Measuring Fishing Capacity: An Application to in North Pacific Groundfish Fisheries

Ronald G. Felthoven
Ph.D. Candidate
Department of Agricultural and Resource Economics
University of California, Davis

Draft, Submitted for the American Agricultural Economics Association Annual Meetings, August 2000, Tampa, Florida

I. Introduction

The presence of excess fishing capacity has become one of the most pressing problems facing fisheries throughout the world. Aside from dissipating rents, shortening fishing seasons, and diminishing efficiency and productivity, excess capacity can have other significant and detrimental effects on a fishery. First, it may create pressure for managers to keep the total allowable catch (TAC) above sustainable levels in order to preserve employment. Second, with the little remaining economic rents spread among so many vessels, fishermen are more vulnerable to changes in regulations and TAC's instituted to curb excess capacity. As a result, policy tools available to resource managers become more difficult to implement, both politically and socially (Kirkley and Squires, 1999).

The aforementioned problems have prompted recent policy initiatives focused on managing capacity, including the FAO's International Plan of Action for the Management of Fishing Capacity (FAO, 1999) and other international agreements[1]. The FAO plan urges countries to develop national fishery management plans by 2002, which would include an assessment of domestic fishing capacity and introduction of measures to prevent or eliminate excess fishing capacity. In response to this plan, the National Oceanic and Atmospheric Association (NOAA) has adopted a formal objective of reducing the number of overcapitalized fisheries by fifteen percent by 2004 (NOAA, 1999). The NOAA plan has led to the formation of the National Marine Fisheries Service (NMFS) Excess Capacity Task Force, which has recommended that capacity estimates be constructed for each of the federally managed fisheries (NMFS, 1999).

[1] Such as the Food and Agricultural Organization (FAO) Code of Conduct for Responsible Fisheries, the FAO Agreement on Compliance, and the United Nations Agreement on Highly Migratory and Straddling Fish Stocks.

To meet the guidelines of the plan, fishing capacity estimates must be generated and subsequently used to assign each fishery to one of the following three categories: “no appreciable excess-capacity”, “moderate excess-capacity”, and “substantial excess capacity” (NMFS, 1999). Such categorizations will require comparisons among the fisheries based on their relative levels of excess capacity. Therefore, it is important that the methods used to estimate capacity in each of the federally managed fisheries are consistent and generate comparable estimates[2]. Unfortunately, this may be more difficult than it sounds, as there is still no consensus among researchers over the “best” method for generating such estimates.

A central purpose of this is paper to illustrate the marked differences in capacity estimates that can arise based on one’s choices over estimation techniques, “definitions” of capacity, and other relevant factors in capacity estimation. In particular, we examine two alternative frameworks that have been recommended by the NMFS Excess Capacity Task Force for estimating fishing capacity: data envelopment analysis (DEA) and stochastic production frontier (SPF) models[3].

The possibility of generating substantially different estimates of fishing capacity (for a given data set) exists not only because of the inherent differences between the two alternative specifications, but also because of the different estimates that can arise *within* each framework due to some subjective choices that must be made. While it is frequently necessary for researchers to make such choices, it is the eventual coordinated comparisons and categorizations that punctuate the need for a consistent method of capacity estimation. In addition, given the

[2] To make appropriate determinations and comparisons among different fisheries, capacity estimates must derived under the same model specifications. Though there may be minor differences in the variables included in capacity estimation models (as data collection efforts are not identical for all federally managed fisheries), the underlying assumptions and empirical techniques should be the same.

[3] The peak-to-peak method is also considered an option, though it has been the subject of much criticism. It is somewhat of a “last resort” option for fisheries in which data is lacking for a satisfactory DEA or SPF model. Given that existing data for the

range of capacity estimates that may be generated by alternative specifications and assumptions, it may be prudent to derive a distribution of capacity estimates for each fishery, rather than just "one number".

To illustrate the proposed capacity measurement techniques -- and the different capacity estimates that may arise -- an empirical application of both DEA and SPF methods is presented. We derive capacity estimates under both specifications as well as for two suggested "definitions" of technical fishing capacity. The analysis focuses on one of the US federally managed fisheries of interest: the Bering Sea and Aleutian Island Groundfish fisheries. In particular, we examine the factory trawlers operating in the pollock fishery.

While much of the fishing effort is geared toward pollock harvesting, there are multiple other species caught throughout the year. As will be discussed further in the paper, the usual SPF framework does not deal well with multiple outputs; to date there have been no studies to use the SPF technique for measuring capacity in multi-output fisheries[4]. Therefore, the standard SPF capacity framework is augmented to allow for multiple outputs through use of a stochastic distance function. This application represents the first use of a stochastic distance function to measure fishing capacity.

Finally, the analysis allows us to addresses one question that naturally arises upon obtaining capacity estimates: "what to do now?" If there is in fact substantial excess capacity in a fishery, how should one curb or eliminate it? One method that has been proposed is the introduction of individually transferable fishing quota (NMFS, 1999). The data used in this empirical application includes observations before and after property rights were established the

---

federally managed fisheries has been deemed sufficient to construct DEA models (NMFS, 1999), the peak-to peak method will not be discussed further in this paper.

[4] A September 1999 draft by Dupont, Grafton, Kirkley and Squires claims to be the first capacity study of a multi-species fishery, and uses DEA.

American Fisheries Act (AFA) of 1998. As a result, it allows one to examine the effect of introducing property rights on fishing capacity. The AFA allowed vessels to form a cooperative and decide for themselves how many vessels to use and how many to idle. An indication of the degree to which introducing property rights can reduce capacity may be helpful for policy makers once they have estimates of capacity in hand for each of the fisheries of interest.

II. Methods for Capacity Measurement

The recent agreements to assess capacity in many of the world's fisheries have accentuated the need to develop better methods for measuring fishing capacity. To date, a variety of methods have been suggested for estimation purposes – as well as many different "definitions" and interpretations of capacity (there will be more on this issue later). One of the reasons for this lack of consensus is because much of the literature on capacity measurement was developed for applications in more "standard" manufacturing industries. Using such models to measure fishing capacity requires one to make adaptations to account for factors particular to fisheries industries.

However, much of the existing literature available for assessing alternative methods does not address applications to fisheries[5], and thus has not led researchers to a strong consensus over the "best" model for fisheries applications. As a result, the lack of a widely accepted method for measuring fishing capacity has slowed the formation of a consensus regarding levels of capacity in many of the world's fisheries. The key points of contention in the literature over capacity measurement have basically revolved two main issues: the use of primal versus dual models, and the empirical techniques used in these models.

[5] One exception is Lee and Holland (1999), which analyzes SPF and DEA models in the context of a fishery setting.

Frameworks: Primal and Dual

The literature on capacity measurement has consisted of two general approaches: primal and dual. Dual models explicitly build upon an economic foundation and incorporate hypotheses regarding agents' objectives. Morrison (1985a,b; 1986), Nelson (1989), Berndt and Fuss (1989), and Segerson and Squires (1990, 1992, 1995) all offer economic approaches for defining and measuring capacity. Alternatively, primal models (Färe, Grosskopf, and Kokkelenberg [1989], (Kalirajan and Salim [1997]) focus solely on the production technology.

When choosing between the two frameworks, one's choice really comes down to two main trade-offs: the interpretability of the resulting capacity estimates and the appropriateness of the underlying assumptions in the model. For example, dual models give a more economic interpretation of capacity -- comparing current levels to "optimal" levels -- but do so at the expense of behavioral assumptions that may not be accurate (cost minimization in a race for fish?)[6]. On the other hand, primal models of capacity say nothing about the economic "optimality" of a particular fleet size, only indicating the maximum that could be produced with the observed factors of production, resource stock, state of technology, etc. However, they do allow one to relax behavioral assumptions that may not hold. This may be particularly important in fisheries, where the presence of regulations may cause standard optimization behavior to be an inappropriate assumption (Coelli, 1998).

Regardless of the theoretical merits of either framework, it is the data that often ultimately decides which approach one must take. Even though some economists have recommended the use of economic notions of capacity for capacity management, these approaches are often not feasible tools for fisheries. The data required for these approaches is

[6] Such models also rely on price data, which is often of questionable quality in many fisheries settings.

typically unavailable, and is currently lacking in the most of the federally managed fisheries[7]. In addition, fishery managers seeking to limit capacity as a means of limiting catch are also interested in estimates of the maximum a fleet can catch, and not just how current catch levels compare to "optimal" levels (Lee and Holland [1999a]).

Therefore, capacity management plans are likely to use, in the near term, technical (primal) rather than economic (dual) measures of fishing capacity. This implies that researchers will be faced with choosing among competing estimators of technical fishing capacity. The two primary methods that have been proposed (and also advocated by the NMFS Excess Capacity Task Force) are DEA and SPF models.

Empirical Methods: DEA and SPF

Both DEA and SPF approaches attempt to identify a production frontier for a group of producers characterized by a particular technology. However, DEA and SPF models differ in the manner in which they generate the frontiers. DEA is a non-parametric method that uses mathematical programming to construct a piece-wise linear representation of the frontier of technology. In an output orientation, those who get the most output from a particular set of inputs define the frontier of the output set. Deviations from the frontier are interpreted as evidence of inefficient production, as other agents were able to produce more output from a given level of inputs.

Although DEA models were originally designed to measure technical efficiency (TE), Färe, Grosskopf, and Kokkelenberg (hereafter "FGK", (1989a)) proposed a variation on the standard DEA model that was explicitly designed to provide measures of capacity output and

[7] Recent changes in data collection, however, may allow for cost-based models to be estimated in the near future.

capacity utilization[8]. To implement FGK DEA model, one computes the maximum proportionate increase in outputs when variable inputs are allowed to vary, but fixed inputs are held at observed values. The following output-oriented linear program also allows for variable returns to scale (VRS):

$$Max_{(\theta, z, \lambda)} \theta = \sum_{j=1}^{J} z_j y_j \tag{1}$$

subject to the following restrictions:

$$\begin{aligned}
&\theta\, y_{j_m} \le \sum_{j=1}^{J} z_j\, y_{jm},\ m = 1,2,\ldots M \\
&\sum_{j=1}^{J} z_j x_{jn} \le x_{jn}\,, \quad for \quad n \in \alpha\,; \\
&\sum_{j=1}^{J} z_j x_{jn} \le \lambda_{jn}\ x_{jn}\,, \quad for \quad n \in \hat{\alpha}\,; \\
&and \quad z_j \ge 0\,,\ j = 1,2,\ldots,J \\
&and \quad \lambda_j \ge 0\,, \quad for \quad n \in \hat{\alpha}, \\
&\sum_{j=1}^{J} z_j = 1
\end{aligned}$$

The variable factors are denoted by $\hat{\alpha}$, the fixed factors are denoted by α. In the FGK specification the use of variable inputs is not restricted to observed levels. As such, the third constraint involving λ tells one the necessary variable input use required to achieve frontier output levels, and thus serves a check on the sensibility of capacity estimates[9]. The "activity levels" (z_j) of y and x are the weights for the points that define the frontier. The first three constraints ensure that such projections stay on or within the feasible set, while the last constraint allows for VRS. A VRS approach ensures that each firm is only benchmarked against firms of

---

[8] Section III provides a thorough discussion of the distinction between TE measurement and capacity measurement for both DEA and SPF models. Here the intention is to provide a brief introduction of the DEA and SPF models.

[9] For example, use of variable inputs such as fishing time (or days at sea) at full capacity should not exceed the fishing time possible. Such input use would be unrealistic, as would the associated capacity estimates.

similar size, as projected points for firms below the frontier are formed as a convex (rather than linear) combination of frontier observations (Coelli *et al.*,1998).

Using the results from the program above, one can determine fishing capacity by analyzing each vessel's frontier output levels. The value of the parameter θ is the reciprocal of the output distance function[10] and therefore provides a measure of the possible (radial) increase in outputs. For example, an objective value of $\theta = 1.1$ indicates that the capacity output equals 1.1 times the current observed output vector.

If instead one employs an SPF model, this approach uses parametric methods to estimate production frontiers by econometrically "fitting" the frontier of the technology. SPF models allow for deviations from the frontier for two reasons: random variation/noise and productive inefficiency. The following section presents a discussion of single output (production function) and multiple output (distance function) SPF models.

To begin, consider the single output SPF model with the production technology expressed as

$$y = f(\mathbf{x};\boldsymbol{\beta}) + \varepsilon \tag{2}$$

Where y is output, f(•) is a functional form of the production technology, **x** is a vector of inputs, **β** is a vector of parameters to be estimated, and ε is an error term. Note that actual output, $\hat{y}$ may differ from potential output due the observed error term, ε. This error is typically specified as including two components.

The first component represents differences in observed and potential output due inefficient input use, and is denoted by *u*. The second component is purely random variations in output (unrelated to inefficient factor use), analogous to the error term in standard regression

---

[10] A thorough discussion of the properties of the output distance function is given in Färe and Primont (1995).

models, and is denoted by *v*. In fisheries contexts, such random errors are often attributed to weather conditions, variations in stock conditions, luck, or possibly introduced by data measurement errors. It is usually assumed that *v* is an i.i.d. normal random variable and *u* is distributed as an iid truncated normal random variable[11]. The resulting specification with $u \geq 0$ can be seen more clearly as

$$y = f(\mathbf{x};\boldsymbol{\beta}) - u + v, \quad (3)$$

$$\varepsilon = -u + v;$$

Given these distributional assumptions, standard MLE routines such as Frontier can be used to estimate the parameters of the model. Note that by accounting for inefficiency, *u*, the fitted values $f(\mathbf{x}, \boldsymbol{\beta}^{\wedge})$ represent the technically efficient output levels for each firm. However, in order to convert estimates of technically efficient output into estimates of capacity output, one must then augment the TE output levels to reflect the relevant definition of capacity. More will be said on this later, but it essentially involves evaluating the TE output levels at a particular level of variable input use[12].

One important limitation of the standard SPF framework is that it does not allow one to specify multiple outputs, which are common in many of the federally managed fisheries where capacity assessment will be undertaken. And, if one chooses to include data on multiple outputs in this specification, one must aggregate outputs into a composite output. Aside from the restrictive assumptions implied by aggregating outputs in such a way, one also loses much of the information contained in a parametric specification, such as the cross-terms between multiple

[11] The truncation ensures that the inefficiency term takes only positive values, thus putting firms *below* the production frontier in cases of inefficient production.

[12] Unfortunately, the existence of various definitions for "capacity" gives rise to multiple resulting ways of evaluating capacity output. For example, one definition of technical capacity involves evaluating technically efficient production at fully utilized levels of variable inputs. Full utilization levels of variable inputs correspond to the maximum observed usage of each variable input for an agent. Alternatively, full utilization levels may be defined as the maximum observed variable input levels for a

inputs and outputs; with estimates of these parameters can examine jointness among and between inputs and outputs[13] and to calculate substitution elasticities.

If instead one estimates a stochastic output distance function, one is able to retain a multi-input, multi-output specification, while still incorporating the error term decomposition discussed in the previous single output model[14]. Written generally, one may define the stochastic output distance function as[15]

$$D_o = f(\mathbf{x},\mathbf{y};\boldsymbol{\beta}) + v, \tag{4}$$

where D_o is a distance measure representing the difference between observed and frontier output (or technical efficiency), $f(\bullet)$ is a functional form of the production technology, $\mathbf{x}$ is a vector of inputs, $\mathbf{y}$ is a vector of outputs, $\boldsymbol{\beta}$ is a vector of parameters to be estimated, and v is a vector of random errors (equivalent to the random noise v in the single output specification discussed above).

Note however, that estimation cannot proceed as usual without data on the dependent variable (D_o), which is typically unknown. Therefore, one must devise a method to "operationalize" the distance function. One suggestion has been a two-step method (Hetemäki, 1996) in which one first obtains values of $D_o(\mathbf{x},\mathbf{y})$ for the LHS using DEA, and then implements the econometric SPF model[16].

---

group of agents with a particular fixed input endowment; in this case it is important that full utilization levels are selected from set of producers with a similar set of limiting fixed inputs.

[13] Tests of jointness may even allow the researcher to test down and actually estimate a simpler model with fewer outputs and parameters.

[14] An alternative to the stochastic distance function is the ray production frontier model proposed by Löthgren (1997). In this model one defines the dependent variable as a Euclidean norm of the output vector and the independent variables as transformations of the inputs and the polar-coordinate angles of the outputs.

[15] Here I discuss the output distance function (rather than the input distance function) since it nests the production function, and also because it indicates the proportional gain in outputs possible from technically efficient production, which has been the focus of the discussion.

[16] However, as one of the goals of this work will be to compare the DEA and SPF, such hybridization would obscure the comparisons and therefore will not be used.

The more common approach is to utilize the homogeneity properties of distance functions. That is, linear homogeneity in outputs for $D_o(\mathbf{x},\mathbf{y})$ implies: $D_o(\mathbf{x},\lambda\mathbf{y}) = \lambda\, D_o(\mathbf{x},\mathbf{y})$ for $\lambda > 0$. This allows one to isolate an observed variable for the LHS of the econometric model. A possible choice for the scaling variable λ is one of the outputs. For example, if one chooses chose the m^{th} output, and set $\lambda = 1/y_m$, the distance function may be written as

$$D_o(\mathbf{x}, \mathbf{y}/y_m) = D_o(\mathbf{x}, \mathbf{y}) / y_m \tag{5}$$

A common functional form in distance function studies is the translog (Färe *et al.* [1993], Lovell [1994], Grosskopf *et al.* [1996], Coelli and Perelman [1996], Coggins and Swinton [1996]). Using this flexible form, equation (5) can then be written as

$$\ln(D_o(\mathbf{x},\mathbf{y})/y_m) = f\,(\mathbf{x}, \mathbf{y}/y_m;\boldsymbol{\beta}), \tag{6}$$

where f denotes the translog functional form and $\boldsymbol{\beta}$ its parameters. Splitting the LHS of (6) into two terms allows us to re-arrange the equation into one with an observable LHS variable:

$$-\ln(y_m) = f(\mathbf{x},\mathbf{y}/y_m;\boldsymbol{\beta}) - \ln(D_o) \tag{7}$$

Note that in the last term in equation (7), $0 \le -\ln(D_o) \le \infty$, and thus, this term is equivalent to the inefficiency term u in the single output production function specification discussed above. By renaming $-\ln(D_o)$ as "u" and appending the additive error term v to (7), one obtains

$$-\ln(y_m) = f(\mathbf{x}, \mathbf{y}/y_m; \boldsymbol{\beta}) + u + v, \tag{8}$$

$$\varepsilon = u + v$$

Thus, the result of the homogeneity transformation is an estimable stochastic distance function in which the observed error, ε, consists of an inefficiency term, u, representing the value of D_o, and a random error term, v. One can then proceed similarly to the single-output SPF model using standard OLS, MLE, or SPF packages[17]. And, analogous to the single-output SPF model, capacity estimates can be obtained by evaluating the technically efficient frontier at the levels of variable input use commensurate with one's chosen definition of capacity.

Once capacity estimates have been derived using either the SPF or DEA models, the estimates results can be used to specify *total* fishery capacity by summing each vessel's capacity output levels over all species. In addition, one may also specify the efficient number of vessels for a fishery. One first orders the vessels' capacity estimates by their respective TE scores and then sums over the ranked capacity estimates until the cumulative output level equals the given level of TAC. This resulting group of vessels represents the most relatively efficient fleet for catching the particular TAC.

III. Issues in Modeling Technical Capacity

General Strengths and Weaknesses of DEA and SPF

The production literature provides a discussion of the relative merits of both DEA and SPF models in general applications (Fried, Lovell, Schmidt [1993], Kalaitzondonakes and Dunn [1995], Sharma, Leung and Zaleski [1997], Hjalmarsson, Kumbhakar and Heshmati [1996], Coelli [1998], Cummins and Zi [1998]). However, since much of the focus is on theoretical properties of the estimators and makes little mention of adaptations to resource applications, I will discuss the two approaches in the context of fisheries applications and capacity estimation.

To begin, DEA easily accommodates multiple inputs and outputs (common in fisheries), while use of SPF in multi-output contexts necessitates restrictive aggregation assumptions or the development of more complicated multiple output models. Another strength of DEA is that is

[17] Hetemäki (1996) notes that the endogenous variable (here, output y_m) now appears on both sides of the equation to be estimated and thus may lead to problems with simultaneity bias. However, Coelli and Perelman (1996) argue that this transformation does not necessarily make the right-hand side variable endogenous. Only *ratios* of the outputs appear as regressors, which may be assumed to be exogenous; since the distance function is defined for radial expansion of all outputs, by

does not impose an arbitrary functional form on the technology, while SPF models require that the researcher assume some form for the technology. However, as noted by Färe et al. (1989), some functional forms are theoretically inconsistent with a maximum level of output, which may make their use inappropriate for measuring technical capacity[18].

DEA also easily accommodates zero valued outputs, which a common occurrence in fisheries data due to seasonal and geographical fishing patterns; fishermen will often target one species at a time, but land multiple species throughout a season. Alternatively, SPF estimates suffer from censoring problems when used along with data that exhibits frequent zero valued outputs (Tobin, 1958). Lastly, DEA allows one to include constraints for stock levels, bycatch or other fishing restrictions, which cannot be said for the SPF models.

Note, however, that there are caveats to DEA's "ease" with multiple inputs and outputs and zero-valued observations. One must be selective in choosing the appropriate variables to include in analysis in order to facilitate the appropriate "peer" comparisons. For example, in analyzing a multi-species fishery there are often many species that comprise "incidental catch", but are still included in the data for completeness. If all of these species were included as outputs in the models output vector, a majority of observations for the incidental species would be zero, and would rise to a large number of permutations of output composition.

Since DEA relies on making comparisons among peers who use similar bundles of inputs and outputs, a large number of permutations of output composition may nullify potential efficiency comparisons among agents whose primary outputs (target species) and input usage are quite similar. Thus, many of the observations will be unique in that they will have no peers, and

---

definition these ratios are held constant for each observation. Therefore, to address said concerns, one should perform a Hausman endogeneity test when implementing the homogeneity transformation.

[18] However, one may not be seeking capacity estimates that represent a *theoretical* maximum. Rather, one may want to estimate the output levels that would be generated under technically efficient production using *realistic* (or observed) input levels (which may fall well below the point where marginal products are zero and a maximal output is obtained).

will form a unique segment of the production frontier. When this occurs, no comparisons are made and an observation is deemed relatively efficient by default. However, it may actually be the case that when these vessels are compared to others who harvest the same composition of target species, the vessels appear to be relatively *inefficient*.

As for the strengths of SPF models, their most appealing trait is the ability to account for random variations and data noise, which are both common in fisheries data. Random variations in output may occur because of the inherent variability of the fishing industry; for a given level of input use, output levels may differ from trip to trip or week to week due to random factors such as weather, luck, resource conditions, etc. Similarly, data noise may be present in fisheries data because of the susceptibility of data collection to reporting errors; the size of the some of the operations and the amount of fish harvested often makes it necessary for data recorders to provide "rough" estimates catch levels and composition. For these reasons, SPF's ability to account for noise is very attractive and valuable in fisheries applications.

Recent Monte Carlo analysis by Lee and Holland (1999b) has provided empirical evidence of the differences that may arise when one uses DEA and SPF models with "noisy" data. The authors generate observations using a Cobb-Douglas production function and examine the effects of introducing various levels of noise. They show that when the SPF model is specified correctly (proper choice of functional form), the mean bias in TE scores is often substantially larger for DEA than SPF. And, as noise levels increase, the bias in DEA models tends to increase quite rapidly relative to SPF[19].

---

[19] However, one could argue that this exercise systematically puts DEA at a disadvantage. While SPF does have the ability to handle random errors, its performance will suffer if one mis-specifies the form of the technology. Given that the authors have eliminated a potentially significant source of bias in SPF models (by using a Cobb-Douglas specification for their SPF model), one might expect *a priori* for the SPF method to out-perform DEA. In an experiment based on how two frameworks handle random noise, it seems quite intuitive that the framework designed to handle errors would certainly prevail. Still, these results do highlight the potential bias that DEA models can introduce when used on noisy data.

An additional benefit of the SPF error structure is the ability to conduct conventional statistical tests on estimates of production inefficiency and other technological characteristics of interest (such as substitution elasticities, scale economies, or scope economies). Statistical tests can provide an indication of the robustness of one's results and may be especially important if capacity estimates are to be used for policy-related decisions.

Defining "Capacity" in SPF and DEA Models

To this point the discussion has focused on the different attributes of the methods proposed for measuring fishing capacity. However, given that both the SPF and DEA models were originally developed for measuring TE, in order to use the models to generate estimates of capacity one must make the necessary adaptations to TE estimates. The changes one makes to each of the standard models depends upon one's interpretation of what represents fishing capacity. The different definitions of technical capacity that have been suggested essentially differ in their views regarding variable input use. Some authors claim that technical capacity should be based on some maximal level of variable input use (Johansen [1968], Färe, Grosskopf, and Kokkelenberg [1989]), while others suggest a more sustainable notion of capacity.

More specifically, the definition offered by Johansen[20] is " the maximum amount that can be produced per unit of time with existing plant and equipment, provided the availability of variable factors of production is not restricted." This definition of capacity corresponds to the output that could be produced under technical efficiency and full utilization of variable inputs (the maximum observed variable input levels for a given stock of fixed factors), but constrained by the fixed factors and the state of technology. These output levels corresponds to those estimated by the aforementioned FGK model.

In contrast, the National Excess Capacity Taskforce has suggested that capacity be defined relative to more “normal” output levels: “the output that a fleet could reasonably expect to catch if variable inputs are utilized under normal operating conditions, for a given resource condition, state of technology, and other constraints.” Using this definition one would generate smaller capacity estimates than with the Johansen definition, due to relaxation of Johansen’s equired “full variable input utilization.” That is, the word “normal” indicates that full utilization levels of variable inputs may not be reasonable for all vessels with a similar endowment of fixed inputs[21].

If one is interested in deriving estimates based on either of these definitions, there are cases in which DEA is easier to implement than SPF and vice versa. The standard TE model is easily accomplished through either method, while the model incorporating TE *and* full variable input utilization is more easily assessed with the DEA model of FGK.

As discussed earlier, in the FGK approach constraints on variable inputs are dropped. Thus, to be on the frontier, firms must have produced the most output for a given level of fixed inputs. Firms that are not on the frontier may be below it because they are either using fixed inputs inefficiently, or because they are using lower levels of variable inputs than frontier firms. Regardless, their production levels do not represent maximal capacity for their fixed input endowment. This framework is based solely on determining the potential output levels for a given endowment of fixed inputs, rather than judging agents’ efficiency or optimality of variable input use. While this focus obviously differs from the standard DEA focus on TE with respect to

---

[20] Johansen’s definition is equivalent to the current FAO definition of capacity agreed upon by researchers agreed upon by researchers representing forty nations at a Technical Working Group meeting. It is also equivalent to that offered by Christy (1996), Prochaska (1978), and the US Congressional Task Force on capacity and subsidies in fisheries.

[21] In addition, the word “reasonably” seems to pertain to whether or not all vessels in the sample can actually attain the “technically efficient” output levels determined my the model. If one thinks vessel-wise comparisons of TE are inappropriate, one could consider estimating single-vessel DEA or SPF models. Such models would define TE output as the most output

all inputs, the results of the FGK model provide what some might think of as a reasonable idea of capacity.

SPF models, on the other hand, estimate each vessel's capacity output for a *given* set of observed inputs. Thus, frontier estimates provide an indication of technically efficient output levels, differing from Johansen's "full variable input utilization" notion of capacity. If one seeks capacity estimates representing full utilization of variable inputs, one must evaluate the estimated frontier at "maximum levels" of variable inputs.

The question that remains, however, is how to determine the appropriate "maximum" for each agent. DEA makes such choices internally (through the selection of peers), while SPF requires that the researcher make the decision, which can be difficult. Should one use the maximum observed variable input levels for a certain vessel when evaluating their capacity, or should one look at the maximum variable input levels used by all vessels with similar fixed input endowments? If so, then what is the appropriate range of comparable vessels sizes?

IV. Empirical Application: The Bering Sea and Aleutian Island Pollock Fishery

The Setting

The North Pacific groundfish fisheries (NPGF) of the Bering Sea and Aleutian Islands are among the largest and most valuable in the world, generating two-thirds of a billion dollars per year in sales at first wholesale. Within the NPGF, the pollock fishery is by far the most valuable, as it accounts for approximately 80% of the yearly value generated. Despite the size and value of the pollock fishery, relatively little is known about the economic performance of the industry. In particular, concern has loomed over the presence of excess fishing capacity and the associated effects on efficiency and productivity.

obtained from the inputs used by that vessel alone (comparing the vessel's production in various weeks within a season). However, one would have substantially fewer observations with which to perform the analysis.

Up until 1998, the NPGF was operated entirely as a regulated open access fishery wherein the TAC was set and vessels were allowed to fish until particular quotas were met. Recent legislation has changed the structure of the fishery in an attempt to address some of the aforementioned concerns. In late 1998 Congress passed the American Fisheries Act (AFA), which altered the open-access characteristics of the pollock fishery. In short, the AFA provided incentives to “rationalize” the pollock fishery by limiting access, specifying those who may harvest and process pollock, and by allowing these agents to form cooperatives.

Therefore, in evaluating the fishing capacity of the pollock fishery, one can look at the changes that occurred after the introduction of property rights specified in the AFA. Such information will provide a preliminary indication of how effective (and quickly) such measures helped to decrease capacity.

The data used in the capacity estimation represents weekly harvesting and processing for 1991-1999, and comes primarily from Weekly Processor Reports (WPR) filed by operators with state and federal authorities. The data used here in the models consists of observations by vessel from 1991-1999 on landings of groundfish, landings of bycatch species, a fictitious vessel id number, vessel characteristics (length, tonnage, horsepower, age, engine and hull type, holding capacity) area fished, crew size, days at sea, number of tows, and duration of tows.

To appropriately develop the models of production technology, one must first separate the sample into groups that are characterized by similar harvesting and processing operations (e.g. vessels that target pollock with trawl gear). The presence of fictitious operator id numbers given in the data makes it possible to track production by individual operators over time, as well as to separate the data into several modes of operation and “fleets” that are defined based on common production patterns. That is, commonality of production patterns in the data suggests commonality of production technology onboard[22]. Such delineations will help ensure that the models characterize all vessels in each sample fairly well, and that any resulting comparisons are made among the appropriate agents.

Model Specifications

Using this data we compute and compare the results from the following specifications:

1) DEA TE model
2) DEA FGK model (with TE and full variable input utilization)
3) SPF TE model
4) SPF TE model with full variable input utilization (evaluated at variable input levels of the "peers" found in (2)

Results

Unfortunately, the data to be used in the empirical analysis was not made available to the author by the NMFS by the submission deadline. When it soon becomes available, all attempts will be made to complete the empirical work in a timely manner and send a revised version of this manuscript to the session moderator -- including a discussion of the capacity estimates and other measures to be derived.

References

Ali, A. and L. Seiford. "The Mathematical Programming Approach to Efficiency Analysis," Chapter 3 in *The Measurement of Productive Efficiency: Techniques and Applications* (H. Fried, C.A.K. Lovell, and S. Schmidt, eds.). Oxford University Press, 1993.

Baumol, W.J., and W.E. Oates. *The Theory of Environmental Policy*. Cambridge University Press, 1988.

[22] These subgroups also correspond to the distinctions along lines that are also used by Council staff in their analyses of allocation issues involving groundfish

Berndt, E.R., and M.A. Fuss. "Economic Capacity Utilization and Productivity Measurement for Multiproduct Firms with Multiple Quasi-Fixed Inputs." National Bureau of Economic Research Working Paper No. 2932. Cambridge, Mass.: National Bureau of Economic Research.

Chambers, Robert G. *Applied Production Analysis: A Dual Approach.* Cambridge University Press, 1988.

Charnes, A., W.W. Cooper and E. Rhodes. "Measuring the Efficiency of Decision Making Units." *European Journal of Operational Research* 2, 429-444, 1985.

Christy, F.T. *Over Capacity in Fisheries: Problems and Approaches.* Washington, D.C.: IMARBIA, 1996

Coelli, Tim, D.S. Prasada Rao, and George E. Battesse. *An Introduction to Efficiency and Productivity Analysis*. Kluwer Academic Publishers, 1998.

Coelli, Tim, and Sergio Perelman. "A Comparison of Parametric and Non-Parametric Distance Functions: With Applications to European Railways." CREPP Draft 13/09/1996.

Coelli, Tim, and Sergio Perelman. "Efficiency Measurement, Multiple-Output Technologies and Distance Functions: with Applications to European Railways." CREPP Working Paper #95/06, Universite de Liege, Belgium.

Coggins, Jay S., and John R. Swinton. "The Price of Pollution: A Dual Approach to Valuing SO_2 Allowances." *Journal of Environmental Economics and Management* 30, pp. 58-72, 1996.

Cummins, D.J., and H. Zi. "Comparison of Frontier Efficiency Methods: An Application to the U.S. Life Insurance Industry." Journal of Productivity Analysis 10, pp 131-152, 1998.

Färe, Rolf, Shawna Grosskopf, and E.C. Kokkelenberg. "Measuring Plant Capacity, Utilization and Technical Change: A Nonparametric Approach." *International Economic Review*, Vol. 30, No.3, August 1989a.

Färe, Rolf, Shawna Grosskopf, B. Lindgren, and P. Roos. "Productivity Developments in Swedish Hospitals: A Malmquist Output Index Approach." Discussion Paper 89-3, Department of Economics, Southern Illinois University, Carbondale, 1989b.

Färe, Rolf, Shawna Grosskopf, C.A. Knox Lovell, and Suthathip Yaisawarng. "Derivation of Shadow Prices for Undesirable Outputs: A Distance Function Approach." *Review of Economics and Statistics*, May 1993, pp. 374-380.

Färe, Rolf, Shawna Grosskopf, and C.A. Knox Lovell. *Production Frontiers.* Cambridge University Press. 1994.

Färe, Rolf, and Daniel Primont. *Multi-Output Production and Duality: Theory and Applications.* Kluwer Academic Publishers, 1995.

Farrell, M.J. "The Measurement of Productive Efficiency." *Journal of the Royal Statistical Society,* Series A, General, 120, Part 3, pp. 253-281, 1957.

Felthoven, Ronald G., Douglas M. Larson, James Sanchirico, and Joseph M. Terry. "Assessing Economic Performance in Selected Alaska Groundfish Fisheries." Report to the Pacific States Marine Fishery Commission, 1999a.

Felthoven, Ronald G., Douglas M. Larson, James Sanchirico, and Joseph M. Terry. "Modeling Multi-Product Fisheries Technology with Routinely Collected Data: Revenue Functions For Alaska Surimi Pollock Production." (In progress) 1999b.

Food and Agriculture Organization (FAO). "Report of the Technical Working Group On The Management of Fishing Capacity." FAO Fisheries Report No. 518, La Jolla, United States of America, pp. 15-18 April 1998.

Food and Agriculture Organization (FAO). The International Plan of Action for the Management of Fishing Capacity. *International plans of action adopted by the 23rd session of the FAO Committee on Fisheries,* Rome, Italy, 15- 19 February, 1999.

Fried, H.O., C.A. Knox Lovell, S.S. Schmidt. *The Measurement of Productive Efficiency: Techniques and Applications.* Oxford University Press, 1993.

Grosskopf, S. K. Hayes, L. Taylor and W. Weber. "Budget Constrained Frontier Measures of Fiscal Equality and Efficiency in Schooling." *Review of Economics and Statistics,* 1996.

Hjalmarsson, L., S.C. Kumbhakar, and A. Heshmati. "DEA, DFA and SFA: A Comparison." *Journal of Productivity Analysis* 7, pp. 303-327, 1996.

Hetemäki, Lauri. "Essays on the Impact of Pollution Control on a Firm: A Distance Function Approach." Ph.D. Dissertation, University of Helsinki, 1996.

Johansen, L. "*Production Functions and the Concept of Capacity*." Recherches Recentes sur la Fonction de Production, Collection, Economie Mathematique et Econometrie 2, 1968.

Kalaitzondonakes, N.G., and E.G. Dunn. "Technical Efficiency, Managerial Ability and Farmer Education in Guatemalan Corn Production: A Lantent Variable Analysis." *Agricultural and Resource Economics Review* 24(1), pp. 36-48.

Kalirajan, K.P. and R.A. Salim. "Economic Reforms and Productive Capacity Realization in Bangladesh; an empirical analysis." *Journal of Industrial Economics* 45(4), pp. 387-403, 1997.

Kirkley, J., Rolf Färe, Shawna Grosskopf, K. McConnell, D. Squires, and I. Strand. "Assessing Capacity and Capacity Utilization in Fisheries When Data Are Limited." Working Paper, September 1999.

Kirkley, J., and D. Squires. "Measuring Capacity and Capacity Utilization in Fisheries." Report presented to the FAO Technical Consultation on the Measurement of Fishing Capacity, La Jolla, CA, April 1998.

Kirkley, J., and D. Squires. "Capacity and Capacity Utilization in Fishing Industries." UC San Diego Discussion Paper 99-16, 1999.

Larson, D.M., B.W. House, and J.M. Terry. "Toward Efficient Bycatch Management in Multispecies Fisheries: A Nonparametric Approach." *Marine Resource Economics* 11, pp. 181-201, 1996.

Larson, D.M., B.W. House, and J.M. Terry. "Bycatch Control in Multispecies Fisheries: A Quasi-rent Share Approach to the Bering Sea/Aleutian Islands Midwater Trawl Pollock Fishery." *American Journal of Agricultural Economics* 80, 1998, pp. 778-792.

Lee, S. Todd and Daniel Holland. "Impacts of Random Noise and Specification on Estimates of Capacity Derived from Data Envelopment Analysis." NMFS, Alaska Fisheries Science Center Working Paper, 1999a.

Lee, S. Todd and Daniel Holland. "The Impact of Noisy Catch Data on Estimates of Fishing Capacity Derived From DEA and Stochastic Frontier Models: A Monte Carlo Comparison." NMFS, Alaska Fisheries Science Center Working Paper, 1999b.

Lovell, C.A. Knox. *"Resources and Functionings: A New View of Inequality in Australia*." In W. Eichorn's, ed., Models and Measurement of Welfare and Inequality, Berlin, Springer-Verlag Press.

Morrison, Catherine J. "Primal and Dual Capacity Utilization: An Application to Productivity Measurement in the U.S. Automobile Industry." *Journal of Business and Economic Statistics* 3, 312-324, 1985a.

Morrison, Catherine J. "On the Economic Interpretation and Measurement of Optimal Capacity Utilization with Anticipatory Expectations." *Review of Economics and Statistics* 52, pp. **295-**310, 1985b.

Morrison Paul, Catherine J. *Cost Structure and the Measurement of Economic Performance.* Kluwer Academic Publishers, 1999.

National Oceanographic and Atmospheric Administration (NOAA). NOAA Fisheries FY 1999 Annual Operating Plan, January 1999.

National Marine Fisheries Service. "A Report of the National Task Force for Defining and Measuring Fishing Capacity." June 30, 1999.

Nelson, R. "On the Measurement of Capacity and Capacity Utilization." *Journal of Industrial Economics* 37(3), 273-286, 1989.

Pollock Conservation Cooperative and High Seas Catchers' Cooperative. "Preliminary Joint Report." Presented to the North Pacific Fishery Management Council, December 1, 1999.

Prochaska, F. "Theoretical and Empirical Considerations for Estimating Capacity and Capacity Utilization in Commercial Fisheries." *American Journal of Agricultural Economics* 60, pp. 1020-1025, 1978.

Segerson, K. and D. Squires. "On the Measurement of Economic Capacity Utilization for Multi-Product Industries." *Journal of Econometrics* 44, pp. 347-361, 1990.

Segerson, K. and D. Squires. "Capacity Utilization Under Regulatory Constraints." *Review of Economics and Statistics* 1, pp. 76-85, 1992.

Segerson, K. and D. Squires. "Measurement of Capacity Utilization for Revenue-Maximizing Firms." *Bulletin of Economic Research* 47(1), pp. 77-84, 1995.

Sharma, K.R., and P. Leung. "Technical Efficiency of the Longline Fishery in Hawaii: An Application of a Stochastic Production Frontier." Marine Resource Economics 13(4), pp. 259-274, 1998.

Sharma, K.R., and P. Leung and H.M. Zaleski. "Productive Efficiency of the Swine Industry in Hawaii: Stochastic Frontier vs. Data Envelopment Analysis." Journal of Productivity Analysis 8, pp. 447-459, 1997.

Shephard, Ronald W. *Theory of Cost and Production Functions*. Princeton: Princeton University Press, 1970.

Tobin, J. "Estimation of Relationships for Limited Dependent Variables." *Econometrica* 26, pp. 24-36, 1958.

US Department of Commerce, National Oceanic and Atmospheric Administration, National Marine Fisheries Service. "Magnuson Fishery Conservation and Management Act As Amended Through October 11, 1996," NOAA Technical Memorandum NMFS-F/SPO-23, December 1996.