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# Estimating Vessel Efficiency Using a Bootstrapped Data Envelopment Analysis Model

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**Abstract** *Technical efficiency, which measures how well a firm transforms inputs into outputs, gives fishery managers important information concerning the economic status of the fishing fleet and how regulations may be impacting vessel profitability. Data envelopment analysis (DEA), and the stochastic production frontier (SPF) have emerged as preferred methods to estimate efficiency in fisheries. Although each of the approaches has strengths and weaknesses, DEA has often been criticized because it is "deterministic" and fails to account for noise in the data. This paper presents a method for examining the underlying statistical structure of DEA models using bootstrap methods and readily available software. The approach is then applied to a case study of the U.S. mid-Atlantic sea scallop dredge fleet. Results show that the 95% confidence interval for technically efficient output is well above the maximum sustained yield (MSY) level of output.*

**Key words** Bootstrap methods, data envelopment analysis, technical efficiency.

JEL Classification Codes C44, Q22.

## Introduction

Fishery managers need basic information on the economic status of the vessels they manage and the potential for those vessels to harvest more fish than they desire. Two measures that will help in this assessment are the technically efficient output of a fleet and vessel technical efficiency. Technically efficient output is the maximum amount of output given a specific bundle of inputs (Ray 2004), and has been widely studied dating back to the work of Koopmans (1951). Technical efficiency (TE) is a relative concept based on comparing actual output with a benchmark output. TE differs from economic efficiency, which compares profit from an actual output-input bundle with the maximum profit available (Ray 2004). Because important data on input and output prices are not collected in many fisheries worldwide, researchers are often limited to a technical measure of efficiency, rather than one based on profit maximization. However, TE is a necessary condition for economic efficiency (Ray 2004; Kirkley, Squires, and Strand 1998).[1] Past studies which have measured TE for

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[1] Even when there are data available on output and input prices, vessel owners still do not have to pay for their most important input, the fish they harvest. This leads to the well-published outcome where vessels owners engage in capital stuffing, or expanded use of unregulated inputs, which leads to increased technical inefficiency.

fishing vessels include work by Kirkley, Squires, and Strand (1995, 1998); Weninger (2001); and Kirkley *et al.* (2003).

Similar to many other types of plants, fishing vessels can be characterized as having a multi-input, multi-output production technology, as they combine several inputs to produce a variety of outputs (fish species) during a fishing trip. However, measuring TE of fishing vessels poses several problems not typically found in other industries. First, vessels travel various distances from different ports to compete in the harvest of a mobile common resource. Second, the fishing process can be characterized as stochastic because vessels do not necessarily know the quantity of fish they will produce (land) once the decision is made to leave the dock and fish.[2] After a trip starts, vessels are subject to changing weather conditions, breakdowns, mechanical problems, and other adverse conditions which influence their production. Third, spatial and temporal variability in fish stocks can lead to different output mixes and quantities for similarly configured vessels. Certain species may not be present at a specific location during the time a vessel is present. A vessel which has similar physical dimensions and horsepower fishing at the same location a week later, or in a slightly different location, may harvest a slightly different species mix.

DEA and SPF have been used to estimate technical efficiency in fisheries (Weninger 2001; Kirkley *et al.* 2003; Kirkley, Morrison-Paul, and Squires 2004; Kirkley, Squires, and Strand 1995, 1998). Both techniques attempt to trace out a production frontier based on observed input and output levels for individual vessels and a vessel's TE is evaluated relative to the frontier. SPF has the advantage that deviations from the underlying frontier are not all attributed to inefficiency. DEA is attractive because no functional form needs to be assumed and the models can often be constructed with minimal data. However, DEA is often criticized because it is "deterministic;" it does not account for the stochastic nature of fisheries production, and thus, all noise is considered as inefficiency.

Numerous studies have examined the statistical properties of both DEA and SPF estimators (Simar 1996; Korostelev, Simar, and Tsybakov 1995; Banker 1993; Park, Simar, and Weiner 2000; Reinhart, Lovell, and Thijssen 2000). Simar and Wilson (1998, 2000a, 2000b) methodically studied statistical properties of DEA models and developed bootstrap algorithms which can be used to examine the statistical properties of efficiency scores generated through DEA. However, the methods of Simar and Wilson have not previously been applied to any study of fishing vessel TE. Additionally, recent articles in the fisheries literature have characterized DEA estimates in an output-oriented model as being biased upward (Tingley, Pascoe, and Mardle 2003), while the work by Simar and Wilson show they are biased downward. Therefore, it is important in studies which use DEA models to correctly characterize the bias, adjust TE estimates based on the estimated bias, and present information to managers using confidence intervals or other statistical measures.

This paper applies the bootstrap methods used by Simar and Wilson (1998) to estimate bias-corrected TE scores, and calculate confidence intervals around those scores, for 201 mid-Atlantic sea scallop dredge vessels. These are fairly large vessels that harvest sea scallops in a discrete area off the mid-Atlantic United States coastline. This study differs from past studies of scallop vessel TE conducted by Kirkley, Squires, and Strand (1995, 1998) and Kirkley, Morrison-Paul, and Squires (2004). First, it captures the multi-output aspect of the technology by including additional species which are also caught by scallop dredge vessels, rather than

[2] The surfclam fishery may be an exception because it is managed through individual transferable quotas (ITQs), and many vessels are owned by processors who want a specified amount of product landed per trip.

measuring TE based on one output. Secondly, it uses data that are typically available to most researchers. The three studies mentioned above used extremely detailed data collected over a four-year period, including data on resource abundance on a trip-level basis. Next, this study includes all full-time vessels landing scallops from the mid-Atlantic resource instead of a small sample of 10 vessels. Last, the analyses presented in this study are conditional on a completely different regulatory regime. In the previous Kirkley *et al.* studies (1995, 1998, 2004), regulation of the fishery was output based (*i.e.*, the number of allowable meats per pound was restricted). In the present study, there are limits on crew size, days at sea per vessel, and gear.

The next section describes the DEA model and the bootstrap methodology and shows the bootstrap algorithm in a seven-part procedure that should be easy to follow and implement by other researchers. This is followed by a description of the data used to estimate efficiency for the mid-Atlantic scallop dredge fleet. Results are then presented, followed by a summary of major points and conclusions.

## Data Envelopment Analysis (DEA)

DEA is a nonparametric mathematical programming technique originally developed by Charnes, Cooper, and Rhodes (1978), which can be used to determine the boundary of a production frontier. The early work by these researchers assessed TE using the concept of Farrell (1957), which radially contracted inputs or expanded outputs along a ray from the origin. Work by Russell (1985) and Coelli (1996) used a DEA-based measure of TE which was non-radial and consistent with Koopmans (1957) definition of TE where the expansion of outputs or contraction of inputs need not be radial. Kirkley *et al.* (2003) estimate and assess TE in the Malaysian purse seine fishery using DEA.

Technical efficiency may be assessed from either an input or output orientation or from a non-orienting perspective (*i.e.*, Pareto-Koopmans). Most assessments in the fisheries literature have used an output orientation, as this is more consistent with how a fishing vessel operates. That is, once the vessel owner or captain has made the decision to make a trip and decided on the time the vessel will spend at sea, the appropriate amount of fuel, food, ice, and water are purchased. The vessel then tries to catch as much fish as possible during the trip.

To formally introduce the concepts behind DEA and frontier models, the activities of a firm are defined by a production set defined as $P \equiv \{(x\ ,\ y) \mid x \text{ can produce } y\}$, which contains feasible combinations of inputs ($x$) and outputs ($y$). The set can further be described in terms of output feasibility sets or input requirement sets (output or input correspondence). This discussion will be limited to the output correspondence $Y(x)$, which gives the feasible level of outputs for a given level of input.[3] The Farrell efficiency boundary of $P$ is a subset of $Y(x)$ and is defined by:

$$y^{\partial}(x) = \left\{ y \mid y \in y(x),\ \lambda y \notin y(x)\ \forall\ \lambda > 1 \right\}. \tag{1}$$

Firms which are technically efficient operate along the frontier; while those that are not technically efficient operate in the interior of $P$. The Shephard (1970) output distance function, $D_O(x,y)$, gives a normalized measure of the distance from point $(x,y)$

[3] Typically, assumptions are made regarding $P$, with the two most usual being convexity and free disposability of both inputs and outputs (Shephard 1970; Färe 1988). However, some studies have dropped the assumption of convexity, resulting in the free-disposal hull problem (FDH).

to the frontier, holding input and the direction of the output vector fixed. It is defined as:

$$D_O(x, y) \equiv \inf\left\{\theta > 0 \mid (x, \theta^{-1}y) \in P\right\}. \tag{2}$$

The value of $D_O(x,y) \leq 1$ for all $(x, y) \in P$. If $D_O(x,y) = 1$, then the point $(x,y)$ lies on the boundary of $P$, while values less than one mean the point is considered inefficient.

Estimation of the Shephard output distance function is accomplished through linear programming techniques. The model adopted here is described in Färe, Grosskopf, and Lovell (1994), and calculates the inverse of the Shephard output distance function, and is provided below:

$$\underset{\theta, z}{Max}\ \theta \tag{3}$$

s.t.

$$\theta\, y_{jm} \leq \sum_{j=1}^{J} z_j y_{jm}\ , m = 1, 2, \ldots\ldots, M, \tag{4}$$

$$\sum_{j=1}^{J} z_j x_{jn} \leq x_{jn}\ , n = 1, 2, \ldots., N, \tag{5}$$

$$z_j \geq 0, j = 1, 2, \ldots\ldots, J, \tag{6}$$

$$\sum_{j=1}^{J} z_j = 1. \tag{7}$$

where: $\theta$ = efficiency measure ($\theta \geq 1$); $y_{jm}$ = quantity of output m produced by firm $j$; $x_{jn}$ = quantity of input $n$ used by firm $j$; and $z_j$ = weight assigned to firm $j$.

Equation (7) imposes variable returns to scale on the underlying technology. Constant returns to scale can be imposed by eliminating equation (7), and non-increasing returns to scale may be imposed by changing to an inequality sign (≤) in equation (7).

Theta ($\theta$) is calculated by running the linear programming problem once for each firm in the sample. Firms which are technically efficient will have a value of one, while inefficient firms will have a value greater than one. A value greater than one shows how much each output should be expanded for the firm to be considered technically efficient. For example, a value of 1.1 means the firm would need to expand all outputs 10%, given its input bundle, to be considered efficient.

The true production frontier, Farrell efficiency measure, and the Shephard output distance function are all unknown. Estimates of the Farrell efficiency measure and the Shephard output distance function can be calculated using observed, or actual, input-output combinations. These estimates will yield information on the input-output pairs that are considered efficient given the observed data. Although this information may appear to be deterministic when compared to the SPF, past studies have examined the statistical properties of the DEA estimators. Banker (1993) proved weak consistency of the DEA estimator for the single input, single output case. Gijbels *et al.* (1999) derived the asymptotic sampling distribution for the single input, single output model along with the asymptotic bias and variance. However, in the multi-input, multi-output case which typifies fishing vessels, the bootstrap seems to be the only way to investigate the sampling distribution of the DEA estimators (Simar and Wilson 2000a).

The "smoothed bootstrap" approach of Simar and Wilson (1998) is used in this study, and the theoretical underpinnings can be found in the extensive work by Simar and Wilson (1998, 1999, 2000a,b). The key assumption behind this approach is that the known bootstrap distribution will mimic the original unknown distribution if the known data generating process (DGP) is a consistent estimator of the unknown DGP. The bootstrap process will, therefore, generate values that mimic the distributions which would be generated from the unobserved and unknown DGP (Simar and Wilson 1998, 2000a,b). Because DEA estimates a production frontier boundary, generating bootstrap samples is not straightforward.[4] The "smoothed" bootstrap is based on the DEA estimators themselves by drawing with replacement from the original estimates of theta and then applies the reflection method proposed by Silverman (1986).

The steps in this procedure are quite simple to implement:

1. Solve the original DEA model and obtain scores $\hat{\theta}_1 \ldots\hat{\theta}_n$.
2. Let $\theta_{B1} \ldots \theta_{Bn}$ be a sample generated from $\hat{\theta}_1 \ldots\hat{\theta}_n$..
3. Smooth the sampled values using the following formula:[5]

$$\tilde{\theta}_i^* = \left\{\theta_{Bi} + h\varepsilon_i^* \quad if \quad \theta_{Bi} + h\varepsilon_i^* \geq 1 \;\; or \;\; 2 - \theta_{Bi} - h\varepsilon_i^* \;\; if \;\; \theta_{Bi} + h\varepsilon_i^* < 1\right\}. \tag{8}$$

4. Obtain the final value $\theta^*$ by adjusting the smoothed sample value using the following formula:[6]

$$\theta_i^* = \overline{B} + \frac{(\tilde{\theta}_i^* - \overline{B})}{(1 + h^2 / \hat{\sigma}_\theta^2)^{1/2}}, \tag{9}$$

where:

$$\overline{B} = (1 / n)\sum_{i=1}^{n} \theta_{Bi} \tag{10}$$

$$\hat{\sigma}_\theta^2 = (1 / n)\sum_{i=1}^{n} (\hat{\theta}_i - \bar{\hat{\theta}})^2. \tag{11}$$

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[4] A simple bootstrap would consist of sampling the pairs $(x,y)$ with replacement from the original pairs. However, this approach generates inconsistent estimates of the efficiency scores (Simar and Wilson 2000a).

[5] The input-oriented model would have the following adjustment:

$$\theta_i^* = \left\{ \theta_{Bi} + h\varepsilon_i^* \quad if \quad \theta_{Bi} + h\varepsilon_i^* \leq 1 \;\; or \;\; 2 - \theta_{Bi} - h\varepsilon_i^* \;\; otherwise\right\}.$$

[6] Since the bootstrap sequence is generated using a kernel estimator, it must be adjusted so that the variance of the final bootstrap sequence is asymptotically correct (Simar and Wilson 1998).

5. Adjust the original outputs using the ratio $\hat{\theta}_i / \theta_i^*$.
6. Resolve the original DEA model using the adjusted outputs to obtain $\hat{\theta}_{kb}^*$.
7. Repeat steps 2-6 $B$ times to provide for $B$ sets of estimates; *i.e.*, each firm will have $B$ estimates of theta. For this analysis, 1,000 samples were generated for each vessel.

In equation (8), $h$ is a smoothing parameter, and $\varepsilon$ is a randomly drawn error term. The most difficult step in the procedure, above, is to find an appropriate value of "*h*." This study maximizes a likelihood cross-reference function using methods developed by Ferris and Voelker (2000).[7] An alternative procedure would be to use the "normal reference rule," which calculates h as follows:

$$h = [4 / (p + q + 2)]^{(1/p+q+4)} * N^{(-1/p+q+4)}, \tag{12}$$

where $p$ equals the number of inputs, $q$ the number of outputs, and $N$ the number of observations in the sample.

Once the number of desired samples is generated, the bias of the original estimate of theta is calculated as follows:

$$bias\ \hat{\theta}_k = B^{-1}\sum_{b=1}^{B} \hat{\theta}_{kb}^* - \hat{\theta}_k. \tag{13}$$

A bias corrected estimator of the true value of $\theta(x,y)$, $\hat{\theta}_k^*$, can then be computed using the following formula (Simar and Wilson 2000b):

$$\hat{\theta}_k^* = \hat{\theta}_k - bias\hat{\theta}_k \tag{14}$$

$$= 2 * \hat{\theta}_k - B^{-1}\sum_{b=1}^{B} \hat{\theta}_{kb}^*. \tag{15}$$

Ray (2004) points out that because the bootstrap procedure is using pseudo-data, the interpretation of results in terms of TE for any individual sample should be interpreted cautiously because the actual input-output bundle may lie above the frontier for any single sample. However, confidence intervals for the outputs based on all samples can be constructed quite easily. Since we do not know the true distribution, we try to select $a_\alpha, b_\alpha$ such that $\Pr(-b_\alpha \le \hat{\theta}_k^* - \hat{\theta}_k \le -a_\alpha) = 1-\alpha$. Finding $a_\alpha, b_\alpha$ is carried out by sorting the values $(\hat{\theta}_{kb}^* - \hat{\theta})$ in ascending order and then deleting the ($\alpha$/2 x 100) percent of the elements from both ends of the sorted list. Then, $-b_\alpha$ and $-a_\alpha$ are set equal to the endpoint values of the sorted list, with $a_\alpha \le b_\alpha$. The bootstrap approximation of the confidence interval is given by the interval $\hat{\theta}_k + a_\alpha^* \le \theta \le \hat{\theta}_k + b_\alpha^*$ (Simar and Wilson 1999, 2000b). Unless $a_\alpha^* = 0$, the original value of $\hat{\theta}_k$ will fall outside the confidence interval, since $\hat{\theta}_k$ is a downward-biased estimator of $\theta$.

The methods outlined above are easily performed using routines developed in GAMS (Ferris and Voelker 2000).[8] The bootstrap routine was constructed and run on

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[7] This study uses MATLAB programs developed by Meta Voelker to calculate *h*.
[8] Currently, these routines utilize four GAMS routines and a C program to calculate confidence intervals. The GAMS routines require a DEA module, which is available free from GAMS Development Corporation, and the CPLEX solver. Additional routines written in PERL are also available to calculate confidence intervals. All GAMS, PERL, and C programs are available from the author upon request.

a computer with the Red Hat Linux operating system. It took approximately seven minutes to generate 1,000 samples and solve the DEA model for each sample.[9]

## Data

Data were obtained from logbooks on vessels which used a scallop dredge to harvest sea scallops in the mid-Atlantic region during the year 2003. Only full-time scallop vessels (as indicated by their permit category) were included in the sample. Inputs used in the analysis were total dredge width in inches, gross registered tonnage, horsepower, vessel length, days at sea, and crew size. Outputs were landings in weights of scallop meats, monkfish, and summer flounder, although monkfish and summer flounder are both bycatch species.

The mean dredge width for the vessels was 326 inches. Although dredge width for a single dredge is restricted to 180 inches in the regulations, some vessels towed two dredges (table 1). On average, vessels were 160 gross registered tons, 83 feet in length, had engine horsepower of 844, spent 94 days at sea, and had a crew of seven. Vessels averaged 165,503 pounds of scallops (meat weight) and had bycatch of monkfish (4,035 pounds) and summer flounder (377 pounds).[10] Regulations limited the vessels to a maximum crew of seven and 120 days of fishing time. However, the log books used for this analysis include steaming time in the calculation of days at sea, which in some cases did not count against a vessel's allocation of fishing time. This is reflected in the maximum time spent fishing shown in table 1.

**Table 1**
Selected Vessel Statistics for Mid-Atlantic Scallop Dredge Vessels

| Number of Vessels | 201 | | | |
|---|---|---|---|---|
| Vessel Stats | Min. | Mean | Max. | S.D. |
| Inputs | | | | |
| Dredge Width (inches) | 126 | 326 | 360 | 40.5 |
| Gross Tonnage | 46 | 160 | 258 | 33.6 |
| Horsepower | 365 | 844 | 1,550 | 268.3 |
| Length (feet) | 60 | 83 | 118 | 9.9 |
| Days at Sea | 17 | 94 | 161 | 34.3 |
| Crew | 5 | 7 | 7 | 0.2 |
| Outputs | | | | |
| Scallops (pounds, meat weight) | 37,644 | 165,503 | 331,533 | 65,299 |
| Monkfish (pounds) | 0 | 4,035 | 22,000 | 4,531 |
| Summer Flounder (pounds) | 0 | 377 | 7,088 | 924 |

[9] Simar and Wilson report that their bootstrap routine, written in Fortran, took nearly 47 minutes on a SUN Sparcstation 20. The PERL routines used to generate the biases and confidence intervals required another 5 minutes of CPU time.
[10] Pounds were estimated by the captain.

## Results

Initial DEA model results for the 201 vessels yielded an average uncorrected TE score of 1.16, while the bootstrap model generated an average bias corrected score of 1.22. The minimum uncorrected score was 1.0 and the maximum was 1.95, while the minimum bias corrected score was 1.03 and the maximum was 2.04 (table 2). Further analysis showed the original scores had a mean bias of –0.06, which was expected.[11] The average score of 1.22 was much lower than a recent study by Kirkley, Morrison-Paul, and Squires (2004), which had an average TE score using DEA of 1.57.[12] However, the results of the two studies are not comparable, since the Kirkley study was based on a limited sample of 10 vessels and only had a single output and, as stated previously, represented a time period when the resource was managed through output controls, and not the current suite of input controls.

Technically efficient output for the vessels used in this study is calculated by multiplying the TE score returned from the DEA model by the vessel's base output. Summing over all vessels will yield the technically efficient output for the fleet. The TE output confidence interval is calculated in a similar manner. Based on the original DEA scores, the TE scallop output for the fleet was 37.7 million pounds. However, the 95% confidence interval based on the bootstrap model yielded an estimate of TE output between 37.9 and 42.2 million pounds of scallops. Additionally, the technically efficient output for monkfish was between 0.9 and 1.04 million pounds; for summer flounder it was between 0.08 and 0.09 million pounds.

Focusing on the scallop resource, the most recent assessment showed that MSY for the mid-Atlantic resource was approximately 30.4 million pounds (Andy Applegate, telephone interview, March 2005).[13] Results indicate that the fleet has the capability to harvest between 7.5 and 11.8 million pounds (24.7 and 38.8%) more than the MSY level. The confidence intervals also showed that technically efficient output was between 4.6 and 8.9 million pounds (14 and 27%) greater then the observed output. It must be remembered that the estimates of technically efficient output are conditional on the current state of the resource, the current state of tech-

**Table 2**
Technical Efficiency Scores Based on the DEA Bootstrap Routine

| | Min. | Mean | Max. |
|---|---|---|---|
| Uncorrected Score | 1.0000 | 1.1646 | 1.9539 |
| Lower C.I. | 1.0032 | 1.1698 | 1.9622 |
| Bias Corrected Score | 1.0287 | 1.2227 | 2.0397 |
| Upper C.I. | 1.0507 | 1.3077 | 2.1372 |
| Bias | –0.1329 | –0.0581 | –0.0158 |

[11] Simar and Wilson (1998) show with an input-oriented model that the DEA estimate is upwardly biased. Since this paper uses an output-oriented model, results will be biased downward.
[12] Interestingly, the results were close to those from the SPF model where the average TE score was 1.19.
[13] The fishing year for the scallop fleet starts on March 1. An anonymous reviewer questioned using MSY as a management target rather than MEY. Currently, no estimates of MEY exist for the mid-Atlantic resource, primarily due to a lack of cost data needed to estimate MEY. Additionally, National Standard One of the Sustainable Fisheries Act requires using MSY to determine whether overfishing is occurring.

nology, and the regulations in place. In this specific model, no impacts of decline in abundance that may occur over a year are included. Since data on scallop abundance are collected once a year, the biological models would not support analysis of changing resource abundance within a year. Current regulations limiting dredge size, crew size, and total days fishing in a year also constrain the technically efficient output. If regulations restricting the crew size to seven were lifted, allowable days at sea increased, or maximum dredge size increased, the technically efficient output would likely be higher. This analysis should cause concern for managers. First, there is a large amount of technical inefficiency (mean bias corrected score equals 1.2227), meaning vessels are not as profitable as possible. Second, vessels could harvest between 24.7 and 38.8% more scallops than the MSY level with the same input use.

One critical step in constructing the bootstrap model was the selection of a smoothing parameter "h." Simar and Wilson (2000b) found that confidence interval results were not particularly sensitive to the smoothing parameter chosen. For this group of vessels, a cross-reference function returned a smoothing parameter of 0.030. In order to see how the confidence intervals changed with different values of the smoothing parameter, the value of h was both increased and decreased by 50%. To conserve space, results for the 40 of the 201 vessels are shown in table 3, and indicate that increasing or decreasing the smoothing parameter by 50% in either direction only slightly alters the confidence intervals. This is consistent with the results found by Simar and Wilson (2000b). An alternative to using the cross-reference function would have been to estimate the smoothing parameter using the "normal reference rule," which would have resulted in a value of 0.54. This is 18 times the value obtained using the cross-reference function, and the resulting confidence intervals are quite different (table 3). For example, observation 56 has a lower bound of 1.6523 using the normal reference rule smoothing parameter of 0.544, which is outside the 95% confidence interval upper bound of 1.5697 using a parameter value of 0.030 obtained through the cross-reference function. Simar and Wilson (2000b) note that the normal reference rule will result in a correct choice of bandwidth when the underlying data are normally distributed and have been pre-whitened to have unit variance and zero covariance, which is not the case in this study. It is apparent for these vessels that care must be taken in choosing the appropriate smoothing parameter.

## Summary and Conclusions

DEA has become a popular method for evaluating technical efficiency in many industries, including fisheries, worldwide. It is easily able to handle the multi-input, multi-output technology that characterizes most fishing vessels, without imposing a restrictive form of technology. However, DEA has also been criticized for being "deterministic" and lacking any statistical foundation. The bootstrapping technique presented here is one method for constructing a stochastic DEA model and is easily implemented using the GAMS language on standard PCs, as well as other platforms. Confidence intervals of efficient output and technical efficiency can be developed giving managers more information than simple point estimates. The methods can be used for any model where outputs (inputs) are radially expanded (contracted), such as the graph efficiency measure, or with directional vectors. Because DEA models are boundary problems, the bootstrapping methods chosen are more complex than simply drawing samples from the observed input and output combinations. Caution must be used in the selection of a smoothing parameter "h," as the wrong choice of *h* can substantially influence results. Algorithms already developed can yield an ap-

**Table 3**
Comparison of Confidence Intervals given Differing Smoothing Parameters ($h$)

| Obs. | $h$ = 0.015 | | $h$ = 0.030 | | $h$ = 0.045 | | $h$ = 0.544 | |
|---|---|---|---|---|---|---|---|---|
| 3 | 1.0018 | 1.3920 | 1.0033 | 1.4037 | 1.0068 | 1.3938 | 1.1026 | 1.3729 |
| 6 | 1.0018 | 1.3811 | 1.0043 | 1.4126 | 1.0075 | 1.4002 | 1.1021 | 1.3593 |
| 9 | 1.0188 | 1.1349 | 1.0216 | 1.1385 | 1.0249 | 1.1434 | 1.1196 | 1.2328 |
| 10 | 1.0019 | 1.0773 | 1.0045 | 1.0841 | 1.0068 | 1.0927 | 1.1014 | 1.1903 |
| 20 | 1.0021 | 1.1470 | 1.0050 | 1.1583 | 1.0067 | 1.1618 | 1.099 | 1.246 |
| 22 | 1.2367 | 1.2946 | 1.2401 | 1.3024 | 1.2439 | 1.3110 | 1.3589 | 1.4398 |
| 27 | 1.1076 | 1.1923 | 1.1110 | 1.2033 | 1.1136 | 1.2109 | 1.2163 | 1.3188 |
| 29 | 1.0662 | 1.1470 | 1.0686 | 1.1553 | 1.0721 | 1.1586 | 1.1732 | 1.2687 |
| 32 | 1.4670 | 1.7664 | 1.4702 | 1.7657 | 1.4756 | 1.7727 | 1.6089 | 1.8388 |
| 33 | 1.2989 | 1.3886 | 1.3020 | 1.3981 | 1.3066 | 1.4048 | 1.4275 | 1.5326 |
| 38 | 1.3816 | 1.4698 | 1.3855 | 1.4872 | 1.3896 | 1.4955 | 1.5169 | 1.6349 |
| 49 | 1.2189 | 1.3140 | 1.2215 | 1.3227 | 1.2257 | 1.3324 | 1.3388 | 1.4594 |
| 52 | 1.2785 | 1.3563 | 1.2819 | 1.3628 | 1.2872 | 1.3711 | 1.4057 | 1.5046 |
| 55 | 1.0025 | 1.4085 | 1.0042 | 1.4191 | 1.0077 | 1.3899 | 1.0994 | 1.37 |
| 56 | 1.5071 | 1.5553 | 1.5118 | 1.5697 | 1.5160 | 1.5790 | 1.6523 | 1.7393 |
| 63 | 1.0016 | 1.1097 | 1.0045 | 1.1148 | 1.0071 | 1.1241 | 1.1038 | 1.2204 |
| 66 | 1.0013 | 1.3818 | 1.0043 | 1.3865 | 1.0080 | 1.3797 | 1.1006 | 1.3625 |
| 67 | 1.3306 | 1.4209 | 1.3351 | 1.4261 | 1.3387 | 1.4345 | 1.4626 | 1.5686 |
| 69 | 1.0017 | 1.4197 | 1.0045 | 1.3763 | 1.0082 | 1.4154 | 1.1031 | 1.365 |
| 74 | 1.4898 | 1.5694 | 1.4930 | 1.5805 | 1.4978 | 1.5892 | 1.6371 | 1.745 |
| 78 | 1.0016 | 1.2267 | 1.0045 | 1.2288 | 1.0073 | 1.2356 | 1.1042 | 1.2948 |
| 80 | 1.0021 | 1.3881 | 1.0046 | 1.3734 | 1.0072 | 1.4259 | 1.1022 | 1.3649 |
| 86 | 1.1640 | 1.3421 | 1.1664 | 1.3431 | 1.1697 | 1.3439 | 1.2812 | 1.4297 |
| 91 | 1.0120 | 1.0434 | 1.0138 | 1.0507 | 1.0170 | 1.0573 | 1.1104 | 1.1634 |
| 93 | 1.0016 | 1.1848 | 1.0050 | 1.1896 | 1.0090 | 1.1956 | 1.0996 | 1.2699 |
| 99 | 1.1213 | 1.1996 | 1.1240 | 1.2083 | 1.1288 | 1.2129 | 1.2347 | 1.3267 |
| 100 | 1.0019 | 1.1203 | 1.0042 | 1.1180 | 1.0079 | 1.1292 | 1.1012 | 1.21 |
| 101 | 1.0658 | 1.1424 | 1.0678 | 1.1475 | 1.0717 | 1.1565 | 1.1712 | 1.2573 |
| 108 | 1.2918 | 1.3477 | 1.2931 | 1.3553 | 1.2980 | 1.3624 | 1.4174 | 1.4975 |
| 112 | 1.1076 | 1.1781 | 1.1099 | 1.1810 | 1.1137 | 1.1911 | 1.2179 | 1.3038 |
| 113 | 1.0024 | 1.0794 | 1.0061 | 1.0887 | 1.0070 | 1.0944 | 1.1016 | 1.1926 |
| 119 | 1.2703 | 1.3337 | 1.2732 | 1.3438 | 1.2770 | 1.3500 | 1.395 | 1.4816 |
| 124 | 1.1412 | 1.2344 | 1.1445 | 1.2323 | 1.1472 | 1.2446 | 1.2532 | 1.3562 |
| 130 | 1.5015 | 1.5951 | 1.5054 | 1.6054 | 1.5103 | 1.6165 | 1.6533 | 1.7679 |
| 131 | 1.0024 | 1.1146 | 1.0042 | 1.1205 | 1.0076 | 1.1254 | 1.1031 | 1.2198 |
| 136 | 1.0019 | 1.0566 | 1.0041 | 1.0628 | 1.0069 | 1.0698 | 1.1001 | 1.1671 |
| 140 | 1.5960 | 1.6784 | 1.5988 | 1.6895 | 1.6041 | 1.6984 | 1.7537 | 1.8609 |
| 148 | 1.2977 | 1.3428 | 1.3006 | 1.3532 | 1.3058 | 1.3597 | 1.421 | 1.4926 |
| 150 | 1.1235 | 1.2061 | 1.1263 | 1.2169 | 1.1300 | 1.2209 | 1.2357 | 1.3291 |
| 157 | 1.4266 | 1.4608 | 1.4299 | 1.4698 | 1.4351 | 1.4792 | 1.5637 | 1.6289 |

propriate value for $h$ which is likely to lead to a better estimation than using a simple approach, such as the normal reference rule.

The bootstrapped DEA model was used to examine the TE of 201 mid-Atlantic scallop dredge vessels operating in 2003. Findings show that there was substantial technical inefficiency in the fleet, and managers should be concerned because the vessels have the potential to harvest far more than the MSY level of output, with no change in input levels. Because other types of vessels (notably trawlers) also harvest scallops, the fact that one gear type has the ability to substantially exceed the MSY leads to the conclusion that there are problems managing this resource in terms of exceeding the total allowable catch. From the perspective of economic efficiency, technical inefficiency in the fleet means that the vessels are not as profitable as they could be if they were operating in a technically efficient manner.

While results presented in this paper are in terms of the technically efficient output, the bootstrap methods can generate additional information for decision makers. For example, in models with discretionary and non-discretionary inputs, 95% confidence intervals for non-discretionary input usage can be estimated. When there is a large number of observations which are deemed efficient with an uncorrected score of 1.0, using the bias-corrected mean or median TE score may give a different ranking of observations in terms of TE. Confidence intervals for the shadow prices of the various inputs could also be constructed. Presented results need to be based on the questions being posed. There will likely be a tradeoff at some point between the volume of information generated and the usefulness of the information to managers.

## References

Banker, R.D. 1993. Maximum Likelihood, Consistency and Data Envelopment Analysis: A Statistical Foundation. *Management Science* 39(10):1265–73.

Charnes, A., W.W. Cooper, and E. Rhodes. 1978. Measuring the Efficiency of Decision Making Units. *European Journal of Operational Research* 2(6):426–44.

Coelli, T. 1996. A Guide to DEAP Version 2.0. Working paper 96/08. Center for Efficiency and Productivity Analysis. Department of Econometrics, University of New England, Armidale, Australia.

Färe, R. 1988. *Fundamentals of Production Theory*. Berlin: Springer-Verlag.

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

Farrell, M.J. 1957. The Measurement of Productive Efficiency. *Journal of the Royal Statistical Society* Series A, General, 120, Part 3, 253–81.

Ferris, M.C., and M.M. Voelker. 2000. Slice Models in General Purpose Modeling Systems. Available at: www.cs.wisc.edu/dmi/tech-reports/

Gijbels, I., E. Mammen, B.U. Park, and L. Simar. 1999. On Estimation Of Monotone and Concave Frontier Functions. *Journal of the American Statistical Association* (94):220–28.

Kirkley, J., C.J. Morrison-Paul, and D. Squires. 2004. Deterministic and Stochastic Capacity Estimation for Fishery Capacity Reduction. *Marine Resource Economics* 19:271–94.

Kirkley, J.E, D.E. Squires, M.F. Alam, and H.O. Ishak. 2003. Excess Capacity and Asymmetric Information in Developing Country Fisheries: The Malaysian Purse Seine Fishery. *American Journal of Agricultural Economics* 85(3):647–62.

Kirkley, J., D. Squires, and I. Strand. 1995. Technical Efficiency in Commercial Fisheries. *American Journal of Agricultural Economics* 77(4):686–97.

___. 1998. Characterizing Managerial Skill and Technical Efficiency in a Fishery. *Journal of Productivity Analysis* 9:145–60.

Koopmans, T.C. 1951. An Analysis of Production as an Efficient Combination of Activities. *Activity Analysis of Production and Allocation, Cowles Commission for Research in Economics*, Monograph No. 13., T.C. Koopmans, ed. New York, NY: Wiley.

___. 1957. *Three Essays on the State of Economic Science*. New York, NY: McGraw Hill.

Korostelev, A., L. Simar, and A. Tsybakov. 1995. Efficient Estimation of Monotone Boundaries. *The Annals of Statistics* 23:467–49.

Park, B., L. Simar, and C. Weiner. 2000. The FDH Estimator for Productivity Efficiency Scores: Asymptotic Properties. *Econometric Theory* 16(6):855–77.

Ray, S.C. 2004. *Data Envelopment Analysis: Theory and Techniques for Economics and Operations Research*. New York, NY: Cambridge University Press.

Reinhart, S., C.A.K. Lovell, and G. Thijssen. 2000. Environmental Efficiency with Multiple Environmental Variables: Estimated with SFA and DEA. *European Journal of Operational Research* 121:559–78.

Russell, R.R. 1985. Measures of Technical Efficiency. *Journal of Economic Theory* 51:255–67.

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

Silverman, B.W. 1986. *Density Estimation for Statistics and Data Analysis*. London: Chapman and Hall.

Simar, L. 1996. Aspects of Statistical Analysis in DEA-Type Frontier Models. *Journal of Productivity Analysis* 7:177–85.

Simar, L., and P.W. Wilson. 1998. Sensitivity Analysis of Efficiency Scores: How to Bootstrap in Nonparametric Frontier Models. *Management Science* 44(1):49–61.

___. 1999. Performance of the Bootstrap for DEA Estimators and Iterating the Principle. Unpublished Manuscript, *Institut de Statistique, Universite de Louvain*.

___. 2000a. Statistical Inference in Nonparametric Frontier Models: The State of the Art. *Journal of Productivity Analysis* 13:49–78.

___. 2000b. A General Methodology for Bootstrapping Nonparametric Frontier Models. *Journal of Applied Statistics* 27(6):779–802.

Tingley, D., S. Pascoe, and S. Mardle. 2003. Estimating Capacity Utilization in Multi-Purpose, Multi-Métier Fisheries. *Fisheries Research* 63:121–34.

Weninger, Q. 2001. An Analysis of the Efficient Production Frontier in the Fishery: Implications for Enhanced Fisheries Management. *Applied Economics* 33:71–9.