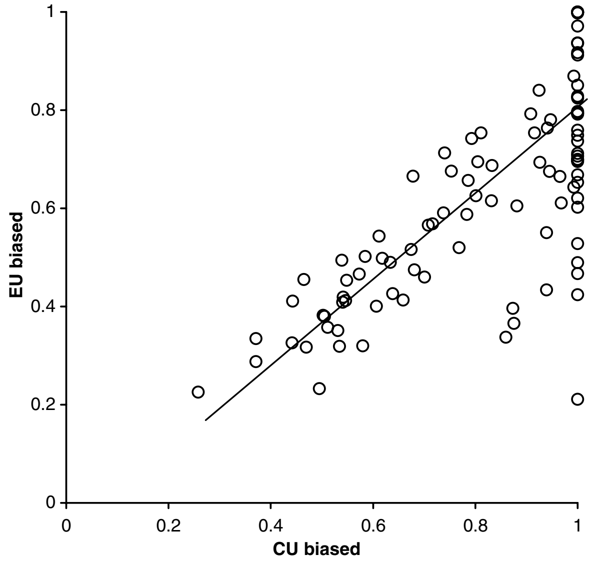

Fig. 5. CU_{BIAS} plotted against EU_{BIAS} scores.

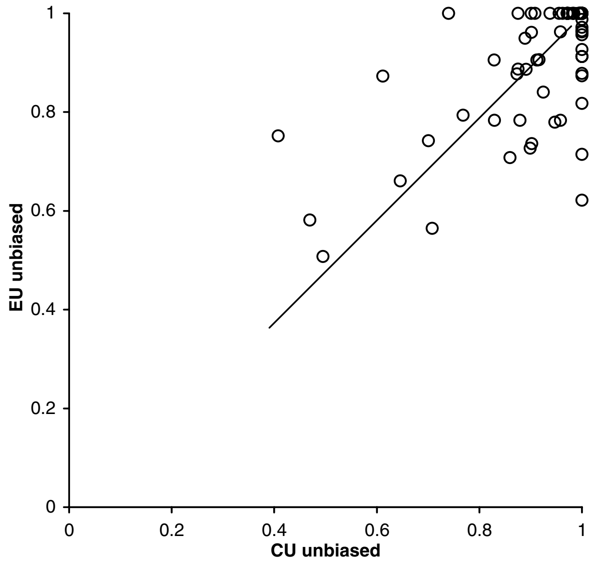

Fig. 6. CU_{UNBI} plotted against EU_{UNBI} scores.

though EU_{BIAS} is systematically lower than CU_{BIAS} as mentioned above. This is illustrated in Fig. 5, which shows CU_{BIAS} plotted against EU_{BIAS}. Contrary to this, both CU and EU unbiased scores are approximately equal, cf. Table 3 and Fig. 6, although there is more correlative noise among the scores, with a Spearman rank correlation coefficient of only 0.53. Hence, a consistent link between the unbiased scores is less obvious than for the biased case.

These tendencies have been further analysed by the Wilcoxon signed-rank test, a statistical non-parametric method of testing the pair-wise equality of scores of two populations. The results of the Wilcoxon test support the correlation analysis. The CU_{BIAS} and EU_{BIAS} scores are shown to be different from each other with a 0.181 difference between medians, and a probability of less than 0.01% that they are equal. CU_{UNBI} and EU_{UNBI}

scores are on the contrary shown to be equal with a probability of 0.58.

As shown in other studies (Vestergaard et al., 2002, 2003), the use of the unbiased approach results in higher utilisation scores than the biased approach. This is because the approach is based on the assumption that the current mix of variable inputs for each vessel is efficient and cannot be expanded. Hence, there is less scope for increasing capacity output and the level of current capacity utilisation is therefore higher. The present analysis likewise shows that this is also the case for the EU scores.

6. Composition of revenue gains

The above results have been applied in an analysis of the composition of the revenue gains that can be obtained by each of the 97 individual trawlers in the sample by moving from observed to full capacity revenue, where the latter is obtained when the vessels utilise their fixed and variable inputs optimally, and land an optimal catch composition.

As mentioned above, there may be several reasons why a vessel is economically inefficient, i.e. why $EU_{BIAS} < 1$. Firstly, it may be technically inefficient, i.e. lie below the technical efficient frontier (defined by Eqs. (8)–(12), and shown in Fig. 2 by the 'inner' frontier containing point B), and thus also lie below the economically efficient frontier,[5] as shown in Fig. 2 (the iso-revenue line containing point E). Secondly, it may be technically efficient but not employing the variable inputs optimally, thus lying below the capacity frontier (the 'outer' frontier shown in Fig. 2 containing point D), and therefore also lie below the economic frontier. Thirdly, it may be operating at full capacity (i.e. lie on the capacity frontier in Fig. 2) but still not economically efficient as it's output mix must be allocated to be economically optimal. This composition of the total possible revenue increase is illustrated in Fig. 7.[6]

[5] As opposed to the technical economic efficient frontier (the iso-revenue line shown in Fig. 2 containing point C) defined by Coelli et al. (1999).

[6] Notice that we in this applications use the radial technical revenue, i.e. the revenue at point B in Fig. 2, rather than the allocative technical revenue used to evaluate EU_{UNBI} in Eq. (21). The reason is that we in the present application only focus on allocation effects at full capacity, and not at the technical efficient frontier.

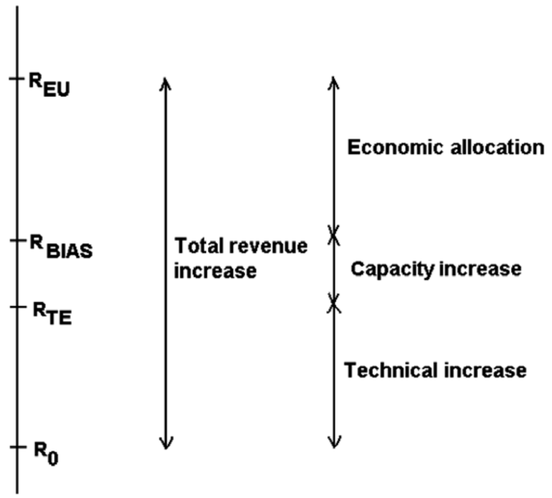

Fig. 7. Illustration of the total possible increase in revenue (R) for a given vessel.

The composition (23) of the biased economic capacity utilisation has been applied to estimate the composition of revenue gains shown in Fig. 7. In short the total revenue increase consists of a technical increase due to optimisation of fixed factors, a capacity increase due to possible variation of variable factors, together with an economic allocative increase resulting from allocating the frontier outputs to the combination that gives the highest revenue.

Given the factors ACU, CU_{UNBI} and TE, which compose EU_{BIAS} (cf. Eq. (23)) and which can all be evaluated from the DEA programmes described above, it is straightforward to estimate how big a fraction each of the three revenue (R) increments constitutes of the total revenue increase. The fractional technical increase is given by:

$$\Delta_{TE} = \frac{R_{TE} - R_0}{R_{EU} - R_0} = \frac{\sum_i p_i y_i^{TE} - \sum_i p_i y_i^0}{\sum_i p_i y_i^* - \sum_i p_i y_i^0}, \tag{24}$$

where

$$y^{TE} = \frac{1}{TE} y^0 = \theta_2 y^0. \tag{25}$$

The optimal revenue R_{EU} is equal to the highest observed revenue in the sample. This is determined by the tangent point y^* between the full capacity frontier and the iso-revenue plane (depicted as point F in Fig. 2) and corresponds to the optimal revenue R_{EU}. As $R = R_{EU}$ at every point on the iso-revenue plane, R_{EU} can also be evaluated using the radial projection of the observation in question onto the iso-revenue plane (for firm A this radial projection is point E in Fig. 2). It is straightforward to show that if $\mathrm{EU_{BIAS}}$ is the biased economic capacity utilisation of the observation in question, then $\theta_{\mathrm{EU}} \equiv 1/\mathrm{EU_{BIAS}}$ projects the observation onto the iso-revenue plane.

Thus

$$R_{\mathrm{EU}} = \sum_i p_i y_i^* = \sum_i p(\theta_{\mathrm{EU}} y_i). \tag{26}$$

Given (25), (26) and the composition (23) the technical increment of the revenue (24) can now be estimated by:

$$\Delta_{\mathrm{TE}} = \frac{\sum_i p_i \theta_2 y_i^0 - \sum_i p_i y_i^0}{\sum_i p_i \theta_{\mathrm{EU}} y_i^0 - \sum_i p_i y_i^0} = \frac{\theta_2 - 1}{\theta_{\mathrm{EU}} - 1}. \tag{27}$$

Likewise it may be shown that the fractional capacity increase (i.e. the fractional revenue increase obtained by moving radially from the technical to the capacity frontier, i.e. from point B to point D in Fig. 2) and the fractional allocative increase (i.e. the fractional revenue increase obtained from output allocation at the capacity frontier) are given by:

$$\Delta_{\mathrm{CAP}} = \frac{\theta_2(\theta_{\mathrm{UNBI}} - 1)}{(\theta_{\mathrm{EU}} - 1)}; \quad \theta_{\mathrm{UNBI}} = \frac{1}{\mathrm{CU_{UNBI}}} \tag{28}$$

and

$$\Delta_{\mathrm{ACU}} = \frac{\theta_2 \cdot \theta_{\mathrm{UNBI}}(\theta_{\mathrm{ACU}} - 1)}{(\theta_{\mathrm{EU}} - 1)}; \quad \theta_{\mathrm{ACU}} = \frac{1}{\mathrm{ACU}}, \tag{29}$$

where the allocative economic capacity utilisation ACU is defined in Eq. (22). It is clear that $\Delta_{\mathrm{TE}} + \Delta_{\mathrm{CAP}} + \Delta_{\mathrm{ACU}} = 1$. From Eqs. (27)–(29) it is now possible to analyse the composition of the revenue increments.

Of the 97 vessels constituting the sample employed in this paper, six have $\mathrm{EU_{BIAS}}$ equal to one, i.e. operate at full economic capacity. Twenty-nine vessels are operating at full capacity but are not economically efficient, meaning that the only increase in revenue is given by allocating the outputs to the economically optimal combination. For the remaining 62 vessels the revenue increase composition is shown in Fig. 8, which shows how big a fraction the technical increase (Eq. (27)), the capacity increase (Eq. (28)) and the allocative increase (Eq. (29)) constitute of the total revenue increase for each of the 62 vessels. Each horizontal column in the figure is the revenue increase composition for an individual vessel. Vessel number one (the bottom column of the figure) can, for example, increase its observed revenue by ~85% by using its inputs in a technical efficient manner, and increase observed revenue by ~15% by using variable inputs in optimal amounts. However, this vessel cannot gain any revenue increase by allocating its output mix.

Fig. 8 shows that the total revenue increase for most vessels is a combination of efficient increase

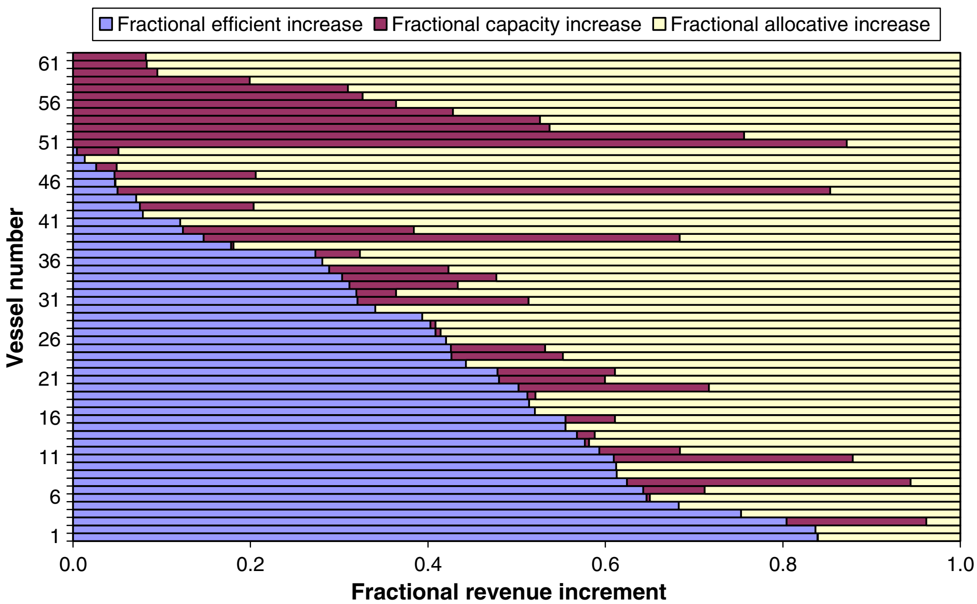

Fig. 8. Revenue gain combination for the 62 trawlers that are not operating at full economic or full physical capacity.

and economic allocation, while the capacity increase is less important, except for a group of approximately 5–15 vessels. This result is in accordance with the results presented in the previous section, where it was shown that it is especially the technical efficiency and the allocative economic capacity utilisation that contribute to the full economic capacity utilisation.

It is concluded that (i) a large fraction of the vessels would be able to increase their revenue by employing their given inputs in an optimal way, (ii) only a relatively small fractions of the vessels can achieve a higher revenue by changing the variable inputs, and (iii) few vessels operate at full economic capacity. With regard to the last conclusion it should furthermore be remarked that a rather large fraction (38%) of the vessels are operating at full physical capacity, but not at full economical capacity, meaning that they would be able to gain higher revenue had they aimed at a different catch combination. However, it is possible that management regulation may constrain such an outcome in practice.

7. Discussion and concluding remarks

Why is it that we wish to find an economic measure of capacity, as opposed to the more standard physical approach? Further, why do we regard the inclusion of economic data as an imperative criterion to performance measurements of fishing vessels? We know that fishers are not purely interested in catching fish, but also wish to maximise their profits. They do so by implementing strategies that both seek to maximise the revenue of their catches whilst attempting to minimise the costs of securing that catch, although fisher behaviour may deviate from this generalised case. We thus maintain that an economic approach gives a more realistic portrayal of who is best placed to operate efficiently in the fishery under current conditions.

In this paper we have taken the first step in this regard, namely by analysing the optimal mix of outputs for each vessel that will help to maximise revenues. We have compared and contrasted the standard physical DEA approach to that of an economic approach based on catch revenues. The estimates of our analyses are intuitively pleasing. Firstly, the results of the physical CU model support previous studies, where unbiased measures are higher than biased measures, since the effect of technical factors is present in the biased measure but has been removed from the unbiased measure. Statistical testing shows that the two sets are highly correlated but are statistically different from each other. That is, unbiased scores are systematically higher than biased scores. The two sets of EU scores are, however, less correlated but are deemed to be statistically equal, possibly caused by the closer proximity to unity (full capacity utilisation). Secondly, fewer vessels at full capacity are identified when the economic EU measure is applied, implied by average EU scores being lower than CU scores in both biased and unbiased cases. That is, average scores of the fleet are systematically lower when an economic factor such as catch revenue is applied. Both these conclusions are in line with the theoretical work discussed earlier in the paper, where unbiased scores should be higher than biased scores and CU scores should be higher than EU scores. Hence, the choice of capacity measure will have a considerable impact if management is to be structured on this form of capacity analysis. What should also be emphasised is that this paper serves as a platform where physical and economic capacity measures can be directly compared for the same set of fishing vessels.

A revenue composition analysis has been performed and has allowed us to attain further insight into the different factors that may lead to increased revenue. It has been shown that the dominant causes of economic inefficiency are technical and economic allocative factors, while a fisher's ability to adjust variable inputs is less important. Hence, our results not only help to identify which vessels are technically and economically in-/efficient, but also by which proportions each vessel needs to adjust their technical and/or economic factors in order to be as efficient as the vessels on the best practice economic frontier. Our analysis has been able to identify these proportions for the 97 North Sea trawlers in our dataset. It is hence intuitive to postulate that through the application of comprehensive fleet and fishery data, important fleet structure information can be attained to allow the implementation of more precise and purposeful structural measures in fisheries.

There are many opportunities to extend our analysis in future research. Firstly, the use of a larger dataset, and possibly different fleet segments, would assist us to verify our results. Secondly, a further step would be to formulate a profit maximisation problem based on Coelli et al. (2002). In such a case we would also need the specification of input prices, as well as the output prices defined in the economic model in this paper. Thirdly, we have used average prices to solve the economic capacity problem. It would also be feasible to use the individual prices obtained by each vessel. This may help to identify those vessels that enhance their economic efficiency levels by locating better market prices (time and place) or by delivering a product of superior catch quality. However, by using average prices we have reduced the effect of outliers in the efficiency analysis, lessening the impact of a vessel that may only have caught one kilo of codfish, for example, but was fortunate enough to attain a far superior price than the prevailing average price. We also consider that it may be more appropriate to include more species groups and quality grades of outputs in the analysis where differential prices are observed. Another way to solve this problem is by introducing 'environmental factors' (e.g. Coelli et al., 1999) that allows us to only compare vessels that have a similar mix of graded outputs.

An issue that should be considered when using this kind of approach to measuring capacity are the underlying principles of the analysis. The results we achieve, and our determination of who is efficient and who is not, much depends on our identification and inclusion of inputs. Our results may therefore be slightly biased, according to whether we have been able to select the most appropriate inputs. Bias may also arise if a vessel, for example, decides to use its engine at is maximum output potential, whereas another vessel is more concerned with fuel efficiency and sails at more modest speeds. This further highlights the need for inclusion of other economic data in order to determine the operating cost of physical inputs at various levels. With the FAO proposing that a tool such as DEA may be applied to capacity analysis on a worldwide basis, given that there is sufficient data, we should be aware that vessel efficiency is influenced by our input and returns to scale assumptions.

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References

Banker, R.D., Charnes, A., Cooper, W.W., 1984. Some models for estimating technical and scale inefficiencies in data envelopment analysis. Management Science 30, 1078–1092.

Berndt, E., Morrison, C., 1981. Capacity utilization measures: Underlying theory and an alternative approach. American Economic Review 71, 48–52.

Brooke, A., Kendrick, D., Meeraus, A., Raman, R., 1998. GAMS: A User's Guide, GAMS Development Corporation, December.

Charnes, A., Cooper, W., Rhodes, E., 1978. Measuring the efficiency of decision making units. European Journal of Operational Research 2, 429–444.

Coelli, T., Rao, D.P., Battese, G., 1999. An Introduction to Efficiency and Productivity Analysis. Kluwer Academic Publishers, London.

Coelli, T., Grifell-Tatje, E., Perelman, S., 2002. Capacity utilisation and profitability: A decomposition of short-run profit efficiency. International Journal of Production Economics 79 (3), 261–278.

FAO, 1998. Report of the FAO Technical Working Group on the Management of Fishing Capacity, La Jolla, USA, 15–18 April.

Farrell, M., 1957. The measurement of productive efficiency. Journal of the Royal Statistical Society Series A: General 120, 253–281.

FD, 2002. Danish Directorate of Fisheries Online Statistics. Available from: <http://www.fd.dk>.

Färe, R., Grosskopf, S., Kokkenlenberg, E., 1989. Measuring plant capacity utilization and technical change: A non-parametric approach. International Economic Review 30, 655–666.

Färe, R., Grosskopf, S., Lovell, C.A.K., 1994. Production Frontiers. Cambridge University Press, New York.

Färe, R., Grosskopf, S., Kirkley, J., 2000. Multi-output capacity measures and their relevance for productivity. Bulletin of Economic Research 52 (2), 101–112.

Herrero, I., Pascoe, S., 2003. Value versus volume in the catch of the Spanish South-Atlantic trawl fishery. Journal of Agricultural Economics 54 (2), 325–341.

Johansen, L., 1968. Production functions and the concept of capacity. Recherches Recentes sur le Fonction de Production, Collection, Economie Mathematique et Econometrie 2.

Kirkley, J.E., Squires, D., Walden, J.B., Ward, J., 1999. Assessing efficiency and capacity in fisheries. Prepared for the National Marine Service Workshop of "Assessing Technical Efficiency and Capacity in Fisheries". Silver Spring, MD, September 29–October 1.

Kirkley, J.E., Färe, R., Grosskopf, S., McConnell, K., Strand, I., Squires, D., 2000. Assessing capacity in fisheries when data are limited. North American Journal of Fisheries Management.

Kirkley, J.E., Morrison Paul, C.J., Squires, D., 2002. Capacity and capacity utilisation in common-pool resource industries. Environmental and Resource Economics 22, 71–97.

Klein, L.R., 1960. Some theoretical issues in the measurement of capacity. Econometrica 28, 272–286.

Vestergaard, N., Hoff, A., Andersen, J.L., Lindebo, E., Grønbæk, L., Pascoe, S., Tingley, D., Mardle, S., Guyader, O., Daures, F., van Hoof, L., de Wilde, J.W., Smit, J., 2002. Measuring Capacity in Fishing Industries using the Data Envelopment (DEA) Approach. EU Project Final Report, 99/005.

Vestergaard, N., Squires, D., Kirkley, J.E., 2003. Measuring capacity and capacity utilization in fisheries: The case of the danish Gill-net fleet. Fisheries Research 60, 357–368.

Walden, J.B., Kirkley, J.E., 2000. Measuring capacity of the new england otter trawl fleet. In: IIFET 2000 Proceedings, Oregon State University.

Ward, J., 2000. Capacity, excess capacity, and fisheries management. In: IIFET 2000 Proceedings, Oregon State University.