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Methodological Reflections on the Short-Run Johansen Industry Model in Relation to Capacity Management

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Abstract *The specification of a convex production technology is a potential issue in estimating firm-level Johansen plant capacity utilisation rates and their subsequent use in the short-run Johansen industry capacity model of the fishery. There are different plant capacity utilisation estimates with convex and non-convex technologies. When entered as parameters in the short-run Johansen industry model, this leads to different distributions in the activity vectors. With non-convex technology, more vessels remain active in the fleet, and there is no longer an overestimation of the number of decommissioned vessels compared to the use of a convex technology. A second methodological reflection involves a way to trace the evolution of capacity over time and the possibility of formulating multi-period, short-run Johansen industry models using appropriate discrete time Malmquist productivity indices. Danish vessels provide an illustration for the convexity issue.*

Key words Convexity, plant capacity, short-run Johansen industry model, Malmquist productivity index, Danish vessels, vessel decommissioning.

JEL Classification Codes D24, Q22.

Introduction

The short-run Johansen (1972) industry model has lately received attention as a planning tool for fishery policies because it allows analysing industry structure on a disaggregated basis for firms, inputs, resource stocks, and species. This model starts from a putty-clay model of production: *ex-ante* firms choose among several production activities, but *ex post* they face fixed coefficient technologies with capacities that are conditioned by the investment decision. Following Dervaux, Kerstens, and

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Leleu (2000), the short-run Johansen industry model is typically computed starting from mathematical programming specifications of production technology frontiers. Applying the approach of Fare, Grosskopf, and Kokkelenberg (1989), estimates of radial efficiency measures are computed relative to nonparametric frontier technologies (also known as Data Envelopment Analysis (DEA) models). This yields a Johansen (1968) plant capacity measure for individual multi-product firms at the production frontier and a measure of ray capacity utilization similar to the one developed in Segerson and Squires (1990). These individual firm-level frontier measures of capacity output are used in the industry model to select the optimal level of activity of firm capacities with the objective of minimising fixed inputs at the industry level given the current total multiple outputs and firm-level capacities.

It is the purpose of this contribution to develop two main methodological reflections with regard to the above sketched static short-run Johansen (1972) industry model. A first reflection concerns the assumption of convexity traditionally maintained on the technology when estimating plant capacity measures at the firm level. We develop a variety of reasons to eventually drop this maintained hypothesis. The second methodological suggestion reflects on proper ways of building multi-period, short-run Johansen (1972) industry models by taking into account technological change. This boils down to tracing the evolution of plant capacity and the short-run Johansen industry model over time using appropriate discrete-time Malmquist productivity indices. Strictly speaking, the issues raised are not necessarily limited to the short-run Johansen (1972) industry model. These developments have the potential of being equally relevant for all industry-level production models focusing on reallocations across units and/or across time. In this context, one can think about a variety of reallocation models in the literature developed by, for instance, Athanassopoulos (1995), Färe and Primont (1984), and Korhonen and Syrjänen (2004).

We first examine the issue of the maintained hypothesis of convexity in the multi-product production set in estimation of plant capacities in the first stage of the short-run Johansen (1972) industry model. From a theoretical position, this would bring the model more in line with part of the fisheries literature discussed further below. From a managerial and more pragmatic point of view, the utilisation of non-convex frontier models in the first stage inevitably leads to lower maximal outputs and hence higher rates of plant capacity utilisation. Higher rates of capacity utilization, in turn, imply in the second-stage industry model that an equal number or more firms remain active in the optimal solution. Furthermore, to remedy eventual technical inefficiencies, one can always point these firms to real observations that dominate them in terms of inputs and outputs. This facilitates the learning and implementation process.

The possibility of non-convexities in the set of technological choices open to individual producers has been discussed in the literature on fisheries management (*e.g.*, Liski, Kort, and Novak [2001]).[1] For instance, some studies, such as Bjørndal (1987), indicate the possibility of increasing returns to scale in fishing with respect to the number of boats operating on the same fishing ground (*e.g.*, because of information sharing). The implications for fishery policies can be important: non-increasing marginal cost can lead to cyclical harvesting strategies (known as pulse fishing), which may well turn out to be optimal rather than a constant exploitation rate (Clark 1976). Squires and Kirkley (1991) and others have encountered potential non-convexity with multiproduct technologies.

[1] This is based on the literature on non-convexities and optimal exploitation of renewable resources (*e.g.*, Lewis and Schmalensee 1977, 1979).

Non-convexities have also been the subject of extended theoretical debate in related fields. In the environmental economics literature, Baumol (1972), Bradford and Baumol (1972), Starrett (1972), and Sandmo (2000) all analyze non-convexities in the production possibility set associated with external diseconomies. In particular, the first three contributions discuss non-convexities that may arise even if firm production technologies are convex; *i.e.*, externally induced non-convexities or non-convexities in the social production possibility set. Sandmo (2000) discusses non-convexity arising from the marginal costs of abatement. The forestry literature has an extensive, on-going discussion of non-convexity, due largely to non-divisibilities, such as fixed costs and administrative constraints, as recently summarized by Boscolo and Vincent (2003). There is a related discussion of non-convexity in fisheries. For example, Clark (1976) formally develops nonconvex cost functions and discusses non-divisibilities, such as large fixed capacity. In a recent article, Dasgupta and Mähler (2003) survey the economic issues surrounding the economic analysis of non-convexities in ecological systems. The Dasgupta and Mähler (2004) book considers non-convex ecosystems on an extensive basis. In this article, we are concerned with non-convexities in the private production possibility set.

In production theory, the assumption of convexity has repeatedly been discussed. Scarf (1981a,b, 1986, 1994), in a series of articles and book contributions, stressed the importance of indivisibilities in production (mainly industrial). Mas-Colell, Whinston, and Green (1995) extensively discuss convexity in microeconomic theory, including production theory. Recently, non-convex nonparametric technologies and cost functions have been devised that provide an alternative to the more traditional convex ones for the private production possibility set (see Briec, Kerstens, and Vanden Eeckaut 2004). They show that cost functions estimated on convex technologies are lower or equal to cost functions estimated on entirely non-convex technologies.

Another unresolved issue is the development of multi-period, short-run Johansen industry models. Starting from the initial literature on this model that traced the evolution of the capacity distribution and the short-run industry model over time using isoquant plotting techniques (*e.g.*, Førsund and Hjalmarsson 1983), a second methodological reflection traces the evolution of capacity over time and the possibility of formulating multi-period, short-run Johansen industry models using appropriate discrete-time Malmquist productivity indices. Since the latter productivity indices have, meanwhile, become quite popular in applied empirical work (see Färe, Grosskopf, and Roos 1998), we limit ourselves to outlining the main ideas, but we refrain from an empirical illustration.

This short paper first reviews the basic convex and non-convex production models involved in the next section. The following section shows how one could easily incorporate productivity growth in the estimation of both plant capacity and the short-run Johansen industry models making use of recent developments in discrete-time productivity indices. The next section empirically illustrates the impact of dropping the maintained convexity hypothesis on the plant capacity estimation as well as on the short-run industry model using a small sample of Danish vessels. A final section concludes.

Firm and Industry Models: Basic Methodological Choices

Choice of Capacity Concept

Capacity is inherently a short-run rather than long-run concept, since capacity arises due to fixity of one or more inputs. In the literature, it is customary to distinguish between technical and economic notions of capacity. Starting the discussion with a technical concept, we thereafter treat a variety of economic capacity notions.

First, Johansen (1968) defined a primal notion of capacity, plant capacity, as the maximal amount of output that can be produced per unit of time with the existing plant and equipment without restrictions on the availability of variable inputs. Färe, Grosskopf, and Kokkelenberg (1989) made this concept of plant capacity operational by estimating firm-level capacity levels using nonparametric frontier approximations of technology. The approach postulates that firms cannot change their fixed input utilisation, but that their use of variable factors is not constrained. A best-practice technology is constructed, and the current output of each firm is evaluated against the maximum potential output at full capacity utilization, giving capacity output. Multiple products are incorporated by the specification of ray measures, keeping multiple outputs in fixed proportions as the output bundle expands along a ray.

Second, it is conceivable to employ any of the economic (often cost based) capacity concepts existing in the literature instead of a technical capacity concept. Segerson and Squires (1990) and Berndt and Fuss (1989) extended the economic concept of capacity from single to multiproduct firms. Specifically, there are three basic ways of defining a cost-based notion of capacity (see Morrison 1985, Nelson 1989). The purpose of each is to isolate the short-run excessive or inadequate utilisation of the existing fixed inputs (*e.g.*, capital stock). The first notion of potential output is defined in terms of the output produced at short-run minimum average total cost, given existing plant and factor prices (*e.g.*, Berndt and Morrison 1981). The second definition corresponds to the output at which short- and long-run average total costs curves are tangent (see Chenery 1952; Klein 1960; Friedman 1963; among others). A third definition of economic capacity considers the output determined by the minimum of the long-run average total costs (see Cassels 1937 or Hickman 1964).[2] These cost-based definitions presume exogenous outputs. The economic notion of capacity was extended to (multiproduct) profit-maximizing firms by Squires (1987) and Segerson and Squires (1993) to account for endogenous and multiple outputs and variable inputs, and to revenue-maximizing firms by Segerson and Squires (1993, 1995) and Färe, Grosskopf, and Kirkley (2000) to account for endogenous outputs and all quasi-fixed or fixed factors. Finally, the economic notion of capacity was extended to firms under regulatory constraints, specifically rations and quotas, by Segerson and Squires (1993) and Weninger and Just (1997).

The renewed interest in the short-run Johansen industry model from Dervaux, Kerstens, and Leleu (2000) focused in the first stage on the usage of the above technical (engineering) capacity notion estimated using nonparametric specifications of technology. But, the short-run Johansen industry model is in no way limited either to this capacity concept or to its estimation method.

Though we are unaware of such applications using frontier methods, the first stage could, in principle, employ any of the economic capacity concepts proposed above. Of course, one should realise that the first and second stages of the short-run Johansen industry model are, to some extent, connected. While it is conceivable to combine a cost-based notion of capacity in the first stage with a technical objective of minimizing fixed input utilisation in the second stage, it is perhaps wise to maintain a minimal coherence in terms of behavioural objectives; *i.e.*, between engineering and economic objectives in the first and second stages of the model. An example of the use of economic objective functions in the short-run Johansen indus-

[2] It has been little used, however, probably because it clearly is heavily intertwined with the notion of scale economies.

try model is the use of industry cost functions, as in Førsund and Hjalmarsson (1983).[3]

Second, capacity notions can be estimated using any of the available estimation strategies. For instance, the plant capacity notion can also be econometrically estimated using parametric, stochastic frontier functions. Kirkley, Morrison Paul, and Squires (2002), for example, review and empirically apply both nonparametric and parametric stochastic frontier functions to obtain plant capacity estimates. In principle, the same remarks apply to economic capacity notions.

In this paper, in line with Dervaux, Kerstens, and Leleu (2000), we opt for the plant capacity concept for various reasons. First, this concept fits best with popular notions among both managers and politicians (as reflected in survey responses to enquiries about capacity utilisation and its widespread use in macroeconomics). Second, the plant capacity notion is especially useful in natural resource industries, like fisheries, where the cost and sometimes revenue data necessary to apply economic capacity concepts are seldom available. The plant capacity concept, for example, is now used by the Food and Agriculture Organization of the United Nations, the United States, and the European Union for fishing industries. In fact, finding even sufficient data for the plant capacity approach can represent a challenge, especially at the disaggregated, firm level. Finally, given the drastic policies called for to arrive at sustainable bio stock levels, the use of a capacity utilisation notion that tends to err on the safe side may well prove advantageous.

The capacity estimates resulting from this first stage already have some limited policy potential. For instance, horizontally summing these firm-level capacity outputs across firms gives a measure of aggregate industry capacity output. Comparing this aggregate industry capacity output to current industry output provides a measure of the overcapacity of the industry.[4] But, the plant capacity measure does not allow reallocation of inputs and outputs across firms. This, in turn, does not allow assessment of the industry's optimal restructuring and configuration. The plant capacity measure implicitly assumes that production of capacity output is feasible and that the necessary variable input is available. In renewable resource industries, such as fishing industries, the resource stock(s) and notions of sustainable exploitation must be incorporated, since total production of the fishery is constrained by the productivity of the resource stock(s). Sustainable target yields, such as Total Allowable Catch (TAC), are typically imposed to ensure a sustainable supply of fish and protect the resource stocks from overexploitation. The TAC thus imposes social constraints on the activities of private firms.

Accounting for TACs in the approach of Dervaux, Kerstens, and Leleu (2000), the optimal industry configuration is found by minimizing the total use of fixed inputs given that each firm cannot increase its use of fixed inputs, and the production of the industry is at least at the TAC level. The output level of each firm in this short-run Johansen sector model, extended to renewable resource industries, is the capacity output estimated from the firm-level capacity model, conditional upon the resource stocks and environmental parameters.

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[3] However, a coherent first and second stage procedure using economic objective functions in the short-run Johansen industry model seems to be lacking.

[4] Johansen-Färe plant capacity was extended to fisheries, giving fishing capacity, by Kirkley and Squires (1999) and by the FAO (Greboval 1999; FAO 2000) by incorporating resource stocks into the stock-flow production technology and accounting for regulatory conditions. Vestergaard, Squires, and Kirkley (2003) examine multispecies (multi-product) issues associated with fishing capacity. Reid *et al.* (2005) extend the model to incorporate environmental parameters, such as sea surface temperature, that serve as technological constraints.

Basic Firm Models: The Role of the Convexity Assumption

Starting with the details of the firm models, the empirical method estimates output-oriented efficiency measures based upon nonparametric, deterministic production frontiers (Färe, Grosskopf, and Lovell 1994). These efficiency measures are extremum estimators that allow determining the best-practice frontier established by the firms. The outputs of these best-practice firms are piecewise linearly enveloped to establish the best-practice frontier or reference technology, which is an inner bound approximation to the true, but unknown, production technology.

Production technologies are based on K observations using a vector of inputs $x \in \Re^n_+$ to produce a vector of outputs $y \in \Re^m_+$. Technology is represented by its production possibility set $T = \{(x,y): x \text{ can produce } y\}$; *i.e.*, the set of all feasible input-output vectors. The n-dimensional input vector, x, is partitioned into fixed factors (indexed by f) and variable factors (indexed by v): $x = (x^v, x^f)$. To determine the capacity output and ray capacity utilization (CU), a radial output-oriented efficiency measure is computed relative to a frontier technology providing the potential output given the current use of inputs:

$$E_o(x, y) = \max\{\theta : (x, \theta y) \in T\}.$$

Assuming strong disposal of inputs and outputs and variable returns to scale, a non-parametric inner-bound approximation of the true technology can be represented by the following set of production possibilities (see Färe, Grosskopf, and Lovell 1994 for details):

$$T^{\Lambda} = \left\{ (x, y) : x \geq \sum_{k=1}^{K} x_k z_k ,\ y \leq \sum_{k=1}^{K} y_k z_k ,\ z_k \in \Lambda \right\}, \tag{1}$$

where $\Lambda \in \{C, NC\}$,

with (i) $NC = \left\{ z_k \in \Re^K_+ : \sum_{k=1}^{K} z_k = 1 \text{ and } z_k \in \{0, 1\} \right\},$

(ii) $C = \left\{ z_k \in \Re^K_+ : \sum_{k=1}^{K} z_k = 1 \text{ and } z_k \geq 0 \right\}.$

In this expression, the acronyms NC and C denote the non-convex and convex technologies, respectively. Following the activity analysis tradition, the vector of intensity or activity variables, z, indicates the intensity at which a particular activity is employed in constructing the piecewise linear reference technology or frontier by constructing either non-convex or convex combinations of observations forming the best-practice frontier (see Briec, Kerstens, and Vanden Eeckaut 2004 or Tulkens 1993). Notice that, in general, the non-convex technology is a subset of the convex technology ($T^{NC} \subseteq T^{C}$).

An intuitive illustration about the essential differences between convex and non-convex technologies is provided in figures 1 and 2. Starting from the same three observations (denoted d_1, d_2, and d_3), non-convex and convex technologies are illustrated in the three-dimensional figures 1 and 2, whereby two inputs generate a single output. Clearly, the resulting non-convex technology is a subset from the convex technology.

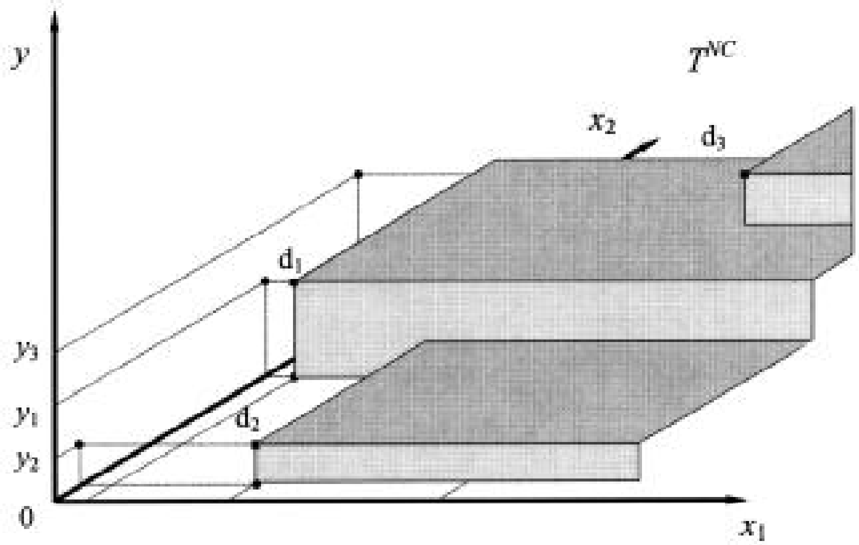

Figure 1. Non-convex Technology

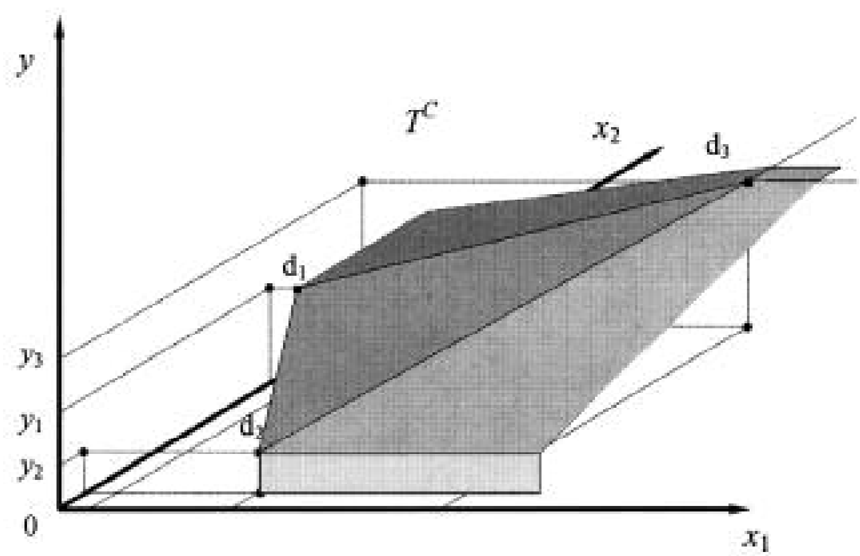

Figure 2. Convex Technology

A short-run version of this production possibilities set is simply defined by dropping the constraints on the variable input factors to form the technology underlying Johansen plant capacity, in which the availability of variable factors is not restricted:

$$\hat{T}^{\Lambda} = \left\{ (x, y) : x^f \geq \sum_{k=1}^{K} x_k^f z_k,\ y \leq \sum_{k=1}^{K} y_k z_k,\ z_k \in \Lambda \right\}, \tag{2}$$

where Λ is again defined as in equation (1). Both of these technologies are, geometrically speaking, non-convex or convex monotonic hulls enveloping all observations.

To illustrate this notion of a short-run technology, starting from figures 1 and 2, assume that one takes a section along the first input axis somewhere between observation d_1 and d_3. This implies that the second input dimension represents a fixed production factor, while the first input dimension is a variable factor that is available in unlimited quantities. Then, the resulting non-convex and convex short-run technologies could resemble something like figure 3. Clearly, the plant capacity output; *i.e.*, the maximum output one can generate with unlimited variable input amounts, is higher under the convex, rather than the non-convex, technology $(y_{\max}^{C} \geq y_{\max}^{NC})$.

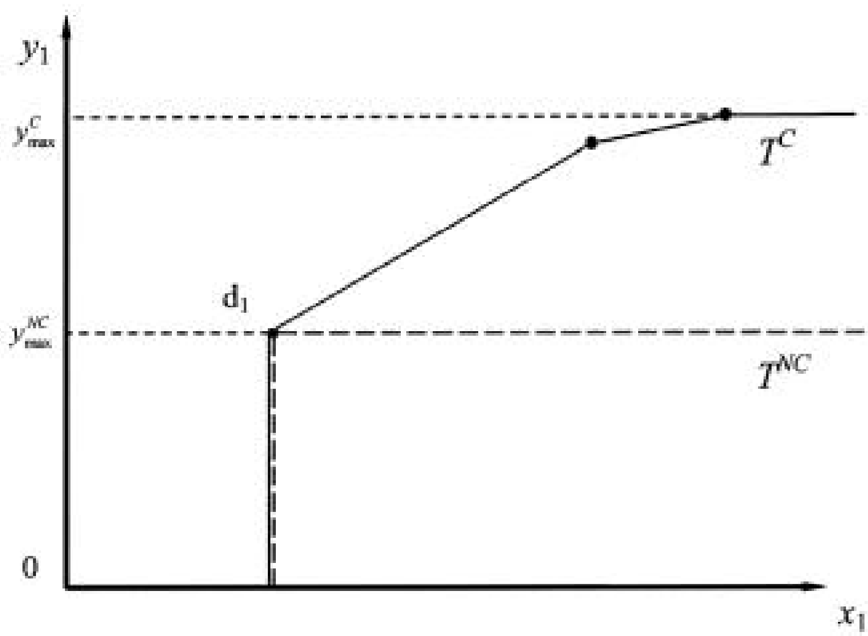

Figure 3. Non-convex and Convex Short-run Technologies

The output-oriented efficiency measure $\hat{E}_o(x^f, y)$ is found by solving the following linear programming problem for each firm $k = 1,2,\ldots,K$ relative to the short-run production possibilities set:

$$\hat{E}_o(x^f, y) = \max\left\{\hat{\theta}: (x^f, \hat{\theta}y) \quad \hat{T}^{\wedge}\right\}. \tag{3}$$

To remain consistent with the plant capacity definition of Johansen, in which only the fixed inputs are bounded at their observed level, the variable inputs in the production frontier model are allowed to vary and be fully utilized. The outcome of the production frontier model is a scalar, indicating the amount by which the production of each firm's output can be expanded.

Another technical efficiency measure can be obtained by evaluating each firm $k = 1,2,\ldots,K$ relative to the production possibilities set T^L. The optimal value shows by how much the production can be increased using the inputs in a technically efficient way:

$$E_o(x, y) = \max\left\{\theta: (x, \theta y) \quad T^{\wedge}\right\}. \tag{4}$$

A ray measure of plant capacity utilization (PCU) that removes the impact of technical inefficiency (see Färe, Grosskopf, and Kokkelenberg 1989) can be defined as:

$$PCU_o(x^f, x^v, y) = \frac{E_o(x, y)}{\hat{E}_o(x^f, y)}. \tag{5}$$

Since $\hat{E}_o(x^f,y) \geq E_o(x,y) \geq 1$, it is clear that $PCU_o(x^f,x^v,y) \leq 1$. The major advantage of this plant capacity utilisation factor is that any technical inefficiencies have been removed by taking a ratio of efficiency measures, which is not possible with more traditional measures.

Basic Industry Model

The short-run Johansen sector model allows reallocation of production between firms by explicitly allowing improvements in technical efficiency and capacity utilization rates. The short-run Johansen sector model is developed in two steps. In the first step, model (3) provides an optimal activity vector, z_k^*, for firm k. Using z_k^*, capacity output and its optimal use of fixed and variable inputs can be straightforwardly computed:

$$y_k^* = \sum_{k=1}^{K} y_k z_k^*, \qquad x_k^{f*} = \sum_{k=1}^{K} x_k^f z_k^*, \qquad x_k^{v*} = \sum_{k=1}^{K} x_k^v z_k^*. \tag{6}$$

The second step employs these "optimal" firm-level, frontier measures of capacity output and capacity variable and fixed inputs as parameters in the industry model. In particular, the industry model minimizes industry use of fixed inputs in a radial way such that total production is at least at the current total level (or at a quota level when the renewable resource model is extended to incorporate TACs) by reallocating production among firms. These reallocation decisions are based on frontier production and input use of each firm. In the short run, it is assumed that current capacities cannot be exceeded at both the firm and industry levels. Define Y as the industry output level and X^f (X^v) as the aggregate fixed (variable) inputs available to the sector; *i.e.*:

$$Y = \sum_{k=1}^{K} y_k, \quad X^f = \sum_{k=1}^{K} x_k^f, \quad \text{and} \quad X^v = \sum_{k=1}^{K} x_k^v. \tag{7}$$

The formulation of the input efficiency measure, which minimises the utilisation of fixed inputs, in a multi-output, frontier-based, short-run industry model can then be specified as:

$$\hat{E}_{fi}(X^f, Y) = \min_{\lambda, z, X^v} \lambda \tag{8}$$

$$\begin{aligned} s.t. \quad Y &\leq \sum_{k=1}^{K} y_k z_k, \\ \lambda X^f &\geq \sum_{k=1}^{K} x_k^f z_k, \\ 0 &\geq \sum_{k=1}^{K} x_k^v z_k - X^v \\ 0 &\leq z_k \leq 1, \quad \lambda \geq 0. \end{aligned}$$

In this second step of the short-run Johansen industry model, the z variables indicate whether and by how much a firm's capacity will be utilized. The components of the activity vector, z, are bounded above by unity and, as a consequence, the current capacities can never be exceeded. The first constraint in equation (8) ensures that the total production by a combination of firm capacities is greater than or equal to the current level. The second constraint in equation (8) ensures that the total use of fixed inputs, given by the right-hand side of the constraint, is greater than or equal to the use by a combination of firms. The third constraint in equation (8) calculates the resulting total use of variable inputs, where the total amount of variable inputs is a decision variable. The objective function is a radial input efficiency measure focusing solely on the fixed input dimensions. This fixed input efficiency measure has a fixed cost interpretation at the industry level. From a geometric viewpoint, this short-run industry model is a set consisting of a finite sum of line segments. The activity vector, z, indicates which portions of the line segments representing the firm capacities are effectively used to produce outputs from given inputs. To sum up, the optimal solution to this simple linear programming problem gives the combination of firms that can produce the same or more outputs with less than or the same use of fixed inputs in aggregate. Extensive variations on this basic short-run industry model for developing policy options to curb overcapacity in fisheries have been discussed in Kerstens, Vestergaard, and Squires (2004).

Temporal Models of Capacity Distribution and Short-Run Industry Models

Over time, the dynamic evolution of a sector reveals itself as a succession of a series of short-run industry models.[5] These dynamics are determined by a succession of *ex ante* technologies and the rates of investments and depreciation. In the single-output case, this has led various authors to trace the evolution of the capacity distribution and the short-run industry model over time using isoquant plotting techniques. Excellent illustrations of this approach are found in Førsund and Hjalmarsson (1983), Førsund, Hjalmarsson, and Summa (1996), and Wibe (1995), among others.

However, a geometric approach to the dynamics of the industry is no longer possible in the multiple-output case. Therefore, we propose to take advantage of the recent developments in discrete-time productivity indices to describe the evolution of both the capacity distribution and the short-run industry model over time in the multiple-output case (see Färe, Grosskopf, and Roos 1998). In particular, we first define a Malmquist index of total factor productivity change to trace the evolution in the short-run or plant-capacity technology. Furthermore, we also define another Malmquist index relative to the short-run industry model over time. The main advantage of employing a Malmquist productivity index is that it allows distinguishing between changes in technical efficiency on the one hand (*i.e.*, changes in the relative positions of observation with respect to the evolving frontiers), and frontier changes on the other hand (*i.e.*, changes in the relative position of the frontiers themselves).

We first define time-related versions of the earlier-defined efficiency measures. The output-oriented efficiency measure, $\hat{E}_o^t(x^{f,t}, y^t)$, in period t is found by solving the following linear programming problem for each firm $k = 1,2,\ldots,K$ relative to the short-run production possibilities set, $\hat{T}^{t\wedge}$, defined in period t:

$$\hat{E}_o^t(x^{f,t}, y^t) = \max\left\{\hat{\theta} : (x^{f,t}, \hat{\theta} y^t) \quad \hat{T}^{t\wedge}\right\}. \tag{9}$$

Another technical efficiency measure can be obtained by evaluating each firm $k = 1,2,\ldots,K$ relative to the production possibilities set, $\hat{T}^{t\wedge}$, in period t. The optimal value shows by how much production can be increased using the inputs in a technically efficient way:

$$E_o^t(x^t, y^t) = \max\left\{\theta : (x^t, \theta y^t) \quad T^{t\wedge}\right\}. \tag{10}$$

A discrete-time, output-oriented Malmquist productivity index computed relative to the short-run technology defining the plant capacity frontier is then defined as:

$$M_o^{t,t+1}(x^{f,t}, y^t, x^{f,t+1}, y^{t+1}) = \frac{\hat{E}_o^t(x^{f,t}, y^t)}{\hat{E}_o^{t+1}(x^{f,t+1}, y^{t+1})} \cdot \sqrt{\frac{\hat{E}_o^{t+1}(x^{f,t+1}, y^{t+1})}{\hat{E}_o^t(x^{f,t+1}, y^{t+1})} \cdot \frac{\hat{E}_o^{t+1}(x^{f,t}, y^t)}{\hat{E}_o^t(x^{f,t}, y^t)}}, \tag{11}$$

where the first part defines technical efficiency change relative to the plant capacity technology, and the second term defines the technological change of the very same technology. As a matter of fact, this Malmquist index is a geometric mean of a period t and a period $t + 1$ index, in an effort to avoid an arbitrary choice of base

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[5] This is the conceptual basis for the economic approach to capacity and capacity utilization when firms minimize the cost of production, where short-run and long-run average cost curves are tangent at the capacity output level.

period. If this output-oriented Malmquist is larger (smaller) than unity, this indicates an improvement (deterioration) in productivity.[6] A similar interpretation applies to the separate components. This productivity index measures the evolution of total factor productivity for each individual firm at the plant capacity level, and it thereby provides a multi-output version of the plant capacity isoquant-tracing algorithms mentioned before.

Based upon the input efficiency measure minimising the utilisation of fixed inputs in a multi-output, frontier-based short-run industry model, a similar discrete time fixed input-oriented Malmquist productivity index can be specified at the industry level as:

$$M_{fi}^{t,t+1}(X^{f,t}, Y^{t}, X^{f,t+1}, Y^{t+1}) \tag{12}$$

$$= \frac{\hat{E}_{fi}^{t}(X^{f,t}, Y^{t})}{\hat{E}_{fi}^{t+1}(X^{f,t+1}, Y^{t+1})} \cdot \sqrt{\frac{\hat{E}_{fi}^{t+1}(X^{f,t+1}, Y^{t+1})}{\hat{E}_{fi}^{t}(X^{f,t+1}, Y^{t+1})} \cdot \frac{\hat{E}_{fi}^{t+1}(X^{f,t}, Y^{t})}{\hat{E}_{fi}^{t}(X^{f,t}, Y^{t})}}\,.$$

This index defines the technical efficiency change relative to the short-run industry model on the one hand, and the technological change of the same industry technology on the other. In the case of this fixed input-oriented Malmquist index, a value smaller (larger) than unity indicates a productivity improvement (deterioration). Again, the same interpretation is applicable to the separate components.

These productivity indices can be put to various uses when building short-run industry models for policy purposes. The first productivity index could be used to neutralise the eventual impact of technological change in terms of plant capacities. Following Tauer and Stefanides (1998), a potential strategy is to adjust the capacity data by using the technological change component of this Malmquist productivity index. This would allow neutralisation of the time dimension when estimating capacity inputs and outputs and to build multi-period, short-run industry models. The latter boils down to extending the static short-run industry model (see equation [8]) to include dated input and output constraints and look for a common reduction of fixed inputs over a given time horizon.[7] Eventually, one could add further constraints on the relation between activity vectors across time periods (*e.g.*, that they should be identical across time).

It is also possible to simply maintain annual production plans and to employ both these productivity indices to trace the evolution in both the capacity distribution and the short-run industry model over time. This leads to a two-year time window sliding over the data across time. The productivity index of each period is simply based upon comparisons composed of measuring efficiency with respect to essentially static production models.

In summary, based upon recent developments in discrete-time productivity indices estimated with respect to frontier technologies, it is straightforward to add a time dimension to the currently static short-run industry model. These indices offer

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[6] The technical efficiency change component has been further decomposed into variations in technical efficiency, scale efficiency, and congestion (Färe, Grosskopf, and Lovell 1994). The important issue of identifying scale effects in the technical change component has led to a discussion from which no consensus has yet emerged (see Balk 2001; Färe, Grosskopf, and Roos 1998). The technological change component has also been the subject of further decompositions in terms of input and output biases, amongst others (see Färe *et al.* 1997).

[7] More details on the development of temporal efficiency measures, including time discounted ones, can be found in Briec, Comes, and Kerstens (2006) and Färe and Grosskopf (1996).

a general solution for tracing the evolution of multiple input and output technology specifications over time, instead of using the earlier isoquant tracing methods that are only valid in the single-output case. The first Malmquist index yields an indication of the total factor productivity development of plant capacity inputs and outputs for each firm. The second Malmquist index characterises the evolution of total factor productivity at the aggregate industry level. Furthermore, for both productivity indices, one can distinguish between technical efficiency change and technological change at the frontier. Of course, it goes without saying that the first Malmquist index could be measured with respect to both convex and non-convex technologies, though empirical applications on the latter are rather sparse to date.

Empirical Illustration: The Impact of Convexity

The sample data set consists of observations of outputs of different fish species (catches in kilo), two variable inputs (labour and fishing days), and one fixed input (gross registered tonnes [GRT]) for individual trawlers operating in the North Sea in 1991. In total, 398 trawlers are included in the sample and they have, on average, the North Sea as their most important catch area. The trawlers vary in terms of catch composition during the year, but they are flexible in selecting fisheries and, hence, output mix. Descriptive statistics for the outputs and fixed and variable inputs are reported in table 1. For each vessel, the fixed input was subsequently transformed into a flow variable by multiplying it by the number of fishing days. This specification guarantees a more balanced picture of the efficiency of fishing firms, because firms are rather heterogeneous in terms of their fishing effort and service flow; *i.e.*, the number of fishing days (normal operating conditions) varies substantially. Traditionally, production models in other industries assume that firms operate in a similar environment during normal working time (depending on how this is defined). Total catch per species is used as the basic output in the model. The number of observed outputs (caught species) has been reduced from 25 to 9. This aggregation of outputs is partly necessary to

Table 1
Summary Statistics for the Trawl Fishery in the North Sea (1991)

	Average	Standard Deviation
Tonnage	133	119
Crew Size	4	1
Fishing Days	120	78
Catch per Vessel (kg)		
Cod	7,796	11,828
Other cod fish	4,771	9,270
Plaice	19,283	57,325
Sole	136	590
Pelagic species	107,755	463,631
Lobster	1,467	4,132
Shrimp	1,047	6,726
Other species	2,299	5,516
Industrial fishery	2,393,392	3,478,853

Source: Danish Directorate of Fisheries (unpublished data).

escape the curse of dimensionality that is inherent to nonparametric methodologies. Each of the remaining nine outputs represents either a species or a group of species.

Comparing the effect of the convexity assumption on the industry models, one observes that the efficiency measure in the non-convex case (0.906) is substantially higher than in the convex case (0.619) of table 2. In terms of the activity vectors, it is clear that more vessels remain active in the fleet when plant capacity is estimated using the more conservative non-convex estimator (89.70% compared to 82.91% in the convex case). The average value of activity vectors computed over all observations indicates a rather substantial difference. But, this difference almost disappears when the same average value of activity vectors is computed over only the non-zero observations.

We also provide a more formal test of these alleged differences by using nonparametric test statistics. We first compare the distributions on the plant capacity utilisation based upon convex and non-convex technologies. A nonparametric Wilcoxon signed ranks test (see Siegel and Castellan 1988) shows that we can reject the null hypothesis that these distributions are identical (the Wilcoxon's W statistic equals 4,027). This is also clear when visually comparing the shapes of the densities. Figures 4 and 5, below, show their distributions estimated using kernel density estimators. The density of plant capacity utilisation based on the non-convex technology is clearly far more skewed to the right.

Table 2
Industry Models (1991)

	Convex	Non-convex
Sub-vector Fixed Input Efficiency	0.619	0.906
Non-zero Activity Vectors	330	357
Active Vessels (%)	82.91	89.70
Average Activity Vector (non-zero obs.)	0.989	0.994
Average Activity Vector (all obs.)	0.820	0.892

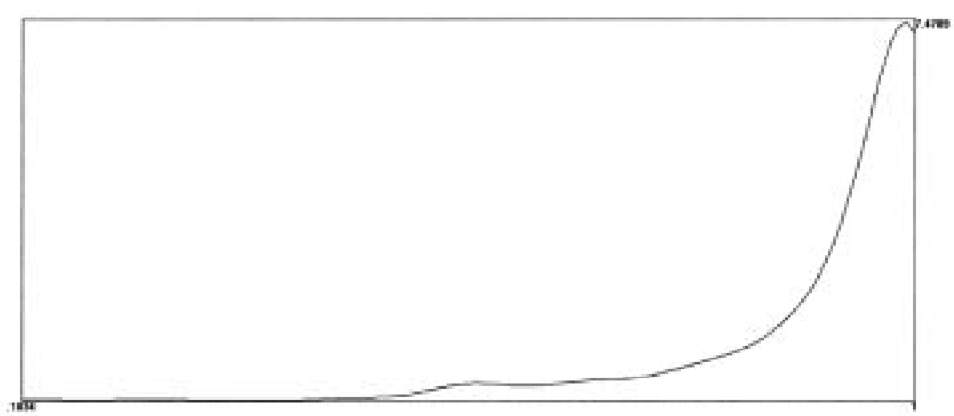

Figure 4. Density of Plan Capacity Utilisation Estimated on a Convex Technology

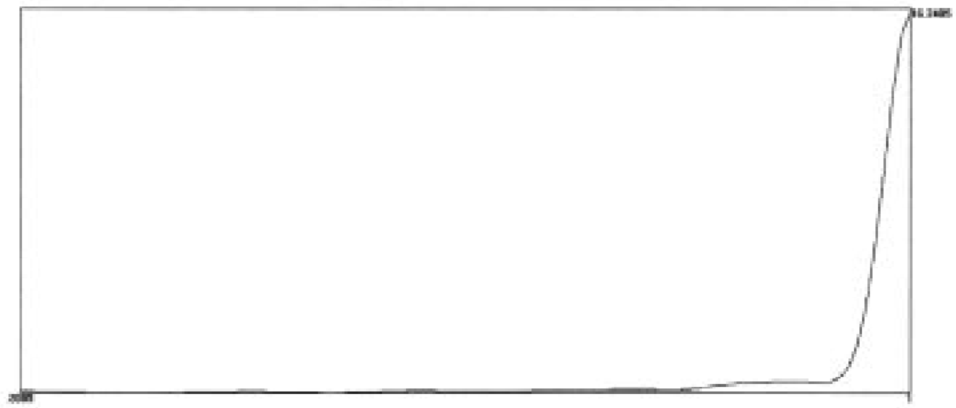

Figure 5. Density of Plan Capacity Utilisation Estimated on a Non-Convex Technology

Turning to the optimal activity vectors obtained from the industry model, we again perform a nonparametric Wilcoxon signed ranks test to compare their distributions when using the plant capacity utilization adjusted inputs and outputs from the first stage resulting from either convex or non-convex technologies. We can once more reject the null hypothesis that these distributions are identical (the Wilcoxon's W statistic now equals 1,685.5).

Clearly, these empirical results underscore the importance of considering the hypothesis of convexity more seriously when estimating plant capacity utilisation rates. They also show that the impact of this choice on the short-run Johansen industry model is non-negligible.

Conclusions

Convexity of the production possibility set is a maintained hypothesis in the emerging fisheries literatures on Johansen plant capacity and the short-run Johansen industry model. Convexity is usually considered a desirable property for a well-behaved production technology, and it is particularly critical to applications of duality theory in order to obtain a well-behaved model. However, non-convexity of the production set has important policy implications in renewable resource economics, including fisheries, allowing for increasing returns to scale, pulse fishing, *etc.* As observed by Clark (1976), non-convexities in fisheries can arise due to indivisibilities, such as lumpy fixed factors. Because fixed factors also lead to the capacity issue, non-convex production possibility sets may be a recurring feature in empirical analyses of Johansen plant capacity and the short-run Johansen industry model in fisheries. Convexity of technology is ultimately an empirical issue, and numerous (especially dual and multiproduct) empirical analyses of fishery production frequently fail to establish convexity. Failure to empirically establish convexity may arise simply due to reasons of model specification or aggregation methods (see Wales 1977), but as noted, non-convexity may also be an underlying, inherent feature of some harvesting technologies, due, for example, to indivisibilities and disaggregated vectors of inputs and outputs, the latter of which is especially important in multiproduct harvesting technologies.

When non-convexity of the production set is empirically established in a fishery, important implications emerge for estimating Johansen's plant capacity and short-run industry model. Allowing for non-convexity in the frontier models of plant capacity in the first stage of the Johansen industry model inevitably leads to lower maximal outputs and higher rates of plant capacity utilisation. When these non-convex estimates enter into the second stage, short-run industry model, this leads to higher rates of capacity utilization, which, in turn, allows at least as many firms to remain active in the optimal solution than would occur when convexity is maintained. Furthermore, not only are there more vessels under non-convexity than under convexity in the solution, but in some cases there are other vessels than those found in the convex solution; *i.e.*, the fleet composition differs. Even analyses and programs predicated upon simply fishing capacity (Johansen's plant capacity extended to fisheries), and not relying upon Johansen's short-run industry model, can be affected by the maintenance of convexity (see Walden, Kirkley, and Kitts 2003). For example, the number, and even composition, of vessels remaining in the fleet under vessel decommissioning programs (such as vessel buybacks) can differ depending on whether or not convexity of technology is maintained.

As a second contribution, this paper spelled out a way to extend the short-run Johansen industry models to include several time periods simultaneously using appropriate discrete-time Malmquist productivity indices. This is of some importance when developing consistent, multi-period planning models for policy purposes, as well as for the simpler fishing capacity models. In the latter case, given the fixed capital and resource stocks and the state of the environment, capacity output measures can differ among firms due to variations in technical efficiency and variable input use as discussed by Färe, Grosskopf, and Lovell (1994), but when evaluated over multiple time periods, fishing capacity can vary due to productivity fuelled by technological innovations, such as vessel electronics or fish aggregator devices. Similarly, given the critical importance of productivity growth in fishing industries, multi-period planning models are also subject to the effects of productivity growth. Indeed, productivity growth rather than capital stock growth *per se* may well be the single most important factor contributing to growth in fishing capacity and resulting pressures on resource stocks.

The brevity of this methodological note does not allow expanding on all details. For instance, the practical use of multi-period planning models may well require taking account of dynamic incentive issues. It suffices here to point out that probably many of these incentive–related implementation problems have already—at least partially—been tackled in the literature (see Agrell, Bogetoft, and Tind 2002).

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