Environ Resource Econ (2009) 43:573–590
DOI 10.1007/s10640-008-9251-7

Ecological Benchmarking to Explore Alternative Fishing Schemes to Protect Endangered Species by Substitution: The Danish Demersal Fishery in the North Sea

Jens Kjærsgaard · Niels Vestergaard · Kristiaan Kerstens

Received: 19 March 2007 / Accepted: 2 December 2008 / Published online: 25 December 2008

Abstract The cod stock in the North Sea is threatened by overexploitation. To recover this fishing stock, pressure needs to be reduced. This implies that catch compositions with small amounts of cod are preferred by public policy makers. The present analysis assesses the technological efficiency of fishing trips in terms of the substitution possibilities away from cod by considering landings of cod as an undesirable output. A conservative non-parametric frontier technology approach imposing minimal assumptions and based on directional distance functions is applied to explore alternative fishing activities for Danish gill netters operating in the North Sea with the goal of reducing cod catches. Since performance on different fishing trips may be influenced by the operating environment, a four-stage approach is applied to correct for exogenous factors (Fried et al., J Product Anal 12(3):249–267, 1999). The corrected directional distance function efficiency scores reveal the behavioural inefficiencies, i.e., prospects for decreasing the catch of cod while catch of other species are increased.

Keywords Capacity · Directional distance function · Fisheries · Output substitution

JEL Classification C61 · D24 · Q22 · Q28

J. Kjærsgaard (✉)
Institute of Food and Resource Economics, University of Copenhagen, Rolighedsvej 25, 1958 Frederiksberg C, Denmark
e-mail: jk@foi.dk

N. Vestergaard
Department of Environmental and Business Economics, Centre of Fisheries and Aquaculture Management and Economics (FAME), University of Southern Denmark, Esbjerg, Denmark

K. Kerstens
CNRS-LEM (UMR 8179), IESEG School of Management, Lille, France

1 Introduction

The cod stock in the North Sea is threatened by overexploitation. It is almost universally agreed that it is necessary to reduce the fishing pressure for this stock to allow it to recover (ICES 2006; COM 2001). In current fishery policies, cod recovery has been based on a mixed fisheries management plan. This presumes that species are caught jointly and to reduce cod catches requires that catches of other species are reduced proportionally. Therefore, as part of the cod recovery plan, the days at sea regulation has been instituted to reduce the overall effort of vessels catching cod (Council Regulation (EC) No. 423/2004 and annex V of No. 2287/2003).

This contribution questions this presumption of fishery policy and investigates whether fishing effort can be redirected towards other demersal species and away from cod. Basically, the best practice production possibility frontier is analysed at the firm level to explore substitution possibilities among outputs. Considering cod landings as an "undesirable" output and landings of other species as "desirable" outputs, the underlying idea is that cod stock protection requires investigating the scope for reducing fishing effort oriented towards cod by substituting these catches with catches of other species along the output transformation curve. If this turns out to be technologically feasible, then it establishes the ground for at least partly reversing current fishery policy approaches aimed at protecting the cod stock presuming that reducing catches of this threatened species depend on reducing catches of other species as well.

Notice that cod catches are considered undesirable only in the short run from a social perspective to restore the cod stock and thus as part of a long term management perspective. Catching cod reduces the likelihood of stock recovery once critical stock levels have been reached. Since cod is a valuable species and reducing cod catches reduces the revenues of fishermen in the short run, ceteris paribus, catching cod is obviously not generally/universally a bad output for producers. This conflict between short run revenue loss and defining a successful stock recovery guaranteeing long term sustainability of the fisheries poses a serious challenge to management. For the purpose of the present analysis, which is aimed at promoting cod recovery, catches of cod are considered a bad output.

The fishing vessels considered in the present study are gill netters between 12 and 24 m. These vessels account for approximately 33% of total North Sea landings of cod in 2005. In addition, more than 28% of their total revenue comes from cod landings, indicating that it is an important species with a noticeable contribution to economic performance. The possibility for all vessels to redirect effort by changing their output mix according to best practice is partially limited in terms of both available resources (i.e., other species), economic viability of the individual units and the current regulation.

The production possibility set is determined by a conservative non-parametric frontier technology specification assuming minimal assumptions, namely weak disposal of bads and null-jointness of good and bad outputs, and it is based on estimating a directional distance function (see Färe and Grosskopf 2004a). An empirical production possibility set is defined by enveloping the observed multi-input multi-output combinations.[1] The directional distance function approach for modelling productivity and undesirable outputs is introduced in Chung et al. (1997). In this setup desirable outputs are expanded while one seeks to contract undesirable outputs. The utilisation of directional distance functions to assess environmental performance relative to environmental technologies characterised by a joint production of

[1] The original study introducing the term Data Envelopment Analysis (DEA) is by Charnes et al. (1978), but the fundament for non-parametric measurement of production efficiency dates back to Farrell (1957). A systematic introduction to the methodology can be found in Färe et al. (1994).

good and bad outputs has meanwhile become rather widespread (see Domazlicky and Weber 2004; Lee et al. 2002; Picazo-Tadeo et al. 2005, amongst others). For instance, the Lee et al. (2002) study shows how the average shadow prices of bads at the frontier are lower than those obtained with traditional methods under the assumption of full efficiency. In Färe et al. (2006) the directional distance function approach is applied relative to a technology assuming weak disposal of bads and null-jointness of goods and bads to consider unwanted discards in the Georges Bank otter trawl fishery. The present analysis basically applies this methodological approach of Färe et al. (2006) to Danish fisheries to obtain a conservative estimate of substitution possibilities away from cod, while adding two innovations. First, to explore the alternatives for the fishing vessels a different efficiency measure is introduced that accounts for the potential underutilization of invested capital. Second, we take into account that exogenous factors may influence observed input–output combinations that provide the basis for the empirical production possibility set, i.e., some observations may be influenced by favourable or unfavourable operating conditions. Therefore, a four-stage approach, introduced by Fried et al. (1999), is applied that separates managerial inefficiencies from inefficiencies that can be attributed to the external operating environment, which are important in fisheries.

Section 2 characterises the assumptions of technology and defines a directional distance function to evaluate inefficiency given the presence of both desirable and undesirable outputs. In Sect. 3, we summarise the procedure that corrects for exogenous factors for the present technology. Section 4 introduces the Danish case study analysed. Empirical results are presented in Sect. 5, while consequences from changing catch composition are discussed in Sect. 6. Concluding remarks are contained in a final Sect. 7.

2 Non-Parametric Frontier Technology and Distance Functions

We start out with defining the production technology and the distance function employed to characterise the technology and evaluate efficiency. Let $y \in \Re_{+}^{J}$ be a vector of good outputs, $u \in \Re_{+}^{K}$ be a vector of bad outputs, and $x \in \Re_{+}^{I}$ be a vector of inputs and consider the technology:

$$Y = \{(x, y, u) | x \text{ can produce } (y, u)\}. \tag{1}$$

Non-parametric technologies (also known as Data Envelopment Analysis (DEA) models) provide an inner approximation of the unknown true technology Y. This technology is estimated based on empirical data such that the actual observations are enveloped by the production possibility set according to a minimal series of assumptions (apart from regularity conditions, these are mainly convexity and disposability assumptions). Assume that there are N production units. Then, imposing variable returns to scale and following Färe et al. (2006), the empirical technology is described by the following system of inequalities (see also Jeon and Sickles 2004, p. 587):

$$Y_0^e = \left\{ (x, y, u) \in \Re_{+}^{I+J+K} | \sum_{n=1}^{N} \lambda_n x_n \leq x, \sum_{n=1}^{N} \lambda_n y_n \geq y, \sum_{n=1}^{N} \lambda_n u_n = u, \right.$$
$$\left. \lambda \in \Re_{+}^{N}, \sum_{n=1}^{N} \lambda_n = 1 \right\}. \tag{2}$$

The equality in the equation for bad outputs imposes weak disposability on undesirable outputs, i.e. there is an opportunity cost in terms of good outputs when attempting to reduce these bad outputs. However, inputs and desirable outputs are both strongly disposable and hence modelled by an inequality (see Färe and Grosskopf 2004a). In addition, the technology has the property of convexity. The last constraint on the activity vector λ imposes variable returns to scale.

A directional distance function generalizes existing distance functions by allowing for both input reductions and output increases simultaneously. Furthermore, it is dual to the profit function and, therefore, it is a proper description of standard goals attributed to production units. Alternative efficiency measurement frameworks are available: for instance, one is the hyperbolic efficiency measure employed in Färe et al. (1989a), another one is the approach developed in Seiford and Zhu (2002). However, these concepts tend to be less general in terms of their relation to traditional economic objective functions (for instance, the hyperbolic efficiency measure is related to a "return to the dollar" objective function (see Färe et al. 2002)).

To focus on the trade-offs between good and bad outputs, this article employs the output-oriented variant of this directional distance function (Färe and Grosskopf 2004a):

$$\vec{D}_0(x, y, u; g_y, g_u) = \max\{\beta : (x, y + \beta g_y, u - \beta g_u) \in Y_0^e\}. \tag{3}$$

This function simultaneously indicates the greatest feasible expansion of good outputs in the direction g_y and contraction of bad outputs in the direction g_u compatible with a given vector of inputs. Furthermore, it has a revenue interpretation. For the present purposes, the direction $(g_y, g_u) = (y, u)$ is considered which makes this distance proportional.

The output-oriented directional distance function evaluated for each of the individual observations $(x_{act}, y_{act}, u_{act})$ can be determined by solving the following mathematical program:

$$\begin{aligned}
&D_0(x_{act}, y_{act}, u_{act}; y, u) = \max \beta \\
&\text{subject to} \\
&\sum_{n=1}^{N} \lambda_n y_{n,j} \geq (1+\beta) y_{act,j}, \quad j = 1, \ldots, J \\
&\sum_{n=1}^{N} \lambda_n u_{n,k} = (1-\beta) u_{act,k}, \quad k = 1, \ldots, K \\
&\sum_{n=1}^{N} \lambda_n x_{n,i} \leq x_{act,i}, \quad i = 1, \ldots, I \\
&\sum_{n=1}^{N} \lambda_n = 1 \\
&\beta, \lambda_n \geq 0, \quad n = 1, \ldots, N.
\end{aligned} \tag{4}$$

Note that $0 \leq \beta \leq 1$ for a feasible solution. This means that the maximal expansion of good outputs is doubling the observed amount (see Färe et al. 2006).

If variable inputs are considered as decision variables, then the production possibility set changes. Let I_f and I_v be the two sets defining the partition between fixed and variable inputs (x^f, x^v). By dropping the constraints on the subset of variable inputs in the above technology (2) one obtains a short-run technology:

$$\begin{aligned}
Y_1^e = \Bigg\{&(x, y, u) \in \Re_+^{I+J+K} | \sum_{n=1}^{N} \lambda_n x_{n,i} \leq x_i, i \in I_f, \sum_{n=1}^{N} \lambda_n y_n \geq y, \\
&\sum_{n=1}^{N} \lambda_n u_n = u, \lambda \in \Re_+^N, \sum_{n=1}^{N} \lambda_n = 1\Bigg\}.
\end{aligned} \tag{5}$$

The corresponding output-oriented directional distance function is evaluated for each of the individual observations $(x_{act}, y_{act}, u_{act})$ by the following mathematical program:

$$\begin{aligned}
&\overrightarrow{D}_1(x_{act}, y_{act}, u_{act}; y, u) = \max \overline{\beta} \\
&\text{subject to} \\
&\sum_{n=1}^{N} \lambda_n y_{n,j} \geq (1+\overline{\beta}) y_{act,j}, \quad j = 1, \ldots, J \\
&\sum_{n=1}^{N} \lambda_n u_{n,k} = (1-\overline{\beta}) u_{act,k}, \quad k = 1, \ldots, K \\
&\sum_{n=1}^{N} \lambda_n x_{n,i}^{f} \leq x_{act,i}^{f}, \quad i \in I_f \\
&\sum_{n=1}^{N} \lambda_n = 1 \\
&\overline{\beta}, \lambda_n \geq 0, \quad n = 1, \ldots, N,
\end{aligned} \tag{6}$$

where $0 \leq \overline{\beta} \leq 1$.

Let us now compare both mathematical programs in some detail. The program in (4) measures technological inefficiency and reveals possible proportionate changes in good and bad outputs, for given levels of both fixed and variable inputs. The program in (6) furthermore captures the potential underutilization of fixed capital, i.e., variable inputs in (6) can be changed at will to maximize the changes in good and bad outputs for given levels of fixed inputs. Since program (6) is less constrained than program (4), $\beta \leq \overline{\beta}$.

Based on these two mathematical programs, plant capacity utilization, defined in terms of the directional distance function, is calculated as the ratio of good output expansion and bad output reduction relative to technologies (2) and (5):

$$\mathrm{CU} = \frac{1+\beta}{1+\overline{\beta}}, \tag{7}$$

where $0.5 \leq \mathrm{CU} \leq 1$.[2]

This naturally leads to the following decomposition of static efficiency:

$$1 + \beta = (1 + \overline{\beta})\mathrm{CU}, \tag{8}$$

whereby the efficiency with respect to the standard technology is decomposed into efficiency with respect to the short-run technology and plant capacity utilization as defined in (7).

Traditionally, the assumptions of strong disposal of inputs and good outputs, the axiom of weak disposal of bads, and the axiom of variable returns to scale are directly imposed on the definition of technology (see (2) and (5)). Furthermore, as pointed out by Färe et al. (1994, pp. 44–45), the matrices of observed inputs and outputs should basically satisfy the following structure: in the aggregate some positive amount of each input must be used to produce some positive amount of each of the outputs, and each producer should use some positive input to produce some positive output.

[2] Expression (7) is akin to traditional ratio based measures of plant capacity utilisation based upon radial output efficiency measures (see, e.g., Färe et al. 1989b). However, notice that the directional distance function lends itself more naturally to difference based definitions and decompositions (in contrast to the multiplicative ratio-based decomposition (8)). Hence, it would be equally possible to redefine expression (7) as follows: $\mathrm{CU}' = \overline{\beta} - \beta$ and subsequently rewrite the decomposition (8) as: $\beta = \overline{\beta} - \mathrm{CU}'$. This has—to the best of our knowledge—not been considered in the literature.

According to Färe and Grosskopf (2004b) the production possibility set is an environmental output set if bad outputs are weakly disposable and good and bad outputs are null-joint. Null-jointness means that production of good outputs inevitably implies production of bad outputs. Following Färe et al. (2006), null-jointness is imposed on all observations in this contribution by limiting the analysis to observations where bad outputs are present. This amounts to strengthening the above requirements on the input and output matrices by partitioning the output vector into a sub-vector of good and bad outputs: each producer must produce at least one bad output, while each bad output is produced by at least one producer. Since we only distinguish one bad output in the specification, this amounts to eliminating any observations with no catches of cod.

Thus, by imposing this assumption about null-jointness we exclude observations with no catches of cod and we obtain an even more conservative estimate of the potential substitution possibilities among the outputs. For the fishery considered it is not realistic that skills alone can eliminate catches of cod entirely. However, it is indeed likely that they can influence the magnitude, meaning that it is possible to reduce catches of cod for example by choice of gear or location. Without imposing null-jointness, the model would reveal even more optimistic substitution possibilities among the outputs, but this would not change the main message of this contribution.

3 Correcting for the Operating Environment

Efficiency estimates may be influenced by exogenous factors outside the control of the producers. This may be environmental conditions or regulations of all kind. When production units are compared, then it is assumed that they operate under similar operating conditions. If this is not the case, then the prospects for improvement are under- or overestimated. A fundamental choice is to consider these environmental variables either as part of the description of technology, or as variables affecting the distance to the frontier (i.e., inefficiency). For non-parametric technologies, a whole series of methodologies have been proposed for handling such environmental variables (see, e.g., Muñiz et al. (2006) for a partial review). Recently, new statistical methods have been developed that propose a two stage approach to modelling environmental conditions (see Simar and Wilson (2007), who also offer an extensive critique of traditional methods). In conclusion, this issue remains the subject of substantial methodological controversy. This leaves the applied modeller with some freedom in selecting a proper method.

We have opted for a method introduced by Fried et al. (1999) that seems to perform rather well in simulation analysis (see Muñiz et al. 2006). These authors introduced a four-stage technique to separate the management (behaviour) component of inefficiency from the exogenous components. This technique is applied to the technologies described in the previous section, whereby a distinction is made between good and bad outputs.

The first stage is to calculate the directional distance function frontier technology (see Sect. 2). Exogenous factors are ignored. Efficiency scores and output slacks are determined for every observation and all output dimensions. Following the terminology in Fried et al. (1999), output slacks comprise radial and non-radial slacks. Figure 1 illustrates radial (ry and ru) and non-radial slack (nry) for observation D given the assumptions of the technology described above (for given input levels). Since the technology implies weak disposability of bad outputs, non-radial slacks are not possible for these output dimensions. The production

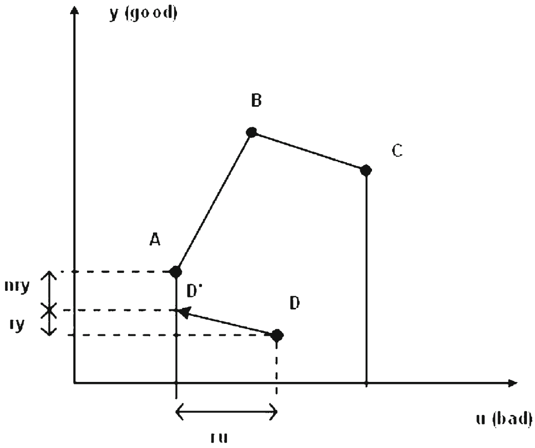

Fig. 1 Radial (ry, ru) and non-radial (nry) output slack

possibility set in Fig. 1 depicts the case with only one bad output under the assumption of null-jointness (as developed in Zhou et al. 2008).[3]

To be explicit, slacks of observation (act) based on the short-run technology are calculated as:

$$ry_{act,j} = \overline{\beta} y_{act,j}, \quad j = 1, \ldots, J \tag{9}$$

$$nry_{act,j} = \sum_{n=1}^{N} \lambda_n y_{n,j} - (1 + \overline{\beta}) y_{act,j}, \quad j = 1, \ldots, J \tag{10}$$

$$ru_{act,k} = \overline{\beta} u_{act,k}, \quad k = 1, \ldots, K. \tag{11}$$

The second stage is a regression considering total slack (sum of radial and non-radial slack) as dependent variables and a series of exogenous factors as independent variables. This is done to investigate the influence of the external environment on performance. For every good output j and bad output k the respective equations are specified as:

$$ry_{n,j} + nry_{n,j} = f(\mathrm{Q}_{n,j}, \alpha_j, \varepsilon_{n,j}), \quad n = 1, \ldots, N \tag{12}$$

$$ru_{n,k} = f(\mathrm{Q}_{n,k}, \alpha_k, \varepsilon_{n,k}), \quad n = 1, \ldots, N, \tag{13}$$

where $Q_{n,j}(Q_{n,k})$ is a vector of independent exogenous variables that characterizes the operating environment of producer n and affect the production of output $j(k)$, $\alpha_j(\alpha_k)$ is a vector of coefficients and $\varepsilon_{n,j}(\varepsilon_{n,k})$ is the error term. The error terms represent the contribution to output slacks not caused by exogenous factors. Finally, the predicted slacks from the regression represent the slacks corrected by the exogenous factors and net of the error terms.[4]

[3] Notice that the formulation of technology (2) seems to deviate slightly from the standard weak disposal axiom. This suits our effort to obtain an as conservative estimate as possible of the substitution possibilities away from cod.

[4] As a matter of fact, the same authors (see Fried et al. 2002) also developed another variation on this method whereby the second stage regression is replaced by a stochastic parametric frontier (also known as a composed error model). It remains an open question to which extent a parametric frontier model improves upon a simple regression when correcting an efficiency measure resulting from a first stage non-parametric frontier itself. It should be kept in mind that correction of efficiency measures using any statistical methodology rarely has as large an impact as a simple change in the axioms of the underlying frontier production model itself.

In the third stage the predicted slacks from stage two are used to adjust the observed outputs to exclude influences of the external environment. The predicted slacks are determined as:

$$\left(ry_{n,j} + nry_{n,j}\right)_{pred} = f(\mathrm{Q}_{n,j}, \hat{\alpha}_j), \quad n = 1, \ldots, N \tag{14}$$

$$\left(ru_{n,k}\right)_{pred} = f(\mathrm{Q}_{n,k}, \hat{\alpha}_k), \quad n = 1, \ldots, N, \tag{15}$$

where $\hat{\alpha}$ is the vector of estimated coefficients.

The adjusted outputs are calculated as:

$$\begin{aligned} y^{adj}_{n,j} &= y_{n,j} - \min_{n' \in \{1,\ldots,N\}} \left\{ \left(ry_{n',\,j} + nry_{n',\,j}\right)_{pred} \right\} + \left(ry_{n,\,j} + nry_{n,\,j}\right)_{pred}, \\ & n = 1, \ldots, N, \quad j = 1, \ldots, J, \end{aligned} \tag{16}$$

for the case of the good outputs, and

$$\begin{aligned} u^{adj}_{n,k} &= u_{n,k} + \max_{n' \in \{1,\ldots,N\}} \left\{ \left(ru_{n',k}\right)_{pred} \right\} - \left(ru_{n,k}\right)_{pred}, \\ & n = 1, \ldots, N, \quad k = 1, \ldots, K, \end{aligned} \tag{17}$$

for the bad output. Adjusting the outputs becomes slightly more complicated when a technology with undesirable outputs is considered. The minimum slack is used to "reset" the observations of good outputs at the level of the most favourable operating environment. Consequently, good outputs corresponding to observations under the most favourable conditions are unchanged, otherwise good outputs are increased. By contrast, bad outputs are "reset" to the least favourable operating environment. In so doing bad outputs are unchanged for observations under least favourable conditions and otherwise increased. Selecting the most favourable conditions as a base for good outputs and least favourable conditions as a base for bad outputs is primarily done for technical reasons, i.e., to prevent adjusted outputs from becoming negative (following Fried et al. 1999, pp. 255–256).

Figure 2a and b illustrate how good and bad outputs are corrected. The observations displayed are obtained from the empirical study that follows, which includes several additional outputs. However, to keep things simple, only consequences for one bad output and one good output are depicted. Correcting for exogenous factors shifts the observations left-and upwards. In this case, observations B, E and F have become relatively closer to the frontier. By contrast, observation A which was previously positioned on the frontier is no longer efficient.

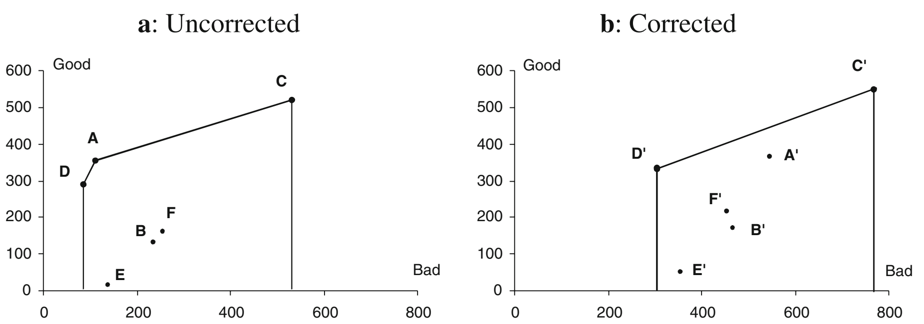

Fig. 2 Illustration of corrected outputs. **a** Uncorrected. **b** Corrected

Finally, in the fourth stage the efficiency scores of the directional distance function technology are recalculated based on the adjusted data. These adjusted scores measure the inefficiency that can be imputed to the behaviour of the productions units.

4 The Danish Demersal Fishery in the North Sea—Gill Netters

The sample includes 1,219 fishing trips by Danish gill netters to the North Sea during 2005. The vessels considered are all between 12 and 24 m of length. Since catches on cod and other demersal species were restricted by monthly rations in 2005 only trips departing in the first third of the month are included, i.e., an unregulated situation is in the focus of the analysis. This is to limit results being biased by discards (appearing when the rations become binding). The efficiency analysis is performed on groups defined by vessel length to achieve homogenous groups. Moreover, the size of rations depends on vessels length which strengthens the motivation for disaggregating along these lines. Basic descriptive statistics of the data are summarised in Table 1. Gross tonnage (GT) and engine horse power (HP) are considered as fixed inputs. Variable inputs are days at sea and labour. Outputs have been allocated within eight groups, one of which is considered undesirable (i.e., cod). The total number of vessels considered is 97, and the smaller vessels are more numerous and account for most fishing trips. The trip length is longer for larger vessels though. The vessels between 12 and 15 m

Table 1 Descriptive statistics of sample (trips) in 2005—inputs and outputs[a]

	Gill Netters			
	12–15 m	15–18 m	18–24 m	All
Number of vessels	50	30	17	97
Number of trips	653	405	161	1, 219
Fixed inputs[b]				
GT (Gross tonnage)	18	47	85	39
HP (engine horse power)	166	238	310	214
Variable inputs[c]				
Labour (crew number)	2.0	3.5	4.1	2.7
Hours at sea (h)	22	60	86	43
Good outputs (kg)				
Other codfish	37, 420	101, 286	42, 773	181, 479
Mackerel	45	159	114	318
Northern prawn and Norway lobster	2, 535	168	26, 415	29, 118
Industrial species	11, 920	196	163	12, 279
Plaice	149, 535	375, 737	265, 217	790, 489
Other flatfish	65, 466	126, 082	86, 846	278, 393
Other species	7, 279	11, 262	5, 379	23, 920
Bad outputs (kg)				
Cod	197, 299	224, 821	90, 041	512, 161

[a] *Source*: Database prepared and maintained by the Danish Fisheries Directorate (www.fd.dk). [b] Average per vessel. [c] Average per trip

Table 2 Results from directional distance function model (stage one)

	$\overline{\beta}$				CU			
	12–15 m	15–18 m	18–24 m	All	12–15 m	15–18 m	18–24 m	All
Efficient trips/full capacity utilization	55	62	37	154	337	182	70	589
Mean	0.78	0.64	0.55	0.70	0.94	0.92	0.87	0.92
Median	0.96	0.82	0.66	0.90	1.00	0.99	0.98	0.99
Standard deviation	0.33	0.38	0.41	0.37	0.12	0.13	0.17	0.13
Minimum	0.00	0.00	0.00	0.00	0.50	0.51	0.50	0.50
Maximum[a]	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

[a] Numbers are rounded at two decimals: the maximum values of $\overline{\beta}$ are all strictly below 1

appear to be most dependent on the catch of cod. Approximately 42% of their total landings weight is cod. Larger vessels are also heavily dependent on cod: for vessels between 15 and 18 m the share is 27%, and between 18 and 24 m it is 17%. However, in terms of aggregated catch of cod, the vessels between 15 and 18 m are dominant, followed closely by vessels between 12 and 15 m. The data also reveal that, besides cod, especially other codfish, plaice and other flatfish are important species.

5 Empirical Results

5.1 Stage One

The preliminary analysis reveals that it is technologically feasible to expand desirable outputs while undesirable outputs are contracted. On average, the potential proportional change is 70% according to the short-run technical efficiency measure $\overline{\beta}$, i.e., when some trips may be favoured by exogenous factors. In this case the overall average in capacity utilization is 92%. Descriptive statistics for the results are shown in Table 2.[5]

The greatest potential changes are calculated for smaller vessels. The average potential decrease in catches of cod and increases in catches of other species for gill netters between 12 and 15 m is 78%, if there are no restrictions on variable inputs.[6] For gill netters between 15 and 18 m the potential change is on average 64%, and between 18 and 24 m it is 55%. The median indicates that there are many observations that are very inefficient. The maximum values close to 1 indicate that some vessels could manage to eliminate close to all their cod catch by close to doubling the other outputs.

Within the three length groups the average capacity utilization CU is 87% for vessels between 18 and 24 m, 92% for vessels between 15 and 18 m, and 94% for vessels between 12 and 15 m. It appears from the results of Table 2 that the largest degree of underutilization is seen for the group of vessels between 18 and 24 m. However, it can generally be concluded that technological inefficiency contributes more to potential changes than underutilization of invested capital.

[5] The stage one results have also been computed for the complete dataset. Results are shown in Table 7 in the Appendix.

[6] In other words, it is assumed that days at sea regulation does not restrict the activity.

5.2 Stage Two

Three exogenous factors are considered relevant for the case study in question. First of all, the length of vessels within groups could have an impact on performance. It is an indicator of the size of fixed capital employed. Secondly, fishing trips took place at different points in time during the year. It is likely that the fishing potential differs between seasons. Quarters 1–4 represent this seasonal aspect. Thirdly, a distinction is made between application of the mesh sizes below 120 mm and above 120 mm. This is because the current regulation implies that cod cannot be caught as target species if the employed mesh size is less than 120 mm. Ignoring this would favour trips with mesh sizes below 120 mm unintended. The following function is considered to predict output slack:[7]

$$\text{slack} = f(\text{length, quarter 1, quarter 2, quarter 3, quarter 4, } \text{mesh} < 120, \text{mesh} \geq 120) \quad (18)$$

Since the dependent variable (slack) is bounded from below by zero a tobit model is applied.[8] Mesh sizes $\geq$120 mm and quarter 4 define the reference categories for these dummy variables (to avoid the dummy variable trap).

There is a regression equation for each output and each vessel group (i.e., $8 \times 3 = 24$ regressions in total). The relevance of the exogenous variables can be evaluated via the statistical significance of these estimates. Table 8 in Appendix summarizes whether the estimated coefficients are significantly different from zero at the 5% and 10% levels. Moreover, it shows the estimated sign of each coefficient which reveals how it influences slack. The results suggest that both length, season and mesh size are relevant exogenous factors to take into account. Level of significance and sign of estimated coefficient differ for the different length groups and species.

5.3 Stage Three

The predicted slacks obtained from the tobit model are used to adjust the observed initial outputs according to Eqs. 16 and 17.[9] In Table 3 the aggregated change in output is outlined. The adjusted outputs are compared to the initial outputs. The changes are quite substantial, confirming that the operating environment substantially influences the catching possibilities for the different species.

5.4 Stage Four

In this last stage, the efficiency scores are recalculated based on the adjusted data. The new scores are corrected for the influence of the exogenous factors; length, season and mesh size regulation. Table 4 shows descriptive statistics for the new short-run scores and capacity utilization measures. The adjusted efficiency scores are more conservative than the scores in stage one, and as expected fewer trips are efficient when the differing operating conditions are taken into consideration. The overall average efficiency score is 0.53, which represents

[7] One could object and claim that vessel length and mesh size should be part of technology rather than environmental variables affecting inefficiencies. Dummy (categorical) variables can be included in these frontier models in a variety of ways (see, e.g., Banker and Morey 1986). However, a problem is that these non-parametric frontier methods suffer from the curse of dimensionality, which necessitates making judicious choices and trade-offs in modelling.

[8] Notice that this approach using single equation tobit models per output can be criticised to ignore the joint nature of production.

[9] Descriptive statistics of the predicted slacks can be found in Table 9 of Appendix.

Table 3 Adjusted output (percentage increase compared to initial output (see Table 1))

	Gill netters			
	12–15 m	15–18 m	18–24 m	All
Good outputs (kg)				
Other codfish	25	28	11	24
Mackerel	0	0	51	18
Northern prawn and Norway Lobster	0	23	15	13
Industrial species	2	52	0	3
Plaice	73	37	37	44
Other flatfish	137	56	68	79
Other species	70	104	58	83
Bad outputs (kg)				
Cod	62	85	62	72

Table 4 Results from directional distance function model (stage four)

	$\overline{\beta}$				CU			
	12–15 m	15–18 m	18–24 m	All	12–15 m	15–18 m	18–24 m	All
Efficient trips/full capacity utilization	41	54	34	129	173	153	40	366
Mean	0.61	0.43	0.48	0.53	0.91	0.91	0.91	0.91
Median	0.69	0.46	0.53	0.59	0.96	0.96	0.96	0.97
Standard deviation	0.28	0.28	0.37	0.30	0.11	0.11	0.11	0.11
Minimum	0.00	0.00	0.00	0.00	0.52	0.52	0.52	0.51
Maximum	0.98	0.94	0.97	0.98	1.00	1.00	1.00	1.00

an overall potential increase (decrease) in good (bad) outputs by 53%. This is considerably less than the 70% resulting from the analysis in stage one. Likewise, the average score for vessels between 12 and 15 m is reduced from 78% to 61%. For vessels between 15 and 18 m the average score changes from 64% to 43%, and for vessels between 18 and 24 m from 55% to 48%. The average capacity utilization does not seem to change quite as much. The number of vessels with full capacity utilization though is reduced quite a bit.

To test whether the stage one and four efficiency measures are significantly different a Wilcoxon signed-rank test has been conducted.[10] The null hypothesis that they are equal is rejected (at the 1% level), meaning that correcting for exogenous factors implies significant differences in scores. A similar test has been done for the capacity utilization. This test suggests that for vessels between 12 and 15 m the scores are different, while they are not for vessels above 15 m.

The analysis so far suggests that it is technologically feasible to reduce the catch of cod while the catch of other species is increased. However, if the catch of cod is reduced, can the

[10] The Wilcoxon signed-rank test is found appropriate since it does not rely on a given probability distribution and it applies to paired observations.

Table 5 Best practice catches and revenues (hypothetical)

	Observed	Best practice (based on $\overline{\beta}$)	Change (%)
Good outputs (kg)			
Other codfish	181, 479	223, 582	23.2
Mackerel	318	361	13.5
Northern prawn and Norway lobster	29, 118	34, 492	18.5
Industrial species	12, 279	12, 418	1.1
Plaice	790, 489	1, 011, 772	28.0
Other flatfish	278, 393	357, 541	28.4
Other species	23, 920	31, 531	31.8
Bad outputs (kg)			
Cod	512, 161	183, 439	−64.2
Revenue (Euro)[a]	6, 297, 903	6, 242, 460	−0.9

[a] 1 Euro = 7.45 Dkk

eventual increase in the catch of other species offset the loss in revenue? Moreover, are the levels of increase realistic to implement? These issues are discussed in the next section.

6 Implications from Changing Catch Compositions

Hypothetical catches and revenue realised from adjusting the output mix of catches according to best practice, based on $\overline{\beta}$ (stage four) and initial outputs, are shown in Table 5. It is assumed that all vessels operate technologically efficient and without any underutilization of fixed capital, thus providing an upper bound estimate.

It appears that cod catches can be reduced by 64%. Since cod is a valuable species, this reduction would imply a severe fall in revenues. However, catches of the other species can be increased quite substantially. The most important species, besides cod, are "other codfish", "plaice" and "other flatfish". Catches of these species (groups) can be increased by 23%, 28% and 28% respectively. It is interesting to see that total revenues remain practically unchanged. There is only a slight overall decrease in revenue by 0.9%.

By aggregating the fishing trips the consequences on vessel level can be approximated. Potential revenue is evaluated relative to the observed level in 2005. This ratio per vessel is depicted in Fig. 3. By changing catch composition according to best practice the revenue is maintained or improved for 49% of the vessels (48 out of 97). By contrast, 51% of the vessels would be worse off if they substitute catches of cod with catches of other species. For 28% of these vessels the revenue is reduced by at least 20%. Large reductions in revenue are likely to have the consequence that vessels are forced out of the fishery. Vessels with reduced revenue mainly belong to the length groups 12–15 and 15–18 m. This mirrors the fact that these vessels were more dependent on catching cod.

Fishermen facing the perspective of reduced revenues are expected to oppose a regulation aimed to redirect fishing effort. Assuming that only vessels that are not worse off in terms of revenue by changing catch composition are willing to redirect their fishing effort, the potential increase in catch of other species and the reduction in cod catches is reduced. However, the changes are still worth mentioning. In Table 6 the potential change in aggregated catches is shown if changes are limited to vessels that can at least maintain their observed level of

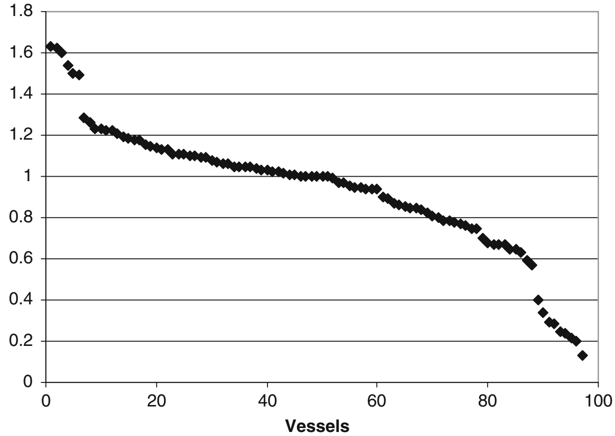

Fig. 3 "Potential" revenue (based on $\overline{\beta}$)/observed revenue per vessel in 2005

Table 6 Best practice catches and revenues (hypothetical)—vessels achieving a lower income in the model do not change catch composition

	Observed	Best practice (based on $\overline{\beta}$)	Change (%)
Good outputs (kg)			
Other codfish	181, 479	207, 483	14.3
Mackerel	318	352	10.6
Northern prawn and Norway lobster	29, 118	34, 065	17.0
Industrial species	12, 279	12, 382	0.8
Plaice	790, 489	946, 106	19.7
Other flatfish	278, 393	339, 367	21.9
Other species	23, 920	28, 107	17.5
Bad outputs (kg)			
Cod	512, 161	396, 430	−22.6
Revenue (Euro)[a]	6, 297, 903	6, 728, 925	6.8

[a] See Table 5

income. A reduction in catch of cod by 23% is still possible and increases in catches of other species are less extensive. The revenue increases by approximately 7%.

These potential gains rely on the assumption that increasing catches of other species is possible and allowable. However, in reality this may not be the case. Most species caught are subject to quota regulation and days at sea regulation has been in effect since 2003. However, this frontier analysis suggests that substitution among species is a possibility.

A cod recovery plan could therefore include some degree of increased catch of other species. The cod quota in the North Sea has been reduced quite a bit during the last 7 years. In 2001 the Danish quota was 8.460 tonnes, while the quota set for 2007 is just 3.388 tonnes (www.fd.dk). However, if fishermen were allowed to increase catches of other species, more vessels could remain economically viable. Moreover, such policy would reduce incentives for illegal landings. But, as revealed by the above results, the current models do not provide a mechanism to implement such a new fishery policy. This would require a different type

Table 7 Results from stage one without null-jointness assumption (1,517 observations)

	$\overline{\beta}$			CU		
	12–15 m	15–18 m	18–24 m	12–15 m	15–18 m	18–24 m
Efficient trips/full capacity utilization	25	36	21	573	294	124
Mean	0.84	0.72	0.68	0.96	0.95	0.93
Median	0.98	0.89	0.85	1.00	1.00	1.00
Standard deviation	0.26	0.34	0.36	0.08	0.10	0.12
Minimum	0.00	0.00	0.00	0.50	0.50	0.50
Maximum[a]	1.00	1.00	1.00	1.00	1.00	1.00

[a] Numbers are rounded at two decimals: the maximum values of $\overline{\beta}$ are all strictly below 1

of modelling approach based a social plan compatible with individual behaviour of fishermen. For instance, one could think about some industry revenue maximization approach which at the same time imposes aggregate quota levels on the industry. We are unaware of the availability of such models in the current literature and postpone this for eventual future work.

7 Conclusions and Final Remarks

Current European cod recovery plans are part of a mixed fisheries management approach. A mixed fisheries management plan assumes implicitly that the joint nature of production implies that a necessary condition for reducing catches of one species (e.g., cod), is that catches of other species are reduced correspondingly. Therefore, the days at sea regulation has been instituted to reduce the overall effort of vessels catching cod.

However, the present analysis suggests the opposite chain of reasoning, i.e., that it is technologically feasible to reduce catches of cod while catches of other species are increased by moving along the output transformation frontier. Assuming our findings are corroborated in other studies, this analysis points out that it may be advantageous to increase quotas for other species to protect the cod stock. Once these results would become firmly established, one could advocate that cod recovery should focus on reducing the effort on cod catches, and not necessarily on downplaying fishing activities all together.

The empirical results are obtained without restrictions on days at sea. The calculated capacity utilization rates were lowest for the gill netters above 18 m, indicating that these vessels have been restricted most by effort regulation. Additionally, these vessels were found to be more capable to redirect effort away from cod and towards other species, since they are, in general, capable of achieving at least the same level of revenues from increasing catch of other species. In the light of these empirical results, the days at sea regulation can have an undesirable effect in terms of economic performance. Thus, it can potentially even be in conflict with the aim of cod recovery.

Finally, when other species are not abundantly available, then it may well be impossible to increase these catches in significant amounts. Under these circumstances, vessels may possibly have to exit the fishery. Therefore, a preliminary goal may be to establish some degree of redirection of effort, more conservative than the potentials shown in Tables 5 and 6. Further research could focus on how such a revised regulatory framework could be implemented via a social planning model, such that fishermen have incentives to comply with the changing conditions. Moreover, taking into consideration the health of other stocks (e.g.,

Table 8 Estimate (sign) of tobit significantly different from zero at 5% and 10% level

	Other codfish	Mackerel	Northern prawn and Norway Lobster	Industrial species	Plaice	Other flatfish	Other species	Cod
12–15 m								
Intercept	10% (−)		5% (−)	5% (−)	5% (−)	5% (−)		
Length	10% (+)	5% (−)	5% (+)	5% (+)	5% (+)	5% (+)		
Quarter 1	5% (+)		5% (−)	5% (−)				5% (+)
Quarter 2		5% (−)	5% (−)		5% (+)	10% (+)		5% (−)
Quarter 3	5% (+)	5% (+)	10% (+)	5% (−)				5% (−)
Mesh <120	5% (−)				5% (−)		5% (−)	5% (−)
σ	5% (+)	5% (+)	5% (+)	5% (+)	5% (+)	5% (+)	5% (+)	5%(+)
Log likelihood	−2, 808	−163	−786	−1, 146	−4, 259	−4, 301	−2, 503	−4, 381
15–18 m								
Intercept		5% (+)		5%(−)	5% (−)	5% (−)	10% (+)	5% (−)
Length		5% (−)		5% (+)	5% (+)	5% (+)		5% (+)
Quarter 1		5% (−)	5% (−)	5% (−)	5% (+)	5% (−)	5% (−)	10% (−)
Quarter 2		5% (−)	5% (−)		5% (+)	5% (−)	5% (−)	5% (−)
Quarter 3	5% (+)		5% (+)			5% (−)	10% (−)	
Mesh <120	5% (+)		5% (−)	5% (+)	5% (−)		5% (−)	5% (−)
σ	5% (+)	5% (+)	5% (+)	5% (+)	5% (+)	5% (+)	5% (+)	5% (+)
Log likelihood	−2, 249	−218	−395	−618	−2, 790	−2, 541	−1, 834	−2, 758
18–24 m								
Intercept	5% (−)		5% (−)		5% (+)	5% (+)	10% (+)	
Length	5% (+)		5% (+)		5% (−)			
Quarter 1		5% (−)				5% (−)		10% (−)
Quarter 2		5% (−)		10% (−)	5% (+)	10% (−)		
Quarter 3	5% (+)	5% (−)	10% (+)			5% (−)		
Mesh <120	10% (−)				5% (−)	5% (−)		5% (−)
σ	5% (+)	5% (+)	5% (+)	5% (+)	5% (+)	5% (+)	5% (+)	5% (+)
Log likelihood	−685	−267	−525	−99	−1, 134	−1, 041	−685	−1, 034

Note: Mesh sizes ≥120 mm and quarter 4 define the reference categories

existing and desired stock levels) is a possibility. One potential way is to consider an industry programming model (see, e.g., Lindebo 2005) that includes appropriate constraints on the catch of various species and the economic performance of individual vessels. However, this would require a comprehensive efficiency analysis including all vessels (not only gill netters between 12 and 24 m) participating in the North Sea cod fishery. Furthermore, such social planning models aimed at, for instance, maximizing industry revenues while implementing a substitution process among outputs as a consequence of a variety of individual quotas have to the best of our knowledge not yet been specified in the literature.[11]

[11] Though a variety of basic industry models have been proposed in the literature for planning fisheries: e.g., Andersen and Bogetoft (2007) or Lindebo (2005).

Table 9 Descriptive statistics for predicted slacks

	Other codfish	Mackerel	Northern prawn and Norway Lobster	Industrial species	Plaice	Other flatfish	Other species	Cod
12–15 m								
Mean	14	0	0	0	167	185	12	243
Median	7	0	0	0	177	191	12	222
Standard deviation	17	0	0	1	69	58	2	103
Minimum	0	0	0	0	0	48	4	0
Maximum	50	0	1	2	319	310	15	431
15–18 m								
Mean	71	0	0	0	345	337	32	379
Median	12	0	0	0	385	299	28	399
Standard deviation	100	0	0	1	276	114	13	216
Minimum	0	0	0	0	0	164	3	0
Maximum	258	0	1	3	864	677	55	850
18–24 m								
Mean	30	0	24	0	605	669	29	327
Median	0	0	0	0	410	615	30	329
Standard deviation	45	1	74	0	577	216	7	240
Minimum	0	0	0	0	0	302	10	0
Maximum	159	3	298	0	1, 687	1, 113	43	676

Appendix: Supplementary Tables

This appendix contains tables that supplement the empirical analysis in the main body of the text. The first Table 7 illustrates that the analysis could also have been conducted without the null-jointness assumption. Relaxing this assumption expands the production possibility set. Therefore, even more optimistic results can be obtained (compared to the conservative results reported in Table 2 in the main text). However, it was decided to present the four-stage model imposing null-jointness, whereby catches of good outputs imply catches of the bad output.

Table 8 shows whether the estimates from the tobit analysis are significantly different from zero, and indicates if a factor has a positive or negative influence on the slacks. The table confirms that these factors do in fact influence slacks. This supports the relevance of correcting the efficiency measures for the operating environment. Finally, Table 9 shows descriptive statistics for the predicted slacks. The slacks are small for species that account for a smaller part of the catch for the vessels considered.

References

Andersen JL, Bogetoft P (2007) Gains from quota trade: theoretical models and an application to the Danish Fishery. Eur Rev Agric Econ 34(1):105–127

Banker RD, Morey R (1986) The use of categorical variables in data envelopment analysis. Manage Sci 32(12):1613–1627
Charnes A, Cooper WW, Rhodes EL (1978) Measuring the efficiency of decision making units. Eur J Oper Res 2(6):429–444
COM (2001) 724 final. Proposal for Council Regulation establishing measures for the recovery of cod and hake stocks (2001/0299 (CNS)). Commission of the European Communities, Brussels
Chung Y, Färe R, Grosskopf S (1997) Productivity and undesirable outputs: a directional function approach. J Environ Manage 51(3):229–240
Domazlicky BR, Weber WL (2004) Does environmental protection lead to slower productivity growth in the chemical industry?. Environ Resour Econ 28(3):301–324
Färe R, Grosskopf S (2004a) New directions: efficiency and productivity. Kluwer, Dordrecht
Färe R, Grosskopf S (2004b) Modeling undesirable factors in efficiency evaluation: comment. Eur J Oper Res 157(1):242–245
Färe R, Grosskopf S, Kokkelenberg E (1989a) Measuring plant capacity, utilization and technical change: a nonparametric approach. Int Econ Rev 30(3):655–666
Färe R, Grosskopf S, Lovell CAK, Pasurka CA (1989b) Multilateral productivity comparisons when some outputs are undesirable: a nonparametric approach. Rev Econ Stat 71(1):90–98
Färe R, Grosskopf S, Lovell CAK (1994) Production frontiers. Cambridge University Press, Cambridge
Färe R, Grosskopf S, Zaim O (2002) Hyperbolic efficiency and return to the dollar. Eur J Oper Res 136(3):671–679
Färe R, Kirkley JE, Walden JB (2006) Adjusting technical efficiency to reflect discarding: the case of the U.S. Georges Bank multi-species otter trawl fishery. Fish Res 78(2–3):257–265
Farrell MJ (1957) The measurement of productive efficiency. J R Stat Soc Ser A 120(III):253–281
Fried HO, Smidt SS, Yaisawarng S (1999) Incorporating the operating environment into a nonparametric measure of technical efficiency. J Product Anal 12(3):249–267
Fried HO, Lovell CAK, Schmidt SS, Yaisawarng S (2002) Accounting for environmental effects and statistical noise in data envelopment analysis. J Product Anal 17(1):157–174
ICES (2006) Report of the ICES advisory committee on fisheries management, advisory committee on the marine environment and advisory committee on ecosystems, 2006. Book 6, Section 6.4.2
Jeon BM, Sickles RC (2004) The role of environmental factors in growth accounting. J Appl Econom 19(5):567–591
Lee J-D, Park J-B, Kim T-Y (2002) Estimation of the shadow prices of pollutants with production/environment inefficiency taken into account: a nonparametric directional distance function approach. J Environ Manage 64(4):365–375
Lindebo E (2005) Multi-national industry capacity in the North Sea flatfish fishery. Mar Resour Econom 20(4):385–406
Muñiz M, Paradi J, Ruggiero J, Yang Z (2006) Evaluating alternative DEA models used to control for non-discretionary inputs. Comput Oper Res 33(5):1173–1183
Picazo-Tadeo AJ, Reig-Martinez E, Hernandez-Sancho F (2005) Directional distance functions and environmental regulation. Resour Energy Econ 27(2):131–142
Seiford L, Zhu J (2002) Modeling undesirable factors in efficiency evaluation. Eur J Oper Res 142(1):16–20
Simar L, Wilson P (2007) Estimation and inference in two-stage, semi-parametric models of production processes. J Econm 136(1):31–64
Zhou P, Ang BW, Poh KL (2008) Measuring environmental performance under different environmental DEA technologies. Energy Econ 30(1):1–14