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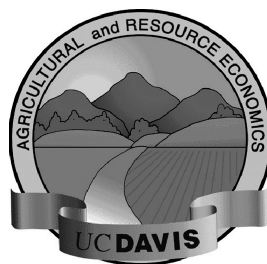
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Giannini Foundation for Agricultural Economics**

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Thoughts on Productivity, Efficiency and Capacity Utilization Measurement for Fisheries

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Introduction

Economic performance in fisheries has been an issue for at least the last century, as virtually all commercial fisheries have experienced dramatic declines in fish stocks, and thus in the economic health of fishermen, industries, and regions that rely on fisheries for their support. In the recent past the importance of performance issues has been highlighted by the global emphasis on reducing capacity levels and thus enhancing productivity in fisheries by the FAO “Code of Conduct for Responsible Fisheries” (FAO [1995, 1997]). In the U.S. this has also reinforced the attention paid to these issues, as exhibited by recent interest expressed in, and research conducted on, performance questions by the National Marine Fisheries Service and other regulatory institutions.

The importance of determining both existing capacity and its optimal levels has played a key role in the resulting literature. The driving force of efforts to model and measure capacity and capacity utilization (CU) is to enhance fisheries’ performance by reducing overfishing and overcapitalization, and to get biomass stocks and fishermen on track toward a healthy economic environment. In order to move in this direction, however, economists, and ultimately policy makers, need reliable methods to calculate capacity and its utilization effectively, and insights about how most appropriately to use the resulting measures for economic guidance.

Most of the recent literature in this area has relied on adaptations of data envelopment analysis (DEA) techniques often used to measure technical efficiency. Evaluating capacity from this perspective requires establishing deviations from “best practice” performance taking all types of fishing effort inputs into account, and comparing the resulting measures to those considering only the use of capital inputs,

unconstrained by the availability of variable factors. The resulting capacity utilization measures are touted as a basis for establishing benchmarks for reducing excess capacity.

Any procedures for measuring such crucial aspects of an industry's performance, and for applying them to policy guidance, generate many questions about their applicability. It is not my intention in this discussion to elaborate on the potential hazards of measuring capacity utilization, or of using DEA analysis, since this is clearly a necessary, if difficult, undertaking, and any methodology used for such an endeavor can be questioned. What I *do* want to do here is emphasize some of the questions that are crucial to keep in mind for both construction and application of such measures, but that are very difficult to get a handle on. I also want to stress the importance for any economic application of comparing alternative types of measures, rather than focusing on one kind of measure or methodology.

That is, to generate measures that at least provide definitive ranges within which we can establish existing and optimal capacity, we must construct and compare different types of measures based on varying methodologies. The two most overriding questions to raise in this context are, in my mind, the extent to which stochastic (parametric), as contrasted to deterministic (nonparametric, such as DEA) methods, or frontier, as compared to more standard econometric models, might generate different implications.

Parametric and nonparametric models each have distinct advantages and disadvantages. But stochastic models should at least provide comparison points for measures generated using nonparametric DEA techniques,¹ especially since they “may be more applicable in situations where the data are heavily influenced by measurement error

¹ This is particularly important because the implications of measures using the different methodologies may vary significantly, as shown by Felthoven [2000].

and the effects of weather or disease”.² This is clearly the case for fisheries where myriad uncontrollable circumstances (weather, breakdowns), and unmeasured factors (including biomass stocks), are significant pieces of the puzzle.

Stochastic frontier models that attribute existing fluctuations to “inefficiency” may be useful for generating certain types of insights. But more standard econometric techniques, which facilitate more detailed identification of production structure determinants, could also be effective for representing performance and its determinants, or at least should be used as a base for comparison. This is particularly true when comparability across observations within or between decision making units is questionable, as is likely the case for fisheries.

In addition to questioning the effects of the methodological basis on resulting capacity measures, it is crucial to recognize unique fisheries characteristics that further complicate economic performance investigation. In particular, a wide swath of stock and property right issues should be taken into account for interpretation of performance measures, and potentially brought directly into the analysis.

So, the “thoughts” I summarize in what follows to some extent take the form of a “laundry list” of such issues, that need to be kept in mind when attempting to analyze performance and capacity utilization (CU) in fisheries. I will first overview fundamental notions underlying the modeling and measurement of productivity and CU, to provide a conceptual foundation. And then I will discuss the usefulness – as well as potential problems – of stochastic frontier and standard econometric models and estimating techniques for defining these concepts and generating such measures, at least for comparison with the DEA measures much more in evidence at this conference.

² Coelli *et al* [1998], as cited by Färe *et al* [2000].

The conceptual foundation for performance measurement

Economic performance measurement and evaluation focuses on representing the productivity and underlying production structure of an industry, region, or individual decision making unit (DMU – in the fisheries context perhaps the vessel/skipper). This in turn involves the definition, specification, and measurement of outputs (benefits) and inputs (costs) into the production process. Productivity is typically represented by the output to input ratio Y/V (where Y is aggregate output, and V aggregate input, somehow defined). “Maximum” productivity, in terms of comparison across time, space, or DMU, is then characterized by some notion of the highest Y/V that can or has been attained.

Simply defining and interpreting such indicators raises a number of important questions, especially in the context of fisheries. An immediate query might be how “maximum” is defined relative to “optimum”. That is, is the highest observed output reached by any one vessel (ideally adapted appropriately for its characteristics) really the “optimal” outcome, and to what extent is it determined by unmeasured/uncontrollable forces and thus cannot be considered a “goal”, or “best practice”? And issues arise about the aggregation of Y and V . If there are multiple inputs and outputs, how are they weighted, and how do changes in composition (output- or input-intensity) contribute to “optimality”? It is of interest and importance even to think about how fishing inputs are *defined* for measurement purposes. For example, are characteristics recognized? Are data on market values (prices), if incorporated in the analysis, representative of the economic factors we’d want to capture in such measures? The role of fish stock “inputs” should also be carefully contemplated. If a very high output level occurred at the same time the fish stock was decimated (obviously a polar extreme case but illustrative), this is

clearly not “optimal”, or even desirable, although it could perversely be interpreted as high productivity. Finally, externalities and regulatory impacts, and how they are taken into account, may be crucially important for defining benefits and costs.

The focus of our discussion at this conference, capacity utilization, is a closely related piece of the performance puzzle. Capacity or over-capitalization questions focus on the Y/K ratio, where K is capital or “capacity”, and maximum (or optimum) Y/K is the implied goal rather than high output relative to input costs as a whole. In this context, an imputed optimal or capacity output level is somehow defined, and compared to actual observed output, to construct a capacity utilization indicator. Most of the issues just identified in the context of productivity also pertain to these performance measures. An additional concern that arises in this case, however, is that if other inputs are not recognized, it is not clear how they fit into the picture, and in particular how they relate to “optimum” versus “maximum” utilization.

This type of problem arises for any single factor productivity measure, which Y/K essentially is – like labor productivity (output per person-hour, Y/L), or agricultural yields (output per acre, Y/A). Essentially, if other inputs are not taken into account it is difficult to interpret the resulting measures. For example, maximum output per vessel might be attained by having twice as many fishermen on board a vessel, but this might not be an efficient outcome, say, in terms of marginal product per person. It is thus ambiguous whether the resulting situation is “optimum”, “best”, or even “good” in terms of overall benefits and costs.

A fundamental issue that at least implicitly arises here is what *behavior* is relevant for defining the notion of “optimal” for the economic actors in this scenario. This is

important since the premise that maximum Y/K would be achieved in some type of “equilibrium” is based on the idea that outputs and inputs are choice variables, determined according to some type of goals and constraints. That is, is “optimal” defined as minimum costs of producing a given amount of output; are fishermen cost-minimizers? Does optimality imply maximum profits or revenue? Is it based on maximum output given observed inputs? Or is behavior instead motivated by incentives set up by regulations, implied by property rights, or restricted by rigidities such as lack of mobility of labor? This in turn emphasizes the central roles of property rights and regulations as determinants of goals and constraints.

If either minimum costs or maximum profits are relevant behavioral goals, then an economic approach to representing choices, and thus performance and CU, should be used to construct performance indicators. But given the structure of commercial fisheries industries, it might well be that a physical primal- or technological- notion of optimization, in terms of technical potential and maximization, is representative. Such a notion may then better be used for defining optimal utilization of capacity – or optimal (“best”) output production for a given amount of capacity (capital). This implies that maximum Y/K may be considered an optimal outcome, qualified by recognition of problems defining K appropriately (taking characteristics of the vessel into account).

The question that then emerges is whether, to provide a base for measuring capacity and thus CU, one should impute the maximum output possible in the theoretical sense. This is, strictly speaking, how capacity utilization is defined by Johansen [1968] (as referred to by Färe *et al* [2000] and most other papers in these sessions). Such a primal optimization concept implies that defining capacity requires identifying the

highest point on the production function expressed in terms of capital, but not constrained by observed input levels. This will theoretically be attained where the marginal product of capital is zero, which raises at least two issues.

First, even if a primal representation seems relevant, the idea that an “optimum” might be defined as the point where the marginal product of capital is zero sounds hollow to any economist, since it implies no costs of capital. This might be justified if K were truly fixed and therefore “sunk”, although one would think that at least the opportunity costs of using capital elsewhere would still be relevant. In addition, it is crucial when appropriately defining capital user costs, as well as optimality, to recognize other stock constraints such as fish stock “inputs” (and resulting biological dynamics).

Second, even if we do not explicitly characterize capital and other input costs to facilitate defining capacity, it is likely the case that such a maximum theoretical point would never be reached in reality. This in turn implies that we might want to compare points within the observed data set rather than using a $Y(K)$ function to impute a maximum potential level. This is the purpose of the DEA methods used in Färe *et al* [2000] and other related papers focused on defining and measuring CU.

An important key here, in terms of limiting the characterization of “optimal” CU to Y/K levels reached at observed data points, is the notion of “customary and usual operating procedures”, which has been emphasized by the directives of the FAO and the National Marine Fisheries Service regarding performance investigation. Since observed output and input values at least implicitly represent the optimization problem carried out by fishermen, the definition of maximum within the implied frontier is accordingly restricted to be within feasible limits. In particular, it is not transparent what the goal or

optimization problem might actually be, so it is difficult to clearly characterize *optimum*. But we can define *maximum attainable or feasible* CU in the physical or technological sense according to the highest output-to-capital level reached in the observed data. This also provides a basis for defining the highest ratio of observed to potential output, Y/Y^* .

Such a procedure therefore collapses to a peak-to-peak representation based on Y/K .³ The points that fall within the resulting measured boundary could be driven by inefficiency or low levels of variable inputs, or may simply occur due to natural variation (depending on existing external economic, physical, technical or biological factors), or luck.⁴ Thus, what the variations from the frontier *do* depend on, in terms of goals or constraints, is important to distinguish if the measured values are to represent a utilization indicator that is meaningful in the sense of guiding policy for reducing capacity.

The piece of this problem that has achieved more attention since DEA analysis has been offered as a way of estimating CU is how “inefficiency” fits into the picture. If technical inefficiency causes observed output to differ from that technically possible, this deviation from “optimal” output defined according to the full production relationship needs to be carefully assessed. And it should be distinguished separately from that associated with capacity determination. That is, the measure of the deviation of capacity output (Y^*) from observed output (Y) based on the Y/K relationship may be purged of the portion of this gap resulting from the “inefficient” use of variable inputs, to identify the divergence associated only with non-optimal utilization. This can be accomplished

³ This is similar conceptually to the peak-to-peak measure used for the Wharton capacity utilization measure. It is also equivalent to an output-based peak-to-peak measure if K is measured simply as number of vessels and output is expressed in per vessel terms.

⁴ See Alvarez [2000] for an analysis of the contributions of luck and efficiency to productive efficiency in fisheries, and a useful overview of the literature.

by measuring CU by comparing two technical efficiency (TE) measures, defined in terms of the $Y(V)$ as compared to the $Y(K)$ relationship, rather than Y^* and Y .

CU definition and modeling in more detail

To explore these methods of defining, modeling, and measuring CU in more detail, it is useful to back up and overview the economic models more often used in the utilization literature. Cost-oriented capacity utilization measures – typically called economic as contrasted to physical or technological measures – are based on imputing optimal or “capacity” output as the steady state level of output consistent with the existing capacity (or capital, K , in this case). Therefore, if the industry is seriously over-capitalized, capacity output, Y^* , or the amount most *economically* produced using the existing K (optimal rather than maximum Y/K), may exceed observed output levels.

Imputing such a capacity output level Y^* is accomplished by finding the point where the short- (given K) and long-run average cost curves are tangent. This in turn implies that long and short run marginal costs, or the shadow and observed market (user) price of capital, are equal: $Z_K = p_K$.⁵ Z_K may be computed, for example, as the (negative) derivative with respect to K of a variable cost (VC) function, thus representing the implicit value of an additional unit of capital. Using this definition and a functional form for VC, and imposing $Z_K = p_K$, Y^* can be solved for (given the observed K level). The resulting estimated capacity output level is then compared to actual Y to construct the capacity utilization measure $CU = Y/Y^*$, where $CU < 1$ implies excess capacity, but $CU > 1$ is possible if capacity is being over-utilized.

From a more primal perspective – directly using a production function to imply profit-maximizing behavior – the equilibrium or steady state condition is based on an

equality of p_K and the value of the marginal product ($VMP_K = MP_K \cdot p_Y$, where MP_K is the marginal product of K and p_Y the output price). This equality can be imposed and Y^* solved for, given a functional form for the production function, to generate a CU ratio.⁶

From a purely primal or technological perspective, where a cost minimization or profit maximization assumption is not invoked, the maximum possible Y/K can instead be defined according to the point on a $Y(K)$ relationship where MP_K reaches zero. If only *observed* points are used to impute the highest potential level of Y/K the resulting measure has been called “technological-economic” by Färe *et al* [2000], although it does not directly imply any economic optimization.

As noted above, it is not at all clear that the goals fishermen pursue – due to economic, regulatory, property right and other incentives and constraints – are economic in nature. So this scenario may be sufficiently representative of actual conditions in fisheries. That is, a primal- or technological-perspective, that implies fisherman simply generate as much output as possible from their available capital stock, seems justifiable since it likely reflects an appropriate optimization assumption. The use of such a perspective is also dictated by data availability for fisheries, since input cost data are difficult to obtain for these industries. And in fact the inputs providing the true cost-base are even troublesome to define and measure, since they involve issues such as days at sea, equipment effectiveness, and other often un-measured physical, technological, and economic factors.

⁵ See Morrison [1985], for a development and empirical implementation of such a model.

⁶ This procedure does not, however, directly build in the subequilibrium between K and Y that is implied by estimation and use of the variable cost function $VC(Y, \mathbf{p}, K)$, where \mathbf{p} is a vector of variable input prices, unless variable-input profit-maximizing equations are used for estimation (which raises other questions). So it is a less desirable mechanism for CU measurement.

The characterization of maximum (technological) Y-K ratios to represent capacity output, while restricting the imputed frontier to be supported by observed data points, implies a boundary- or frontier-notion underlies the analysis. The use of DEA models in turn suggests that some form of inefficiency, as well as lack of full utilization, might be driving deviations from this frontier. And this should be isolated separately.

DEA methods are designed to establish technical efficiency, TE, or lack thereof. This is accomplished by constructing (using programming techniques) a piecewise linear frontier or boundary – like a production function, or with multiple outputs a distance function – encompassing all the observed data points. The DMUs that fall within the frontier are identified, and the extent of their inefficiency measured as the difference between the distance from the origin (or sometimes a point on an axis) to the observed data point, and to the frontier (along the same ray), TE_V .

A DEA-based *capacity* measure carries out this experiment in Y-K instead of Y-V space, where K could be a combination of capital characteristics comprising the capital base (an aggregate of the vector of K components, \mathbf{k}). This procedure identifies points that fall short of the frontier in terms of output falling short of maximum Y^* (Y/K) levels, resulting in the TE indicator TE_K .

CU is sometimes measured directly according to this measure, which implies that the measured “best practice” output is attainable by each vessel (or perhaps even on each trip). However, at least some portion of this deviation is attributable to “inefficiency”, which may not even be well defined (resulting from unmeasured/uncontrollable factors), and most likely should not be interpreted as potential capacity. Thus, an “unbiased” CU indicator (Färe *et al* [2000]) might instead be constructed by comparing the TE_K

measures to the associated standard DEA measures, TE_V , to purge the amount the Y/K -based deviations from the frontier, or capacity indicators, can be “explained” by inefficiency. CU is thus represented by a ratio of two TE measures, TE_V/TE_K , rather than of actual as compared to capacity output, Y/Y^* .⁷

A problem with the application of frontier DEA methods in general is that little structure is imposed to facilitate interpreting the deviation from the frontier attributed to “inefficiency”, although the use of the TE-ratio measure reduces the potential for convoluting CU measures by these forces. In particular, the impacts of specifically identifiable characteristics of the DMU (or the targeted observation) might ideally be measured, incorporated, and interpreted as explicit determinants of the production structure, rather than treated as an unexplained residual erroneously termed “inefficiency”. Such an approach could facilitate direct consideration of shifts or differences in the relevant frontier from exogenous or uncontrollable forces.

That is, if characteristics of the boat or skipper can help to explain these deviations, but are not directly measured, their effects might be called inefficiency when instead this driving factor might specifically be built into the production representation. If, for example, relatively low output is observed because a skipper is less experienced, this could well be deemed evidence of relative “inefficiency”. However, one might alternatively try to explicitly identify the impact of experience on observed productivity, rather than lump it into something called “inefficiency”, thus facilitating the interpretation and use of resulting performance indicators.

⁷ Note that instead imputing capacity from the estimated frontier, whether in terms of TE_V or TE_K will erroneously attribute any measured “inefficiency” to potential expansion in capacity that may not in fact be possible to attain given the unmeasured/uncontrollable characteristics of the production process, inputs, and circumstances. Such “biases” are therefore a real concern.

And if an observed deviation from the frontier instead arises from a vessel characteristic such as size, or power, or amount of high-tech equipment – which have well-defined costs – the vessel might not be truly inefficient but be working efficiently given the amount of effective capital invested in the vessel. If this is not appropriately captured in the representation of the capital base and resulting production process, ambiguous or uninterpretable measures may result. Such interpretation difficulties are particularly misleading if the idea ultimately is to determine which of these boats is to be taken out of the fishery to reduce capacity, to increase productivity or “efficiency”.

It is even more problematic to compare trip-level data in the efficiency framework, since so many unmeasured/uncontrollable factors may contribute to one trip being “better” than another. One very high output trip might not, for example, be ideally interpreted as “best” or representative of “efficient” behavior if trips are on *average* or *customarily* plagued by breakdowns, weather problems, or other uncontrollable events. Such issues involve comparability of data points; the observations under analysis need to be analogous in terms of technological and environmental characteristics to be directly comparable in a frontier framework.

These potential difficulties will tend to cause upward biases in measured inefficiency levels, although there may not be a clear bias in the resulting DEA-based capacity utilization measures if the measured inefficiency is equivalently captured in both the numerator and denominator of the CU measures, TE_V and TE_K .⁸ The associated interpretational difficulties still, however, imply at least some ambiguity of measures based on an efficiency or frontier framework.

⁸ Such biases are analyzed directly by Monte Carlo comparison in Lee and Holland [2000].

In sum, most capacity and utilization definitions that have recently been applied to measuring CU in fisheries are based on a primal, (in)efficiency-oriented representation of production processes. It seems reasonable to use a primal representation, due to questions about the economic goals fishermen pursue in this industry, as well as data limitations, as long as we think carefully about how to measure “optimum” within this framework, and how to interpret the resulting answers. It is less clear that an efficiency framework is desirable – or at least facilitates clear interpretation. It seems particularly important to consider whether frontier-based or even more standard stochastic empirical specifications might be desirable for estimation purposes.

CU measurement methods

Once the conceptual base for defining capacity utilization has been established as a comparison of “optimal” versus observed output, or a ratio of TE measures reflecting the Y/K as compared to the Y/V relationship, we must think about how these components of the CU measure might be estimated.

First, note that if we accept the conceptual base we have been focusing on (primal, efficiency-based analysis) as appropriate, these indicators can be measured with stochastic production frontier (SPF) methods, rather than deterministic linear programming DEA techniques, to provide an alternative perspective. Second, if one does not think the efficiency framework is a relevant – or substantive – part of the analysis, more standard econometric procedures based on a primal representation of production processes might instead be used. Or if data availability allows, and consideration of relevant optimization processes suggests, dual economic methods characterizing cost minimizing or profit-maximizing behavior might even be applied.

One justification for stochastic as compared to deterministic approaches is that the former method will be less sensitive to outliers, measurement errors, and (good *or* bad) outstanding circumstances. Although it is true, as Färe *et al* [2000] note, that outliers bias parametric as well as nonparametric measures, the impact will be less dramatic with SPF estimation due to the recognition of “white noise” that by definition limits the impact of mis- or un-measured factors. Thus stochastic frontier models are at least a useful alternative for constructing capacity and capacity utilization measures, particularly in an industry fraught with great variability of circumstances under which production occurs, and the potential for measurement errors.

In addition, it may well be that if we want to represent true capacity and capacity utilization this experiment is better based on the “representative” vessel or trip, rather than on “best practice” observations where everything went as well as physically and economically possible. The latter is simply not representative of usual operating procedures. Standard econometric measures of production/distance (or cost/profit) function models that represent positive as well as negative deviations from the “average” frontier as white noise could thus be preferable to those based on DEA or SPF models.

It is therefore worth thinking further about the explicit representation of capacity and capacity utilization in parametric (SPF and standard econometric) models. To pursue this, the SPF models can be conceptually motivated analogously to the DEA models, and the econometric models may be developed either in this context or by superimposing additional optimization assumptions (goals and constraints) to define “optimal” capacity.

That is, using SPF modeling and measurement techniques, the functions $Y(K)$ and $Y(V)$ may be estimated and compared to identify the two TE measures necessary for

characterization of CU. First the optimum or capacity output given K is established through estimation of the $Y(K)$ relationship, resulting in the technical efficiency measure TE_K . This does not constrain the Y/K max representation by observed use of the variable factor; the availability of the variable factors is not limiting, and thus not included in the functional specification. The $Y(V)$ relationship is then also estimated to isolate the amount of inefficiency reflected in the first estimation that may be attributed to inefficient use of the variable inputs: TE_V .

The resulting $CU=TE_V/TE_K$ measure, analogous to that developed by Färe *et al* [1989] for DEA analysis, indicates how much more output could be produced if K levels were employed at full capacity.⁹ It thus is comparable to the more standard measure Y/Y^* , which could be measured directly from the $Y(K)$ estimation, with the impacts of efficiency purged to generate an “unbiased” measure. If this measure equals one, observed output levels are capacity levels. The amount the measure falls short of one therefore indicates the extent of excess capacity, so $1/CU$ is the order of magnitude existing output would be multiplied by to reach full capacity.

This procedure has sometimes erroneously been said to suffer from omitted variable problems if $Y(K)$ is measured using stochastic frontier rather than DEA methods. It *is* true that the resulting estimates will not directly represent the parameters of the full production function; in this sense omitted variable bias will exist. However, representation of marginal products is not the goal of estimating the $Y(K)$ relationship. The stated optimization problem is instead to establish maximum output levels given capacity, and within the observed data. The $Y(K)$ representation is exactly the relevant

estimating equation or mechanism to answer this question. So the TE estimates are directly comparable to establish CU, even if the production function parameters are not.

If multiple outputs exist this procedure becomes somewhat more problematic, but not seriously so. An output-oriented distance function, which is essentially a multi-output version of the production function, with deviations from the frontier allowed for, can be used for analysis. Capacity utilization may thus be represented in the multi-output context via a comparison of the (output) distance functions $D_O(\mathbf{y}, \mathbf{K})$ and $D_O(\mathbf{y}, \mathbf{v})$, where \mathbf{y} and \mathbf{v} are the output and input vectors underlying the Y and V aggregates.

The resulting estimating equation becomes, with linear homogeneity in outputs imposed and based on a logarithmic (translog) functional form, as in Paul *et al* [2000], $\ln y_1 = -f(\mathbf{y}_m/\mathbf{y}_1, \mathbf{v}) + \ln D_O$, where $f(\cdot)$ is the negative of the homogeneity-constrained distance function (with $\ln y_1$ subtracted out), and $\ln D_O$ is the one-sided error representing inefficiency.¹⁰ This function is alternatively estimated with only K (or the \mathbf{k} components of the vector determining the capital base) recognized as “inputs”, and with all inputs included, to generate $TE_K = D_O(\mathbf{y}, \mathbf{K})$ and $TE_V = D_O(\mathbf{y}, \mathbf{v})$, and construct the TE_V/TE_K ratio.¹¹

Note, however, that since the stochastic measures purge noise from each estimation, they may not be directly comparable (some of the variation in variable inputs could be construed as “noise”, so the resulting CU measure could straddle 1, even with

⁹ Note again that, as for the DEA measures, the TE measures individually address a somewhat different question than that associated with capacity utilization. This problem does not, therefore, depend on the measurement method used, but is instead a conceptual issue.

¹⁰ A white noise error would also be appended for SPF estimation, as for Y(V) and Y(K) above.

¹¹ Although multiple-output representations can generate problems defining a unique CU measure, particularly in the cost context since multiple optimization equations exist, this is not a difficulty here. Any increase in the left hand side of the equation (y_1) is defined holding all output ratios constant due to the homogeneity requirement, so it implies a general increase in output.

the primal/technical perspective).¹² Another possibility is thus to incorporate the variable inputs as “determinants” in a SPF framework, compute the TE_K measure, and impute the contributions of the variable inputs through their estimated impacts on inefficiency.

If one makes the more standard econometric assumption that analyzing the true effective potential of the industry involves characterizing the representative or average production relationship rather than a frontier, $D_O=1$, so $\ln D_O=0$. Or, similarly, the one-sided error appended to the single-output production function falls out of the estimating equation. This allows more general estimation of the productive relationships, with perhaps $Y(K)$ or $D_O(y,K)$ specified in levels (as opposed to logs) and in a non-linear form (to reduce functional form limitations). Fitted output values from the $Y(K)$ or $D_O(y,K)$ functions (Y^*) may then be compared to the attained levels (Y) to determine if vessels are typically under-producing compared to their potential, given their capacity.¹³

This procedure in some sense shifts the measured frontier in even further than using SPF techniques as compared to DEA analysis, since it not only recognizes white noise, but also at least implicitly interprets customary operating procedures as those observed on average in the fishery. That is, if the behavior of fishermen is to maximize output in an expected sense given their effective capital base, this optimization behavior would be well reflected by fitting the function through – rather than around – the data. One could then evaluate whether systematic deviations from this technical relationship appeared for some vessels. Boats that fall primarily outside (inside) the (average) frontier

¹² This could well be relevant and interpretable for fisheries, which will be the subject of subsequent investigation for specific fisheries, but is usually not how these models are construed.

¹³ The TE measures are both equal to 1 in this case so the problem again becomes a comparison of Y^* , from the $Y(K)$ estimation, and observed Y . Also, instead of imposing $D_O=1$ and adding a white noise error, the “distance” from the (average) frontier D_O can be defined as a two-sided normally distributed error and standard estimating techniques used, as noted by Coelli [2000].

might be thought to have more (less) effective capital, or be utilizing their capital (capacity) more (less) fully. The associated distance from the estimated frontier thus still provides us some indication of capacity and its utilization, while allowing a more detailed representation of the production structure since the structural model is less restrictive.¹⁴

More specifically, the standard econometric approach may provide a useful framework for analysis because to establish the capacity of the fleet under “customary” or “usual” operating conditions average behavior is relevant. In particular, in such a framework, low production values due to natural or unmeasured forces do not become attributed to inefficiency. This reduces the likelihood of an upward bias in capacity measurement, that arises using estimates based on “best practice” performance which may not be possible to achieve under standard operating conditions, due to important but unobserved input and output characteristics. The primal model does, however, require framing the relevant capacity “optimization” problem in the context of the $Y(K)$ or $D_0(\mathbf{y}, K)$ (where $D_0=1$) relationships, which is a somewhat novel notion in the literature on econometric CU measurement.

If cost/price data for inputs and outputs were available, and economic optimization behavior were deemed representative, standard econometric techniques could instead be used to estimate the production relationship through a cost-minimizing or profit-maximizing system of equations. This could be accomplished by, for example, appending $p_j = y_j / v_j \cdot p_Y = VMP_j$ equations for variable inputs to the production function

¹⁴ Note that although this procedure in some sense suggests observed average capacity is optimal, it does allow determination of which vessels may over- producing (or “best” producers) relative to others. This is particularly valid if observations are specified by trips (or day), where many unobserved/uncontrollable impacts affect the deviation from the frontier. One would think in this context that the CU question is how much more could be produced if the boats were

specification to represent input cost minimization given Y and K levels. The resulting optimal output (Y^*) given K could then be solved for by imposing a $VMP_K = p_K$ equality. Alternatively – and more appropriately given that the choice of v_j should be endogenous rather than exogenous (a right-hand-side variable), and vice versa for p_j – a cost function model could be used to construct input demand equations and capital stock shadow values. A $Z_K = p_K$ equality could then be imposed to solve for Y^* .

Such approaches require suitable data for the effective prices for inputs, including the true user cost of K . These values may, however, be very difficult to measure, particularly since constraints in addition to observed market prices may drive observed behavior. Alternative goals may also be relevant for fishermen, such as revenue maximization. Adapting standard production models to reflect appropriate goals (benefits) and constraints (costs) of production in fisheries, and using the resulting equalities of marginal benefits and costs to represent behavior, and the optimal level of output, Y^* , given the existing capacity, is ultimately the goal of economic CU analysis.

Advantages and Disadvantages of the approaches

Potential problems have often been raised about the application of stochastic (especially frontier) methods in general, as well as to CU measurement. Some exploration and evaluations of such allegations thus seems requisite to justify promoting these techniques. I will first focus on issues that are specific to stochastic models, and then mention others that may permeate any representation of this sort, and thus should be kept in mind for the interpretation and use of any CU and performance measures for fisheries analysis.

allowed to fish unencumbered, rather than how much more they could produce per trip or day, since that likely already approximates the maximum possible under normal operating conditions.

The issue that is most often raised about stochastic/parametric models is the necessity of making functional form assumptions – for both the production technology and the error structure – for their implementation. This problem is much less serious, however, than early SPF models based on Cobb-Douglas production functions and simple half-normal or half-gamma assumptions for the one-sided error term might imply.

In terms of functional forms for the production technology, the issue of flexibility comes to the forefront. Although 1st-order functions such as the Cobb-Douglas are often used for estimation, and impose serious *a-priori* structure on the production relationships, flexible (2nd-order) functional forms instead allow a full specification of interactions among arguments of the function. In my view this ability to approximate second order relationships reduces the restrictiveness of the specification to easily credible levels, especially given the predominance of other measurement issues in implementation.

Assumptions about the form of the one-sided error term representing inefficiency, as contrasted to the 2-sided white noise error (typically assumed to be normal), also must be made for SPF models. However, the resulting measures – at least in terms of relative efficiency levels – are often quite insensitive to these assumptions. Also, any perceived restrictiveness of the assumptions may be at least partly assuaged by making the error a function of “environmental” variables that may be considered determinants of any measured inefficiency, as in Coelli and Battese [1995].¹⁵ This again raises the dimensionality of the problem to facilitate identifying interactions, thus relaxing the limitations of the simpler models.

¹⁵ An additional issue that arises if such a specification is used is whether these determinants should appear as part of the technological representation or the stochastic structure. This is not easily answered but might be dealt with using judgement about where it might intuitively appear, and empirical evidence (plausible estimates).

Troubles that might remain for such specifications arise primarily from three sources. First, stochastic frontier models cannot readily be estimated as systems,¹⁶ so multicollinearity and degrees of freedom difficulties can arise. This is difficult to address without restricting the functional approximation, or aggregating across inputs/outputs.

Second, flexible functions are often specified in logarithms (translog), making zero observations problematic, especially when multiple outputs are recognized – a third problem often asserted for SPF estimation, but less onerous than often implied.

Although not fully justifiable, one way to deal with the problem of zero values for outputs (or inputs) in a typical log-log specification is to substitute a “small” value for the zeroes. Sensitivity tests can then be carried out to illustrate the (hopefully negligible) impact of this treatment (as in Paul *et al* [2000]). Although it would be preferable to specify the function instead in levels, so the zeroes can be accommodated using dummy variables, this causes problems defining the left-hand side variable and separating the “distance” as a one-sided error term in a SPF framework.

That is, in logarithms, $-\ln D_O$ can be distinguished as a (one-sided, 0-) additive error term in a SPF model based on a logarithmic distance function, as in Paul *et al* [2000], whereas this does not work for a function based on levels (since D_O is a 0-1 variable). However, if a standard econometric specification were implemented instead of the stochastic frontier representation, so $D_O=1$, this is no longer a problem. Also, nonlinear functions may be estimated for such a specification, which is not feasible with SPF programs. In addition, a functional form based on levels can then be used, which is attractive since imposing optimization assumptions such as $Z_K=p_K$ may more directly be

¹⁶ And in any case economic optimization assumptions providing the base for construction of estimating systems may be moot for CU analysis in fisheries.

accomplished in such a framework. And, as a practical matter, empirical researchers often find that curvature conditions are less likely satisfied using functions estimated in logs than in levels (especially with quasi-fixed capital inputs). Thus, if one thinks the inefficiency part of the problem is not crucial – or at least not well defined, as is likely for fisheries applications – many potential problems may be side-stepped.¹⁷

Finally, it has often been stated that stochastic models cannot readily accommodate multiple outputs. However, allowing for multiple outputs in a primal stochastic specification simply requires estimating a distance instead of production function (as in Paul *et al* [2000], and others cited therein). They are even more easily built into a cost-based model, particularly if standard econometric techniques are used.

But one problem does arise in the distance function context. Estimating a distance function requires imposing homogeneity assumptions (with respect to an output or input, depending on whether the function is output- or input-oriented). This in turn requires normalization by one output (input) to obtain a left-hand-side variable, resulting in ratios of outputs (inputs) with respect to this normalizing netput appearing on the right hand side of the equation.

This is typically said to generate “endogeneity” problems – some of which might be relevant, and others that do not stand up to direct scrutiny. The more problematic endogeneity issue is what might be called “econometric endogeneity” as opposed to “economic endogeneity”. That is, if output 1, for example, appears both on the left hand side (LHS) and in the denominator of ratios on the right hand side (RHS) of the estimating equation, when the LHS variable is large the RHS output variables are small.

¹⁷ Note also that “negative” or undesirable outputs, such as bycatch, may also be included in a multi-output representation.

The result of such a relationship is correlation between the error term and the RHS variables, which implies biased estimates. The extent of the problem can be determined, however, via a Hausman endogeneity test, and in most cases is not substantive, as noted by Coelli *et al* and Coelli [2000].

Economic endogeneity, by contrast, is not really an issue in this framework, although it is often raised as a criticism. In particular, if one uses a production or distance function as a representation of the technology, and then imposes profit maximization to define $p_j = VMP_j$ equations for the inputs, an endogeneity problem could arise. Input (and perhaps output) levels are chosen variables and yet appear on the right hand sides of the estimating equations. If, however, one instead measures the production or distance function directly, which is a true primal approach based on characterizing technological possibilities, the *choice* of inputs (or output) is irrelevant. And, in fact, even if economic optimization is postulated, under very reasonable assumptions about the form of this optimization process the resulting estimated parameters are *consistent*, even though input (output) choice may be endogenous.¹⁸

More specifically, a strictly primal model simply represents the most of the normalizing output technically possible to produce, given observed levels of the inputs and the remaining outputs (with constant relative output levels for an output distance function). Or it characterizes the least input, given observed outputs and other inputs, from an input perspective. Such a purely technological perspective has nothing to do with choice behavior. And there is no clear rationale for thinking that input demand *decisions* would result in a systematic connection with the error term in the context of

technological possibilities. “Endogeneity bias” questions therefore emerge only if the resulting marginal product estimates are assumed to reflect actual (relative) prices, which implies economic optimization or allocative efficiency instead of technical efficiency.

A conceptual issue that also arises here for the construction and interpretation of CU measures – irrespective of the chosen modeling and measurement framework – is whether the function the measures are based on should have an input or output orientation. That is, an output distance function, like a production function, implies maximum output given inputs, so for capacity estimation it generates information on the maximum output that has been produced given a certain level of capital inputs (without being constrained by the variable inputs). In reverse, an input distance function, like an input requirement function, represents the minimum input possible to use in a technological sense to produce a given output (vector) and given the levels of other inputs. In a utilization context, therefore, this can be used to represent the minimum amount of capital required to generate observed output levels.

In certain cases (like constant returns to scale), these are simply inverse experiments. But the latter might be more applicable to the type of questions we want to ask for fisheries: Do we want to know how much output the existing fleet can catch, or how much the fleet could be cut back and still yield the same output levels?

Other estimation problems, largely pertaining to data measurement, also occur no matter what conceptual framework and estimating method are chosen for the representation of capacity and CU. For capital, recognizing characteristics of vessels to determine their relative “effectiveness” is obviously a central issue. And it is important

¹⁸ Coelli [2000] shows that even with distance function estimation consistent estimates are achieved when assumptions of, for example, expected profit maximization are maintained. And

to carefully think about what the vessel characteristics are measuring; for example, should higher horsepower vessels be considered more effective capital units, or does this simply imply an older, heavier, more cumbersome boat?

And how might the variable inputs be defined? In the fisheries literature inputs are often lumped into “effort”, but the specific definitions and measures of these inputs are central to the representation of production processes and performance. For example, is a fisherman a unit of labor/effort? Or should hours or days worked be taken into account, or other characteristics that underlie the true shadow or effective quantity or price (opportunity cost) of labor?¹⁹

Another data-oriented issue has to do with aggregation. Although aggregation is often raised as an issue for empirical work, it seems especially critical for representing an industry where unmeasured or uncontrollable factors contribute significantly to the observed outputs produced and inputs used. It may make a substantive difference, for example, especially in an inefficiency framework, if averages across netputs are constructed prior to estimation as compared to averaging results across observations after estimation. Much more variation and lower average efficiency is likely to be reflected in the first case, since aggregation is essentially a smoothing device. Similarly, averaging across trips to generate yearly values might purge the resulting estimates of extraneous/uncontrolled for factors. Again, this reduces variation and the likelihood of calling something “inefficiency” that has a potentially identifiable cause that should not

in fact that “fixes” using instrumental variables may generate more problems than they solve.
¹⁹ Note also that input measurement is typically more difficult, and thus prone to error or misspecification, than output measurement, which is often asserted to be a justification for using stochastic rather than deterministic techniques for estimation. This also could be used as an argument for assuming an input-orientation for the distance function problem, since more accurately measured levels are better assumed exogenous.

really be interpreted in this manner. More generally, aggregation issues arise in dimensions such as area (spatial), time (week, month, year?), and target species.

A particularly crucial problem for construction and interpretation of performance indicators for fisheries, is how to measure – and build into the analysis – fish stock “input” levels, and intra-season variations in conditions that determine stock density. As alluded to above, increased output levels are not beneficial or welfare enhancing – and thus “productive” – if they result in biomass decimation. In reverse, if higher stock levels allow greater output per unit input, this contribution to “productivity” should be recognized and measured rather than attributing the higher catches to greater efficiency.

Definitive measurement of fish stocks is, however, obviously difficult. It would clearly be desirable to compare harvesting to biomass growth, and therefore generate some type of net benefit measure to augment productivity/performance evidence, where in most cases increases in the stock would be considered a “good” and reductions a “bad”. This implies a treatment similar to that for adjustment costs, where stock reductions are an additional cost of harvesting, with the costs perhaps increasing at the margin. The stock could alternatively be included as a fixed input or control variable, or a production or inefficiency determinant, in a stochastic model of production processes.

A final measurement issue to highlight involves costs and benefits that are not directly related to measured output and input levels, but result from interactions or spillover from dynamics or externalities. If, for example, social or economic variables should be considered (external) outputs/benefits or inputs/costs of production, measures of these factors – in addition to the fish stock measures reflecting biological dynamics – should be recognized in the model of production processes. Such factors might include

social capital, public goods/spillovers, and externalities of various sorts (including bycatch of joint species that is discarded, and therefore reduces other biomass levels).

If these factors can be measured, they may also be incorporated in a parametrically measured production relationship to determine their shadow values and their interactions with input use, output production, and netput composition. The importance of such externalities and spillovers is becoming a focal point of the literature on economic performance. Although challenging to address empirically, this seems an increasingly central component of our “new economy”, and thus of effective performance measurement also for fisheries in our era.²⁰

Concluding Remarks

In the end, I may not have added many new insights to those that have already arisen in the rapidly emerging literature on performance and CU measurement in fisheries that is well represented at this conference. However, hopefully I have at least highlighted and packaged them in a useful fashion, as well as stressing two fundamental points.

First, for relevant policy guidance it is crucial to seriously ponder the implications of myriad complicating factors for CU modeling and measurement, many of which arise due to unique and key characteristics of fisheries industries, rather than sweeping them under the rug. Such factors as behavioral incentives, input-output interactions, dynamics, externalities, and stock effects, are important to recognize at least for interpretation and qualification of the measures generated, and at best for eventually building their impacts directly into the models used for analysis of production processes and performance in fisheries. Also, evaluating the difference between unmeasured/uncontrollable factors

²⁰ See Paul [2000] for further discussion of this issue and the associated literature.

determining “noise” or “luck”, and “inefficiency”, is central to the analysis of performance and utilization in fisheries.

This leads into the second point; stochastic methods have potential for incorporating these types of structural characteristics into production models, and thus measurement of performance/CU, even though they have not yet been used much in this literature and may be somewhat more complex to implement than DEA approaches. Models that do not focus on inefficiency measurement, thus allowing more functional and theoretical structure to be incorporated since less stochastic structure is necessary to identify and interpret, may be especially worth considering as alternatives.

Overall, we, as fisheries performance analysts, need to evaluate the impact of the methodological foundation used on the conceptualization, interpretation, and use of the resulting performance measures. Providing comparison measures based on alternative specifications and assumptions is crucial for determining sensitivity, generating valid measures, gaining (or at least moving toward) consensus, and ultimately guiding policy development and implementation.

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