Factors Affecting Technical Efficiency in Fisheries: Stochastic Production Frontier 'v' Data Envelopment Analysis approaches

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Abstract

Technical efficiency (TE) measures the relationship between a vessel's inputs to the fishing process and its outputs, with full efficiency being achieved when outputs are maximised from a given set of inputs. Inputs can be physical (e.g. the vessel, gear, engine, onboard equipment, etc.), flexible (time spent fishing, size of crew) and also heavily influenced by skipper skill. Finally, there will always be an element of luck and other unaccountable factors involved. TE scores can be calculated using the econometric Stochastic Production Frontier (SPF) or the non-stochastic, linear-programming Data Envelopment Analysis (DEA) methodologies. This paper compares the results of both techniques for segments of the English Channel fisheries. The influence of factors most affecting technical efficiency is also analysed using an SPF inefficiency model and tobit regression of DEA-derived scores. Such factors include vessel and skipper characteristics. It is argued that DEA can be used as an alternative to SPF techniques when there is difficulty specifying the correct SPF model. There is consistency in results of factors affecting TE between SPF and DEA analyses.

Keywords

Technical Efficiency, Data Envelopment Analysis, Stochastic Production Frontiers, tobit regression, fisheries

1. INTRODUCTION

If a vessel is operating at maximum technical efficiency (TE) it is assumed to be using its full range of inputs in the most efficient manner possible. Inputs to the fishing process can take a physical form, i.e. the vessel size, gear type, engine, onboard equipment, etc. or they can also take a more flexible form, such as time spent fishing and size of crew. It is also recognised that fishing efficiency can be heavily influenced by the skill of the skipper. Finally, there will always be an element of luck and other unaccountable factors involved.

In the UK, a major component of fisheries management takes the form of input regulations. As part of the EU's Common Fisheries Policy UK national fleet capacity targets, to be met as part of the Multi-Annual Guidance Programmes (MAGP) Structural Policy, are based upon total measures of fishing vessel Gross Tonnage and engine power. Limits on numbers of days at sea have also been used in the past to control fishing effort.

The long-term success of input-based fisheries management policies is affected by the level of TE present in a fishery. Low levels of TE in a fishery imply that inputs are being used at less than optimal-efficiency levels to generate outputs. Therefore, if current levels of inputs were used efficiently the implication is that output levels could be increased. Alternatively, a more efficient use of less inputs could generate the same current levels of output.

As a fisheries manager, it is therefore important to understand which factors are driving efficiency. If input-based regulations are in use, understanding the relationship between key physical (e.g. vessel size, engine power) or flexible inputs (e.g. days at sea) is crucial to determining the potential success of the management measure. Alternatively, TE may be partly driven by the level of vocational education received by the skipper. An understanding of this relationship may help to determine the need for skills training provided to the industry. It may be the case that the family fishing history of the skipper plays an equally important role in establishing levels of efficiency which may provide evidence promoting a more community-orientated style of fisheries management. In short, any increase in the understanding of factors which drive TE must improve the potential for more effective management, and improvement of efficiency, in fisheries.

Technical efficiency (TE) is estimated in this paper, for a range of fishing activities in the English Channel, using two contrasting methodologies. Deriving a Stochastic Production Function (SPF) is the most traditional, econometrically based method of estimating a quantitative measure of TE. The results from SPF are compared with those estimated with the same data set using Data Envelopment Analysis (DEA), a newer linear-based programming method.

2. ESTIMATION OF EFFICIENCY

The level of efficiency of a particular firm is characterised by the relationship between observed production and some ideal or potential production (Greene 1993). The measurement of firm specific technical efficiency is based upon deviations of observed output from the best production or efficient production frontier. If a firm's actual production point lies on the frontier it is perfectly efficient. If it lies below the frontier then it is technically inefficient, with the ratio of the actual to potential production defining the level of efficiency of the individual firm.

Two methodologies were used to describe the efficient production frontier and so estimate efficiency scores: Stochastic Production Frontier (SPF) analysis and Data Envelopment Analysis (DEA). The influence of factors affecting efficiency scores was also tested in two separate ways: (1) an inefficiency model was developed as part of a one-step procedure with the SPF analysis, and (2) DEA-derived scores were regressed over factors thought to be of influence.

3.1 Stochastic Production Frontier and inefficiency model

A general SPF model can be given by:

$$\ln q_j = f(\ln \mathbf{x}) + v_j - u_j \tag{1}$$

where q_j is the output produced by firm j, $\boldsymbol{x}$ is a vector of factor inputs, v_j is the stochastic error term and u_j is the estimate of the technical inefficiency of firm j. Both v_j and u_j are assumed to be independently and identically distributed (iid) with variance σ_v^2 and σ_u^2 respectively.

In order to separate the stochastic and inefficiency effects in the model, a distributional assumption has to be made for u_j. While a range of distributional assumptions are available, one approach is to define the inefficiency as a function of the firm specific factors such that:

$$\mathbf{u} = \mathbf{z}\boldsymbol{\delta} + \mathbf{w} \tag{2}$$

where $\mathbf{z}$ is the vector of firm-specific variables which may influence the firms efficiency, $\boldsymbol{\delta}$ is the associated matrix of coefficients and $\boldsymbol{w}$ is a matrix of iid random error terms. The parameters of the inefficiency model are estimated in a one-step procedure (Battese and Coelli 1995) along with the parameters of the production frontier.

3.2 Data Envelopment Analysis

DEA is a non-parametric, linear-programming approach to the estimation of TE. The technique does not require any pre-described structural relationship between the inputs and resultant outputs, as is the case with SPF analysis, so allowing greater flexibility in the frontier estimation. It can also accommodate multiple outputs into the analysis. A disadvantage of the technique, however, is that it does not account for random variation in the output, and so attributes any apparent shortfall in output to technical inefficiency.

The technique can be illustrated using a simple example (Figure 1), based on a set of five boats ($j = \{A,B,C,D,E\}$) catching two species($m = \{1,2\}$). The catch per unit of fixed input, $u_{j,m}$, can be plotted to determine the production possibility frontier, defined by boats A, B, C and D. As these boats lie on the frontier, they are assumed to be operating at full technical efficiency. In contrast, boat E is producing less of both species relative to the frontier and is therefore assumed to be operating at less than full efficiency. The production potential of boat E can be found by expanding the output of both species radially from the origin until it reaches the frontier (point E*). OE*/OE is the expansion factor (θ) by which output of boat E could be increased. Thus the TE of boat E is given by OE/OE* (i.e. $1/\theta$).

The shape of the frontier will differ depending on the scale assumptions that underlie the model. There are generally *a priori* reasons to assume that fishing would be subject to non-constant returns, and in particular non-increasing returns to scale.

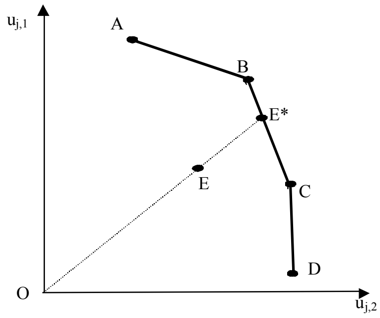


Figure 1 Two-output production possibility frontier

The NIRS DEA model is formulated as a linear programming (LP) model, where the value of θ for each vessel can be estimated from the set of available input and output data. Following Färe *et al.* (1989, 1994), this DEA model of technically efficient output requires both variable and fixed inputs to be considered. The NIRS DEA model for this technically efficient measure of output is given as:

$$Max\ \theta$$

subject to

$$\begin{aligned} &\theta u_{0,m} \leq \sum_j z_j u_{j,m} \quad \forall\, m \\ &\sum_j z_j x_{j,n} \leq x_{0,n} \quad \forall\, n \in \alpha, \hat{\alpha} \\ &\sum_j z_j \leq 1 \\ &z_j \geq 0 \end{aligned} \tag{3}$$

where θ (≥1) is a scalar denoting the multiplier that describes by how much the output of the target boat (i.e. j=0) can be expanded using inputs in a technically efficient configuration. Further, $u_{j,m}$ is the output m produced by boat j, $x_{j,n}$ is the amount of input n used by boat j, and z_j are weighting factors such that technically efficient output is the weighted sum of the output of other vessels in the data set. The value of θ is estimated for each vessel separately, with the target vessel's outputs and inputs being denoted by $u_{0,m}$ and $x_{0,n}$ respectively. Inputs include both fixed and variable factors (i.e. sets _ and _) which are constrained to their current levels. The restriction $\Sigma_j z_j \leq 1$ allows for non-increasing returns to scale. The technically efficient level of output is defined as θ multiplied by observed output (i.e. $u_{0,m}^{TE} = \theta u_{0,m}$). The level of TE is estimated as:

$$TE = 1/\theta \tag{4}$$

3.3 DEA vs SPF

Both SPF and DEA have been used to estimate technical efficiency in a wide range of industries. Both methods have a number of advantages and disadvantages. A criticism often applied to the use of DEA in the estimation of technical efficiency in fisheries is that the derived efficiency scores are adversely affected by random error. In contrast, the SPF approach separates the random error from the inefficiency measure. However, the SPF approach assumes a common production function exists for all firms in the industry being examined. While the functional form can be flexible in terms of scale of the operation (i.e. allowing for variable returns to scale), it assumes that, for a given scale, the production process is the same for all firms. In many industries, a single production function may be appropriate for the production technologies used. However, this may not be appropriate in the case of multi-purpose fishing fleets, where different operators use their gear in different combinations to achieve different levels of output of potentially many different species. DEA has a direct advantage in such circumstances as it can readily encompass multi-outputs, and also does not require the specification of a production function.

A small number of studies have compared the results from the two methods, although the number of studies comparing the two methods in fisheries is relatively limited (e.g. Coglan et al 1998). These studies have focused on comparing the estimated efficiency scores using the two techniques (e.g. Neff et al. 1993, Sharma et al. 1997), or confirming the trends in efficiency through using both techniques (e.g. Zaibetand and Dharmapala 1999, Uri 2001). Generally, the studies have found that the DEA efficiency scores are lower as a result of the random error (Holland and Lee 2002), but are usually correlated with the SPF scores.

In more recent studies of efficiency, attention has been focused on factors that affect efficiency rather than the level of efficiency *per se*. This can be undertaken using a one-step process with SPF, where the distribution of the efficiency scores are based on a range of variables believed to affect efficiency (Battese and Coelli 1995). With DEA, a two-stage process is required. In the first stage, the efficiency scores are estimated, and then these are regressed against the factors believed to affect efficiency. Given the limited range of the efficiency scores (i.e. zero to 1), tobit regression analysis is more appropriate than ordinary least squares.

In this paper, factors affecting DEA-derived measures of TE are estimated using tobit regression analysis. Results are compared with those estimated using the SPF one-step inefficiency model with the same data set. The influence of a range of factors are tested, including physical, flexible and technological inputs. Skipper education, experience, family history and age characteristics are also tested as proxies for 'skipper skill'.

3. DATA

The data set used in this analysis was derived from two main sources. The first source was log-book records of trip-level data for vessels fishing in the English Channel, provided by the UK's Department for Environment, Food and Rural Affairs (DEFRA). These data were used primarily to generate TE scores and included information on the value of catch landed, gear type, area fished, length of trip and vessel and engine size. Trip records were summarised by vessel at the annual level for the period available, 1993-98.

The second source of data was provided by a survey of skippers fishing a range of mobile and static gears in the English Channel area. Only skippers fishing full-time were interviewed, with full-time being defined as activity in more than four months of a year and in at least three of the years being studied. The survey collected information on annual revenues and fishing activity in 1999 and 2000 thus allowing the original DEFRA data set to be updated to cover the period 1993-2000.

TE estimation requires data on inputs and outputs to the production process. Average annual real revenue per vessel was used as the output measure in the estimation of efficiency. These data were adjusted for stock effects following the method of Herrero and Pascoe (2001). Input data were available in the form of number of days fished per year, vessel engine power and overall length (Table 1).

Table 1 Input and output data used to calculate TE scores (1993-2000)

	No. of Boats in sample	Total number of observations	Inputs: Avg. annual days fished	Inputs: Engine power (kW)	Inputs: Overall length (m)	Outputs: Adj. avg. annual revenue (£)
Mobile	18	117	171	217	14	144,613
Pots	26	95	72	72	12	39,101
Net-line	23	87	120	113	10	53,635

The production data were divided into three categories according to main fishing activities: (1) mobile gears (beam trawl, pelagic trawl and scallop dredge), (2) pots (crustaceans) and (3) nets and hand line. Mobile fishing activities were kept as one category, with just over half of the vessels fishing more than one of the three gear types in any one year, whilst the static fishing activities were separated into two categories, pots and netter-liners. Crustacean pot fishing is a quite separate activity to hand lining and netting. Most of the vessels in the data set carried out both hand lining and netting in a year therefore vessels fishing this type of gear were kept together in this third category.

The main objective of the skipper survey however, was to gather information about the level of a vessel's fishing activity, operational details and onboard technology as well as the skipper's characteristics. Specifically, data was collected to create vessel specific variables such as an index of average annual fishing activity, average crew size per overall boat length (OL), boat age and engine power (kW) per OL. The onboard electronic technology category included data on whether vessels were using navigational aids (GPS, GPS Plotter), echo sounder, sonar and autopilot. Skipper characteristics included information on age, length of fishing experience, family fishing history, formal and vocational education levels and training in boat handling skills.

These data were used in the SPF inefficiency model and the comparative regression of DEA-derived TE scores to determine which factors affect efficiency. A full summary of this additional data and discussion of their expected impact on efficiency scores is presented in Pascoe, S. et al (2002)[1].

4. MODEL SPECIFICATION AND RESULTS

4.1 SPF

A translog frontier production function was initially specified for each of the three groupings of fishing activity. Inputs and outputs used in the model were as shown in Table 1. Gear specific dummy variables were used in each function to test the effect of specific gear types on the model. The inefficiency component of the model included data on vessel characteristics, onboard electronic technology and skipper characteristics. Full details of the translog specification and related inefficiency model are given in Pascoe et al (2002).

As with all econometric analysis, results are highly dependent on specifying the correct functional form of the model. As detailed in Pascoe et al (2002) the initial translog functional forms of the model were tested by imposing restrictions on the model to determine whether a Cobb-Douglas specification was a more appropriate functional form. The generalised likelihood ratio rejected this hypothesis for the mobile fishing activities at the 1 per cent level of significance and also more marginally for the potting activity (just over the 5 per cent level of significance). However, the hypothesis could not be rejected for the net-liners.

The presence of inefficiency was confirmed for all gear types using the one-sided generalised likelihood ratio-test. The test to determine whether inefficiency variables were jointly insignificant was also applied. This hypothesis was rejected at the 1 per cent level for all models, except it was found that skipper characteristics for the net-liners could be excluded without significant effect on the model. The contribution of vessel characteristics and onboard electronic technology to the model was also found to be non-significant however some individual variables were significant and so were left in (Pascoe et al 2002).

The R_ values show the proportion of the variation in efficiency scores, generated using the specified form of the SPF model, that is explained by changes in the level of inputs used in the model. For all three gear types, the level of inputs was the main determining factor affecting the level of output, explaining 94, 63, and 83 per cent of the variation in output of the mobile gear boats, potters and netter-liners respectively.

4.2 DEA

To allow for a direct comparison of results, the DEA measures of efficiency were estimated using the same set of inputs, derived from the same data set, as used in the SPF analysis (i.e. average annual days fished, engine power and overall vessel length). Despite the method's ability to handle multiple-output data, the same single composite output measure was used for direct comparison.

Each of the three fishing activity categories were analysed in isolation. Separate DEA analyses were run for each year in the 1993-2000 period. As DEA is a non-parametric method, no econometric tests are available to gauge the appropriateness of the estimated frontier and efficiency scores. Linear and log-linear forms of tobit regression were used to determine which factors were influencing efficiency.

4.3 Efficiency scores

The variation of results between methods can be seen in Figure 2 which shows the frequency distribution of efficiency scores for each method and activity. Table 2 presents average TE scores derived from both SPF and DEA methods. SPF TE scores are 88% greater than DEA scores for mobile and potting activities, and 122% greater for net-liners. The variance is smallest for mobile gears across both methods. The variance of DEA scores is much greater than that for SPF scores (70% greater for mobile and 80% for potters) though only 28% greater for net-liners.

[1] This paper is also being presented at IIFET 2002, Wellington.

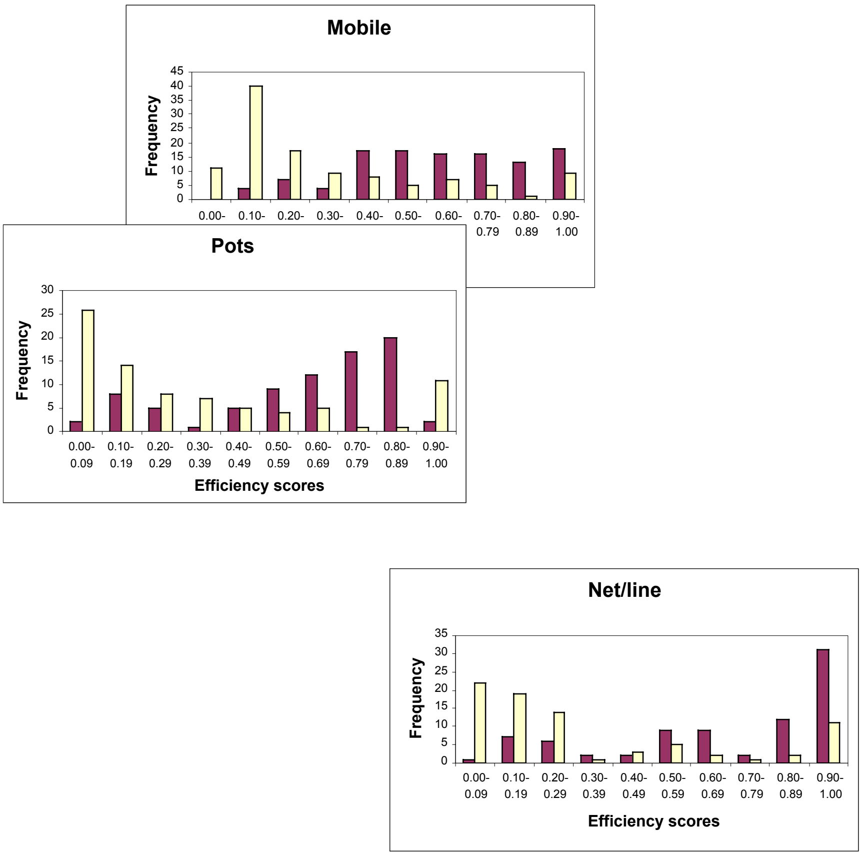
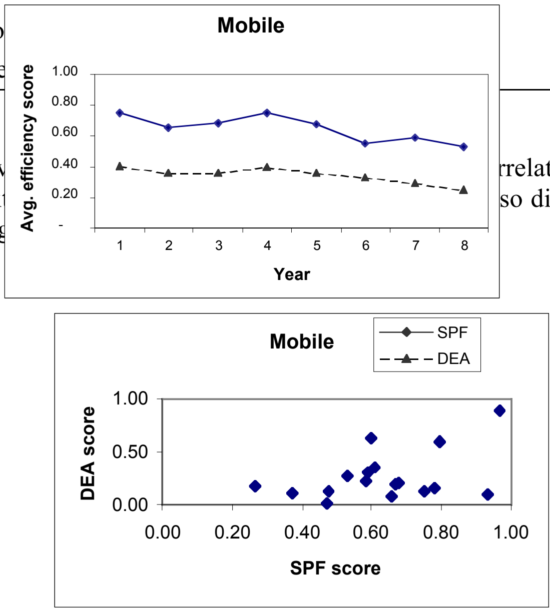


Figure 2 Distribution of efficiency estimates

The correlation between both sets of results is shown in Table 2 by fishing activity for average vessel scores (1993-2000) and average annual scores (across all vessels). These results are also depicted in Figures 3 and 4. SPF and DEA average vessel scores are most highly correlated for potting activities (0.596) and lowest for net-liners (0.293); correlation for mobile gears is in between at 0.443.

Table 2 TE scores derived from SPF and DEA analyses (average, 1993-2000)

	SPF		DEA		Correlation between SPF & DEA scores	
	TE	variance	TE	variance	Avg. vessel score	Avg. annual score
Mobile	0.64	0.037	0.34	0.063	0.443	0.915
Po			0.33	0.106	0.596	0.697
Ne			0.32	0.106	0.293	0.203



Av … rrelated for mobile and potting activities than for net-liners. The ex … so displays the result that SPF efficiency scores are consistently hig …

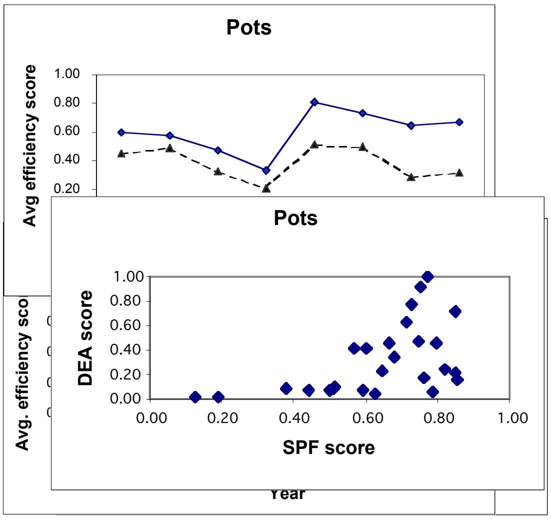


Figure 3 Average vessel efficiency estimates **Figure 4 Average annual efficiency estimates**

4.4 Factors affecting efficiency

The results of the SPF inefficiency model and tobit regression of the DEA-derived scores are summarised in Table 3. For the SPF analysis, the relative importance of inefficiency and random error in the catch component not explained by the inputs, can be estimated. Inefficiency was found to represent 38% of the residual variation of mobile activities (γ^*), 77% for potting and only 3% for net-liners. From this, random error explains 62%, 23% and 97% of the non-input related variation in catch respectively for the three gear types. In each of the mobile and potter models, eight variables were found to have a significant impact (at the 5% level) on efficiency scores. Only two variables were significant in the net-liner model; skipper characteristics had already been removed from the inefficiency model as their exclusion was found to have no significant effect.

The components within the inefficiency model explained varying proportions of the actual efficiency. For the mobile gear and netter-liners, the factors explained over three quarters of the variation in efficiency. In contrast, these factors explained less than 10 per cent of the variation in efficiency for the potters, suggesting non-measurable factors such as skipper or crew skill (that are not related to training or experience) are a dominant influence.

The tobit regression of factors affecting efficiency was carried out using both linear and log-linear forms. The Correlation Coefficient Squared gives an indication of the goodness-of-fit of tobit regression results. The log-linear form of the regression of mobile activity explained 85% of the variation in efficiency scores, with the linear form performing almost as well. The log-linear form of the net-liner regression explained over 55% of the variation with the linear form explaining only slightly less. The log-linear regression of changes in potting efficiency scores was very poor explaining only around 6% of the variation, however the linear form performed much better explaining around 50% of the variation.

Table 3 Summary of effects on efficiency

	Mobile gear			Potters			Net-Line		
	SPF	DEA (linear)	DEA (log-linear)	SPF	DEA (linear)	DEA (log-linear)	SPF	DEA (linear)	DEA (log-linear)
Boat characteristics									
▪ Activity	↓		↑	↓			↓		
▪ Crew OL^{-1}	↑	↓				[↑]		↑	↑
▪ Boat vintage	↑			↓					
▪ kW OL^{-1}	↓	↑	↑	↑	↑	↑			↑
Technology									
▪ Navigational aid				↑	↑	↑	↑		
▪ Sounder/Sonar		↑				[↓]			
▪ Auto-Pilot	↑	↑							
Skipper characteristics									
▪ Age		↓		↓				↓	↓
▪ Fishing experience	↓	↓	↓	↑					
▪ Family history	↑		↑					↑	
▪ Formal education		↑	↑	↓				↓	↓

▪ Vocational education	↑	↑							
▪ Boat Handling		↑	↑	↓					
Variation explained by model									
▪ γ	0.63			0.90			0.08		
▪ γ^* (% inefficiency) [2]	0.38			0.77			0.03		
▪ Mean Square Error		0.01	0.01		0.08	0.56		0.05	0.05
▪ $\bar{R}^2$/Correlation Coeff. Sq. (r^2)	0.79	0.84	0.85	0.07	0.50	0.06	0.76	0.54	0.55

Key: ↑ significant at the 5% level [↑] significant at the 10% level $\bar{R}^2$ relates to SPF model r^2 relates to DEA models
↓ denotes inconsistency in direction of result between SPF and DEA analyses

There is a general consistency in results for mobile vessels between the inefficiency model and tobit regressions with the variables, autopilot, fishing experience and vocational education being consistently signed and significant between the inefficiency model and linear tobit regression. The variables fishing experience and family history are consistently signed and significant between the mobile inefficiency model and log-linear tobit regression. Two variables in each of the linear and log-linear regressions are significant, but signed in the opposite direction to that in the inefficiency model (highlighted in Table 3).

A general consistency between results is also shown for potting vessels, though fewer variables are significant (at the 5% level) in the tobit regression and signed in the same direction between models (kW OL^{-1} and navigational aids). No skipper characteristics were significant in the tobit regression for potting vessels, whereas four were in the inefficiency model.

No variables are significant and similarly signed between the net-line inefficiency and tobit regression results; only two variables were significant in the inefficiency model, whilst four were significant for each of the tobit regression forms.

5. DISCUSSION AND CONCLUSIONS

The difference between estimates of SPF and DEA scores is clearly shown in Figures 2 to 4. From Table 2, the SPF TE scores are consistently greater than DEA-derived scores, while the variance of SPF scores is consistently smaller than that for DEA scores. This result is largely expected, as the DEA scores are affected by the random error. For the netter-liners in particular, this random error is considerable.

Average vessel and average annual efficiency scores were presented to reduce the effects of random variation in observations. A reasonable level of correlation was found between average vessel scores for the mobile and potting activities indicating that there is a significant consistency in the relationship, despite the magnitude of difference, between scores for these individual vessels across methodologies.

The level of correlation is increased for mobile and potting activities when average annual scores are considered. It is appropriate to directly compare average annual SPF and DEA scores as output data used in the analysis were standardised across years using a stock index. Further, between 1993 and 2000, there were no significant changes to inputs that could have caused a shift in frontiers.

Similar levels of correlation were not observed for the net-line activity. This finding may reflect the fact that the SPF net-liners model was mis-specified, and so the resultant TE scores may be biased due to the specification error. Further, from the SPF model, inefficiency was only 3 per cent of the total variation in output not explained by the level of inputs. As a result, it could be concluded that the DEA estimates are substantially influenced by random variation. Alternatively, the poor performance econometrically of the SPF model for this fleet segment could also mean that the SPF TE scores are biased (possibly also explaining their relatively small share of the combined error term).

While the overall DEA TE score may be affected by random error, the results also demonstrated that both techniques are able to produce reasonable models of factors that affect efficiency. With only a couple of

[2] The estimate of γ provided in the MLE results is only an approximation of the contribution of inefficiency to total variance as the true variance of u_i is proportional but not exactly equal to σ_u^2 (Coelli, Rao and Battese 1998). The corrected relative contribution of inefficiency is given by $\gamma^*=\gamma/[\gamma+(1-\gamma)\pi/(\pi-2)]$ (Coelli 1995).

exceptions, the analysis of the efficiency scores from the two methods (DEA and SPF) were consistent, at least in terms of direction of the effect. Further, more variables were significant in the DEA-based two-stage analysis than in the SPF analysis for the mobile gear and netter-liners. These additional variables were largely in accord with a priori expectations. Based on the explanatory power of the models, and the number, sign and consistency of significant variables between models, it can be concluded that the tobit regression of DEA-derived scores for mobile and net-line vessels is more informative than the comparative SPF inefficiency model. However, the opposite finding appears to be true for the potting vessels.

These results indicate that despite there being a systematic difference in the level of DEA- and SPF-derived efficiency scores, there is a close consistency in results between the SPF inefficiency model and comparative tobit regression of DEA-derived scores, used to determine which factors affect technical efficiency. Therefore, where SPF model specification is problematic, tobit regression of DEA-derived TE scores can be used as an alternative method to explain inefficiency.

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