Marine Resource Economics, Volume 13, pp. 259–274
Printed in the U.S.A. All rights reserved
0738-1360/98 $3.00 + .00

Technical Efficiency of the Longline Fishery in Hawaii: An Application of a Stochastic Production Frontier

KHEM R. SHARMA
PINGSUN LEUNG
University of Hawaii at Manoa

Abstract *This paper examines the level and determinants of technical efficiency for a sample of domestic longline fishing vessels operating in Hawaii in 1993. The data on per-trip costs and revenues, fishing targets, vessel ownership, experience and education level of fishermen, vessel size, and vessel age are analyzed using a translog stochastic production frontier, including a model for vessel-specific technical inefficiencies. Output elasticities, marginal productivities of inputs, and returns to scale are also examined. The technical inefficiency effects are found to be highly significant in explaining the levels of and variation in vessel revenues. The mean technical efficiency for the sample vessels is estimated to be 84%. Vessels that target swordfish, and those varying target by season, set, or trip, tend to be less efficient than those vessels targeting tuna and those mixing targets in all trips. Owner-operated vessels seem to be more efficient than those operated by hired captains. The experience of fishermen has a strong positive influence on technical efficiency. Although insignificant, vessel size and fishermen's education level have a positive influence, and vessel age has a negative influence on vessel efficiency.*

Key words Hawaii, longline fishery, pelagic fishery, stochastic production frontier, swordfish, technical efficiency, tuna.

Introduction

The management and regulation of ocean fisheries continues to be one of the biggest challenges for fishery agencies worldwide. In most cases, the regulations which have been developed based on traditional bioeconomic models have failed to deliver the expected results. Several economists have provided a number of reasons why

---

Khem R. Sharma is an assistant professor/researcher and PingSun Leung is a professor; both are in the Department of Agricultural and Resource Economics, University of Hawaii at Manoa, Gilmore Hall 112, 3050 Maile Way, Honolulu, HI 96822, USA, e-mail: khem@hawaii.edu and psleung@hawaii.edu, respectively.

The authors are thankful to Marcia Hamilton, Joint Institute of Marine and Atmospheric Research, University of Hawaii at Manoa for providing the data. The authors also thank Samuel G. Pooley, National Marine Fishery Service, Honolulu, two anonymous reviewers, and the editor and associate editor of this journal for providing helpful comments and suggestions on earlier drafts. The authors are responsible for any remaining errors. An earlier version of this paper was presented at the Ninth Biennial Conference of the International Institute of Fisheries Economics and Trade, Norwegian College of Fishery Science, University of Tromsö, Norway, July 8–11, 1998. This research was funded by Cooperative Agreement Number NA37RJ0199 from the National Oceanic and Atmospheric Administration (NOAA). The views expressed herein are those of the authors and do not necessarily reflect the views of NOAA or any of its sub-agencies.

traditional measures have not been successful when analyzing the characteristics of multi-product (multi-species) technologies of fishing firms in terms of profit or revenue functions. Most frequently cited reasons include the disregard of jointness-in-technology (Kirkley and Strand 1988; Squires 1987a), substitutability among regulated versus unregulated inputs (Dupont 1991), and the possibility of rent dissipation through inefficient fleet composition (Dupont 1990).

In addition to technology characteristics, the knowledge of the productive performance of individual fishermen relative to the available technology and its interaction with other socio-economic factors can also be useful for fishery managers in formulating appropriate regulations. Depending upon the availability of data, the productive performance of multi-product firms can be determined by estimating production, cost, or profit frontiers (Kumbhakar 1996). Despite recent developments and widespread use of various production frontier approaches to assess the various measures of productive efficiencies of firms in many industries, the application of these techniques in commercial fisheries is very limited.[1] To our knowledge, Kirkley, Squires, and Strand (1995) and Campbell and Hand (1997) have produced the only two studies that have employed production frontiers to commercial fisheries issues. The lack of frontier studies in marine fisheries can largely be attributed to their inherent complexity and consequent difficulty in collecting necessary production data. Furthermore, fishery management authorities are generally more concerned with biological aspects of fishery resources than with the economic performance of fishermen. However, both the sustainable management of fish stocks and the efficient utilization of resources associated with fishery production (such as labor, capital, etc.) are crucial in order to maximize the social benefits of the fishing industry.

Given the inherent, stochastic nature of harvesting marine resources, the stochastic frontier production function approach developed by Aigner, Lovell, and Schmidt (1977) and Meeusen and van den Broeck (1977) appears to be appropriate for assessing technical efficiency in a commercial fishery. Technical efficiency measures the ability of firms to produce maximum output using a given set of inputs and technologies.

The main objective of this paper is to examine the level and determinants of technical efficiency of a sample of Hawaii-based, domestic longline vessels, based on their 1993 operating cost and catch data. Due to its flexible properties, a translog stochastic production frontier is estimated utilizing the Battese and Coelli (1995) model for firm-specific technical inefficiency effects in order to identify the relevant vessel- and operator-specific variables that may influence technical efficiency.[2]

Output elasticities, marginal productivities of inputs, and returns to scale are also investigated. Other efficiency measures, especially allocative efficiency, are important in fisheries management, but due to data constraints, this paper focuses only on technical efficiency.

---

[1] See Coelli (1995a) for the most recent review of these approaches, including their estimation procedures.

[2] Kirkley, Squires, and Strand (1995) also specified a stochastic translog frontier for the analysis of technical efficiency of the mid-Atlantic sea scallop fishery, but they used a second-stage procedure to determine factors explaining technical efficiencies. Recently, several authors (Battese and Coelli 1995; Kumbhakar, Ghosh, and McGuckin 1991; Battese, Coelli, and Colby 1989) have questioned this second-stage approach by arguing that such factors should be incorporated directly into the estimation of the production frontier model because they may have a direct impact on efficiency.

Hawaii's Longline Fishery

The longline fishery in Hawaii has been in existence since the early 1900s, but significant growth did not occur until the late 1980s. This was due to the entry of modern longline vessels, development of local and export markets for fresh tuna, and improved swordfish fishing methods. The longline fishery is now the largest domestic commercial fishery in Hawaii (Boggs and Ito 1993).

In 1993, longliners landed over 25 million pounds of pelagic species with an ex-vessel value of $54 million. The longline catch included 79% of total pelagic catch and 84% of the total ex-vessel revenue in Hawaii. Landings of important pelagic species by Hawaii's longline vessels include four tuna species (yellowfin, bigeye, albacore, and skipjack), three billfish species (swordfish, blue marlin, and striped marlin), dolphinfish, and wahoo (*Acanthocybium solandri*). The Hawaiian pelagic fishery also lands small quantities of shortbill spearfish (*Tetrapturus angustirostris*) and black marlin (*Makaira indica*). Swordfish (*Xiphias gladius*) and bigeye tuna (*Thunnus obesus*) are the two major species targeted by the longline fleet. In 1993, the longliners landed about 13 million pounds of swordfish and 4.7 million pounds of bigeye tuna. Other selected pelagic species landed by Hawaii's longline fishery included 1 million pounds of striped marlin (*Tetrapturus audax*); 1.4 million pounds of yellowfin tuna (*Thunnus albacares*); nearly 1 million pounds of albacore (*Thunnus alalunga*); 0.8 million pounds of blue marlin (*Makaira mazara*); and 1.7 million pounds of shark, mostly blue shark (*Prionace glauca*) [WPRFMC 1994a]. Statistics for subsequent years can be found in various annual reports on the Hawaii-based longline fishery (Ito 1995; Ito and Machado 1996, 1997).

The present longline fleet in Hawaii includes a few older wood vessels, wood and fiberglass vessels, and many newer steel vessels, most of which were previously engaged in the U.S. mainland fishery (WPRFMC 1995). In 1993, there were 167 longline vessels registered with federal limited-entry permits, of which only 122 were active.

Hawaii-based longline vessels are categorized by length into three size classes: small (< 56 feet), medium (56–74 feet), and large (> 74 feet). Of the 122 vessels operating in 1993, 30 were categorized as small, 48 as medium, and 44 as large (Dollar 1994). Some vessels target either swordfish or tuna, while others shift targets by season, trip, or set. Furthermore, some longline vessels engage in the longline fishery year-round, while others may switch to other Hawaiian fisheries or move to the U.S. mainland during part of the year (WPRFMC 1995).

The older longline vessels are 42–70 feet in length and are capable of taking two-week trips. The newer, modern vessels average 70–98 feet in length and can travel up to 2–3 months. These vessels are often equipped with water, ice-making machines, and modern electronic equipment for navigation, communications, and locating fish. When targeting tuna, longliners typically take 14–21 day-trips with a captain and a crew of three. When targeting swordfish, longer trips of 30–45 days are usually taken with a captain and a crew of four (WPRFMC 1995).

Expansion of longline activities in the early 1990s heightened the conflicts between longliners and the troll and handline fisheries. In addition, concern over impacts on endangered species (*e.g.*, sea birds and turtles) and the possibility of localized overfishing led to tighter regulations for the domestic longline fishery in 1990 (Pooley 1990; Boggs and Ito 1993) and subsequent regulations for longliners under the Pelagic Fishery Management Plan (WPRFMC 1994b).

After a rapid increase in the early 1990s, swordfish catch by the Hawaii-based longline fleet experienced a significant decline (almost 50%) in 1994, and further slight declines in 1995 and 1996. The reasons for these declines are still under investigation. Some preliminary explanations include a decline in catch-per-unit-effort

(CPUE) for swordfish trips in 1994, combined with a subsequent decline in longline effort directed toward swordfish (Ito and Machado 1997). Due to poor swordfish catches in the central Pacific, several swordfish vessels migrated to the U.S. mainland, and many of the remaining swordfish vessels shifted their fishing activities toward targeting tuna. The recent decline in swordfish catch has generated considerable debate whether the swordfish stock can sustain any further increase in longline activities. Examining the productive efficiency of the 1993 fleet can potentially shed some light on possible future changes in longline fishing strategies. Furthermore, the information on longline cost and production structure and its underlying technology can be useful when considering new fishery regulations.

Data and Variables

The data for this paper came primarily from two sources. The first was a cross-sectional survey of longline vessels which was undertaken for a cost-earnings study of the Hawaii-based domestic longline fleet (Hamilton, Curtis, and Travis 1996). Of the 122 longline vessels operating in 1993, 101 vessel owners and/or captains were interviewed during May through December of 1994 to collect detailed information on various aspects of the longline fishery, including vessel characteristics, fishing targets, and operating costs. The second source was the 1993 sales and revenue data from the Hawaii Department of Aquatic Resources (HDAR) commercial catch reports, and dealer reports of pounds sold per trip by each vessel. Since inputs (crew size, fuel, gear, and other supplies) were collected as averages of all trips for the entire year, trip level outputs/revenues reported by the sample vessels in 1993 were also averaged to form an estimate of output/revenue variable. Information on trip length (days at sea) was obtained from the National Marine Fisheries Services (NMFS) vessel inventory database, and the average days per trip for 1993 was estimated in the same manner as the output/revenue variable. With the omission of six vessels due to incomplete data, the number of vessels considered in the cost-earnings study was ninety-five. For this study, another four vessels were dropped due to missing information. Thus, ninety-one vessels were analyzed. Some key characteristics of the longline fleet are discussed next, followed by a description of variables used in the estimation of the stochastic production frontier.

The selected vessels showed considerable heterogeneity in terms of size, age, and fishing targets, as well as experience, education level, and ethnicity of fishermen. Vessel size for the sample longline fleet ranged from 46 to 93 feet, with an average length of 69 feet. Similarly, gross registered tons (GRT) for the selected vessels ranged from 10 to 127 GRT, with a sample mean of 95 GRT. The age of the longline vessels varied from 3 to 68 years, with a mean age of 13 years. Of the 91 vessels analyzed, 21 targeted swordfish, 31 targeted tuna, 30 were mixed ("catch whatever you can"), and the remaining 9 vessels varied their target by set, trip, or season.

On average, the tuna vessels were generally smaller (64 feet) and older (21 years) than the others. Interestingly, fishing targets followed an ethnic line, with most tuna vessels owned and operated by Koreans, most varied and mixed vessels owned by Vietnamese, and the majority of swordfish vessels owned by Caucasians (Hamilton, Curtis, and Travis 1996).

All output and input variables used in the production frontier analysis were measured on a per-trip basis as, except for trip days, all data on input variables were collected as per-trip averages. Landings of longline fleets typically feature multiple species, often receiving different prices in the market. Thus, the aggregated quantity of fish landed is not a suitable measure of output for the stochastic production frontier analysis. For this reason, the output variable (Y) is represented in terms of revenue per trip.[3]

Longline fishery production involves multiple inputs, including number of days at sea, crew size, fuel, bait, ice, gear, and other miscellaneous supplies. However, for the purpose of this study, these inputs are aggregated into three categories; namely, trip days, crew size, and other inputs.[4] These are described in table 1, as are a number of relevant vessel-specific and operator-specific variables hypothesized to influence technical efficiency for the longline fleet. Summary statistics of output and input variables, as well as vessel- and operator-specific variables included in the analysis, are presented in table 2.

The Stochastic Frontier Model

Following Zellner, Kmenta, and Drèz (1966), a single-equation translog stochastic production frontier for the Hawaii-based longline fishery is specified as:[5]

$$\ln Y_i = \beta_0 + \sum_{j=1}^{3} \beta_j \ln X_{ji} + \sum_{j=1}^{3} \beta_{jj} (\ln X_{ji})^2 + \sum_{j=1}^{3} \sum_{\substack{k=2 \\ j<2}}^{3} \beta_{jk} \ln X_{ji} \cdot \ln X_{ki} + V_i - U_i \qquad (1)$$

---

[3] As noted by one of the anonymous reviewers, using value instead of quantity as the output variable results in a specified frontier that is not truly a production function. Nevertheless, this has been standard practice in empirical work involving multi-product firms. An alternative would be to estimate profit or cost frontiers. However, there is a limited scope for applying dual frontiers to cross-sectional data because of the lack of variation in prices. Some economists may be concerned with price instability in using prices to aggregate outputs. However, as noted by Squires (1987b), fishermen form their production decisions based on expected relative species prices and prior knowledge subject to available technology, resource availability, and environmental conditions. Thus, changes in relative prices do not affect their fishing strategies. Moreover, relative prices of major species landed by Hawaii's longliners have remained fairly constant in recent years. One limitation of using revenue as an output variable is that such analysis may confound the measures of technical efficiencies with allocative efficiencies; *i.e.,* producer's ability to choose a revenue-maximizing species combination given the prices and technological constraints. However, because of bycatch of incidental species harvested in conjunction with targeted species, it will be difficult to calculate a true measure of allocative efficiency in multi-species fisheries.

[4] Kirkley, Squires, and Strand (1995) do not include other inputs for the assessment of technical efficiency in the mid-Atlantic sea scallop fishery. They assume that these inputs are embodied in days at sea. However, as indicated by a wide variation in other inputs/trip days by fishing target, this assumption does not hold for Hawaii's longline fishery. For instance, on average, other inputs ranged from \$483/day for tuna vessels to \$1,141/day for mixed vessels. Initially, fixed inputs (insurance, depreciation, and dry-dock cost) were also considered but are not included in the final analysis because their output elasticity was insignificant. Similarly, although stock abundance is an important input in fishery production, due to the lack of data, no variable could be included in the analysis to reflect the stock situation in 1993. In the absence of direct observations of fish stocks, CPUE figures are commonly used as indicators of stock abundance. However, because of its dependence on other inputs (crew size, fuel, and gear type) [Squires 1987b; Pascoe and Robinson 1998], CPUE is not suitable to include as an input variable in production function analyses. In practice, a series of dummy variables is used to capture the effect of stock availability in different areas, seasons/months, and years (Campbell and Nicholl 1994; Pascoe and Robinson 1998). However, because of one-period data, we are unable to include such variables in our analysis. Thus, the results presented here are conditional on stock availability and targeting strategies chosen by the sample vessels in 1993. The results for subsequent years may be different, as some of the vessels previously targeting swordfish have shifted effort toward targeting tuna or mixed species.

[5] Although, as noted by Kirkley and Strand (1988), the economic behavior of fishermen is not well established in the literature, this formulation implies that the fishing firms maximize expected profits. Under limited-entry conditions and with no restrictions being imposed on variable inputs, as in Hawaii's longline fishery, it is quite a realistic assumption. Because of the lack of sufficient observations to estimate a separate production frontier for each target group, a single frontier is specified for the vessels involved in the study. The authors are currently investigating the possibility of using longline trip level catch data to estimate a separate frontier for each target. However, the lack of information on other inputs (crew size, fuel, gear, etc.) used on each trip precludes us from using the same model specification as presented in this paper.

Table 1
Description of Input and Vessel- and Operator-Specific Variables

Variables	Description
Input	
Trip days (X_1)	Total trip length (in days), including days spent on travel
Crew size (X_2)	Number of persons on the boat, including the captain
Other input (X_3)	Other variable operating costs ($/trip), including fuel, bait, ice, and other miscellaneous items
Vessel- and operator-specific	
Target dummy: Swordfish (Z_1)	Value 1 if the vessel targeted only swordfish all year, 0 otherwise
Target dummy: Tuna (Z_2)	Value 1 if the vessel targeted only tuna all year, 0 otherwise
Target dummy : Varied (Z_3)	Value 1 if the vessel changed its target by trip, season, or trip, 0 otherwise
Owner-operated dummy (Z_4)	Value 1 if the vessel was owner-operated, 0 otherwise
Experience (Z_5)	Captain's longline fishing experience (years)
Education dummy (Z_6)	Value 1 if the operator had high school or college education, 0 otherwise
Vessel size dummy: Medium (Z_7)	Value 1 if the vessel is medium size (56 to 73 feet), 0 otherwise
Vessel size dummy: Large (Z_8)	Value 1 if the vessel is large size (≥ 74 feet), 0 otherwise
Vessel age (Z_9)	Age of vessel as of 1993 (years)

where subscript i refers to the ith vessel in the sample; ln represents the natural logarithm; Y represents output; and Xs are input variables, defined in the previous section; βs are parameters to be estimated; V_i is assumed to be an independently and identically distributed N(0, σ_v^2) random error, independent of U_i; and U_i is a nonnegative random variable, associated with technical inefficiency in production, which is assumed to be independently and identically distributed and truncations (at zero) of the normal distribution with mean, μ_i, and variance, $\sigma_u^2(|N(\mu_i, \sigma_u^2)|)$. Maximum likelihood estimation of equation (1) provides the estimators for βs and variance parameters, $\sigma^2 = \sigma_v^2 + \sigma_u^2$ and $\gamma = \sigma_u^2/\sigma^2$.

Following Battese and Coelli (1995), it is further assumed that the technical inefficiency distribution parameter, μ_i, is a function of various operator- and vessel-specific variables hypothesized to influence technical inefficiencies as:[6]

$$\mu_i = \delta_0 + \sum_{j=1}^{9} \delta_j Z_{ji} \tag{2}$$

where Zs are various operator- and vessel-specific variables, defined earlier, and δs are unknown parameters to be estimated.

It should be noted that the above model for technical inefficiencies in equation (2) can only be estimated if the technical inefficiency effects, U_i, are stochastic and have particular distributional properties (Coelli and Battese 1996). Therefore, it is of

[6] This specification assumes a neutral stochastic frontier. Because of an inadequate sample to estimate a large number of parameters involved, the non-neutral frontier model (Huang and Liu 1994) is not considered.

Table 2
Summary Statistics for Variables Involved in the Stochastic Production Frontier and Technical Inefficiency Models for the Longline Fishery in Hawaii in 1993

Variable	Average	Standard Deviation	Minimum	Maximum
No. of trips	10.7	3.6	3.0	17.0
Output ($/trip)	49,654.7	28,239.2	12,275.0	128,072.0
Inputs				
Trip days (days/trip)	20.3	8.4	7.0	39.0
Crew size (no. of persons)	5.4	0.8	3.0	7.0
Other input ($/trip)	17,516.0	10,752.0	4,689.0	38,830.0
Vessel- and owner-specific variables				
Target dummy: Swordfish (0 or 1)	0.23	0.42	0	1
Target dummy: Tuna (0 or 1)	0.34	0.48	0	1
Target dummy: Varied (0 or 1)	0.10	0.30	0	1
Owner-operated dummy (0 or 1)	0.56	0.50	0	1
Experience (years)	9.8	6.8	1	30
Education dummy (0 or 1)	0.74	0.44	0	1
Vessel size dummy: Medium (0 or 1)	0.43	0.50	0	1
Vessel size dummy: Large (0 or 1)	0.36	0.48	0	1
Vessel age (years)	12.8	11.8	3	68

Note: Figures for number of trips and output and input variables are the 1993 averages for 91 vessels involved in the study.

interest to test the null hypotheses that the technical inefficiency effects are absent, $\gamma = \delta_0 = \delta_1 = \ldots = \delta_9 = 0$; technical inefficiency effects are nonstochastic, $\gamma = 0$; and vessel-specific factors do not influence the technical inefficiencies, $\delta_1 = \ldots = \delta_9 = 0$. Under $\gamma = 0$, the stochastic frontier model reduces to a traditional average response function in which the explanatory variables in the technical inefficiency model are included in the production function. These null hypotheses can be tested using the generalized likelihood-ratio statistic, λ, given by:[7]

$$\lambda = 2[\ln\{L(H_0)\} - \ln\{L(H_1)\}] \tag{3}$$

where $L(H_0)$ and $L(H_1)$ denote the values of likelihood function under the null (H_0) and alternative (H_1) hypotheses, respectively.

Given the specifications of the stochastic production frontier model in equations (1) and (2), the technical efficiency index for the ith vessel in the sample (TE_i), defined as the ratio of observed output to the corresponding frontier output is given by:

$$TE_i = \exp(-U_i). \tag{4}$$

The prediction of technical efficiencies is based on the conditional expectation of expression, equation (4), given the values of $V_i - U_i$ evaluated at the maximum

[7] If the given null hypothesis is true, λ is approximately Chi-square distributed or mixed Chi-square distributed when the null hypothesis involves $\gamma = 0$ (see Coelli 1995b).

likelihood estimates of the parameters of the stochastic frontier model (Battese and Coelli 1988). The frontier production for the ith vessel can be computed as its actual production divided by its technical efficiency estimate.

Since the coefficients of the translog stochastic production frontier, equation (1), do not have straightforward interpretation, the elasticity of output with respect to the kth input variable, ε_k, evaluated at the mean values of relevant data points can be derived as:

$$\varepsilon_k = \frac{\partial \ln Y}{\partial \ln X_k} = \beta_k + 2\beta_{kk} \ln \bar{X}_k + \sum_{j \neq k} \beta_{kj} \ln \bar{X}_{ji} \tag{5}$$

where $\bar{X}_S$ are the means of input variables used in the production frontier. The elasticity, ε_k, measures the responsiveness of output to a 1% change in the kth input. The measure for returns to scale, *RTS*, representing the percentage change in output due to a proportional change in the use of all inputs, is estimated as the sum of output elasticities for all inputs. If this estimate is greater than, equal to, or less than one, we have increasing, constant, or decreasing returns to scale, respectively. Imposing the restriction that the sum of output elasticities of all inputs be equal to 1, one can formally test the assumption of constant returns to scale.[8]

Finally, marginal product of kth input at mean values of output and relevant input variables can be computed as:[9]

$$\frac{\partial Y}{\partial X_k} = \varepsilon_k \cdot \frac{\bar{Y}}{\bar{X}_k}. \tag{6}$$

Empirical Results

The parameters for the stochastic production frontier model, equation (1), and those for the technical inefficiency model, equation (2), are estimated simultaneously using the maximum-likelihood estimation (MLE) program, Frontier 4.1 (Coelli 1994). These results are presented in table 3. Given the lack of direct interpretation of parameters in the translog production frontier, the parameter estimates of the stochastic production frontier, equation (1), will be summarized and explained later in terms of output elasticities with respect to various inputs.

Tests of Hypotheses

Generalized likelihood-ratio tests of various null hypotheses involving restrictions on the variance parameter, γ, in the stochastic production frontier and the δ-coefficients in the technical inefficiency model are presented in table 4. Both first and second null hypotheses, that technical inefficiency effects are not present and that inefficiency effects are not stochastic, are rejected. Thus, the

[8] The constant returns to scale assumption in the translog stochastic production frontier, equation (1), imposes a number of linear restrictions in the parameters as follows: $\beta_1 + \beta_2 + \beta_3 = 1$, $2\beta_{11} + \beta_{12} + \beta_{13} = 0$, $\beta_{12} + 2\beta_{22} + \beta_{23} = 0$, $\beta_{13} + \beta_{23} + 2\beta_{33} = 0$ (for mathematical details, see Boisvert 1982).

[9] The marginal product estimated here is, in fact, the value of marginal product (VMP) since the output variable in the production frontier is measured in value instead of quantity.

Table 3
Parameter Estimates of Stochastic Production Frontier and Technical Inefficiency Models

	Coefficient	Asymptotic T-ratio
Stochastic production frontier		
Constant	25.47**	25.81
ln (trip days)	−1.10	−1.14
ln (crew size)	−6.60**	−6.23
ln (other input)	−2.19**	−5.64
ln (trip days) x ln (trip days)	−0.42	−1.18
ln (crew size) x ln (crew size)	−2.93**	−3.00
ln (other input) x ln (other input)	−0.34**	−4.29
ln (trip days) x ln (crew size)	−4.70**	−5.15
ln (trip days) x ln (other input)	1.25**	3.91
ln (crew size) x ln (other input)	3.21**	7.44
Technical inefficiency model		
Constant	0.63	1.17
Target dummy: Swordfish (0 or 1)	0.43	1.50
Target dummy: Tuna (0 or 1)	−0.08	−0.10
Target dummy: Varied (0 or 1)	0.53	1.30
Owner-operated dummy (0 or 1)	−0.36*	−1.87
Experience (years)	−0.07**	−3.24
Education dummy (0 or 1)	−0.18	−0.93
Vessel size: Medium (0 or 1)	−0.20	−0.56
Vessel size: Large (0 or 1)	−0.29	−0.74
Vessel age (years)	0.01	1.13
Variance parameter		
σ^2	0.11**	3.39
γ	0.68**	5.75
Ln (likelihood)	−0.11	–

Notes: * statistically significant at the 0.10 level. ** statistically significant at the 0.01 level.

traditional average (OLS) function is not an adequate representation for the analysis of longline vessels in this study. This is also confirmed by the estimated value of the variance parameter, γ, which is statistically different from zero.

The third null hypothesis, that the intercept and all the coefficients associated with various vessel- and operator-specific variables in the technical inefficiency model are zero (that the technical inefficiency effects have a traditional half-normal distribution with zero mean), is rejected. The less restrictive fourth null hypothesis, that all the parameters of the technical inefficiency model except the intercept are zero (that the technical inefficiency effects have the same truncated-normal distribution with mean equal to δ_0), is also rejected. Given the specifications of the stochastic production frontier model, defined by equations (1) and (2), likelihood-ratio tests indicate that the technical inefficiency effects are significant in explaining the variation in productive performance of the Hawaii-based longline vessels. The fifth null hypothesis of constant returns to scale for the longline fishery is rejected by the data. Finally, the hypothesis that type of species targeted has no effect on technical efficiency of longline vessels is also rejected at the 0.10 level of significance.

Technical Efficiencies

The estimated technical efficiencies for the Hawaii-based longline vessels range from 0.29 to 0.97, with a mean efficiency level of 0.84. The frequency distribution of the estimated technical efficiencies is depicted in figure 1. The majority of vessels (42%) has a technical efficiency index of 0.9 or above, followed by those with efficiency indices of 0.8 to 0.9 (34%). Thus, more than 75% of the sample vessels have a technical efficiency index of 0.8 or higher, suggesting that, in 1993, a large proportion of the vessels operated close to the efficient frontier. However, substantial inefficiencies prevail among the remaining 25% of the vessels involved in this study. The mean technical efficiency for the longline fishery in Hawaii is somewhat higher than 0.75 for the mid-Atlantic sea scallop fishery (Kirkley, Squires, and Strand 1995).

Table 4
Generalized-likelihood Ratio Tests of Hypotheses for Parameters of the Stochastic Production Frontier and Technical Inefficiency Models for the Longline Fishery in Hawaii

Null Hypothesis	Log-likelihood Value	Test Statistic (λ)
H_0: $\gamma = \delta_0 = \delta_1 = \ldots = \delta_9 = 0$	−17.82	35.43**
H_0: $\gamma = 0$	−7.01	13.81**
H_0: $\delta_0 = \delta_1 = \ldots = \delta_9 = 0$	−14.24	28.27**
H_0: $\delta_1 = \ldots = \delta_9 = 0$	−11.91	23.61**
H_0: $\sum_{j=1}^{3} \varepsilon_i = 1$	−6.38	12.54**
H_0: $\delta_1 = \delta_2 = \delta_3 = 0$	−3.60	6.98*

Notes: * statistically significant at the 0.10 level. ** statistically significant at the 0.01 level. The correct critical values for the first and second hypotheses involving $\gamma = 0$ are obtained from table 1 of Kodde and Palm (1986, p. 1246), with degrees of freedom equal to 11 and 2, respectively.

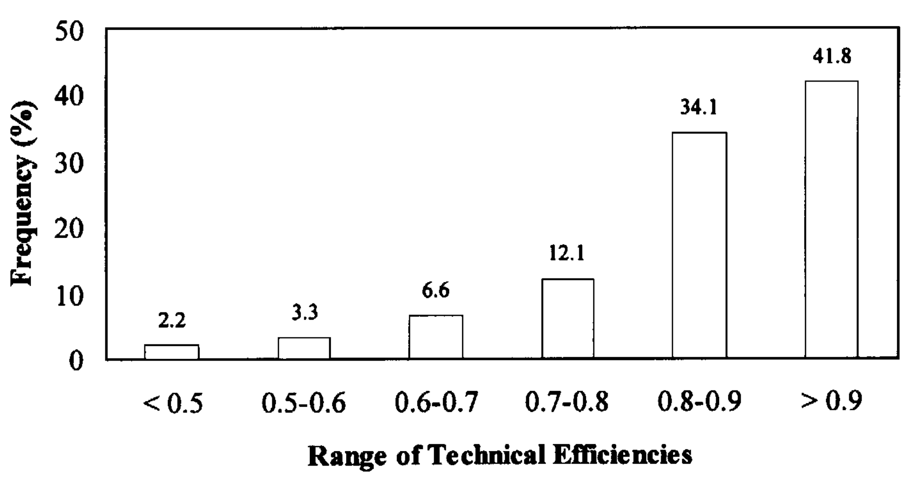

Figure 1. Frequency Distribution of Technical Efficiencies for the Longline Fishery in Hawaii

Factors Affecting Technical Inefficiencies

The results of generalized likelihood-ratio tests reveal that the joint effect of vessel- and operator-specific variables on technical inefficiencies is highly significant. However, as shown in table 3, the individual effects of several of these variables are statistically insignificant. Based on asymptotic t-ratios, none of the coefficients associated with target dummies have a significant effect on technical efficiency. However, according to the likelihood-ratio test, the net effect of target dummies on technical efficiency is found to be significant at the 0.10 level, with mixed and tuna vessels being technically more efficient than varied and swordfish vessels.

The mean technical efficiencies for mixed, tuna, swordfish, and varied vessels are 0.86, 0.89, 0.80, and 0.69, respectively. The differences in technical efficiency should be interpreted carefully. In view of varying conditions facing the fishery, it is hard to draw any firm conclusions regarding the performance of vessels targeting different species based on results for a single year. Although the varied vessels performed poorly in 1993, they may have a long-run advantage over specialized vessels because of their greater ability to shift targeting strategies. However, because of the cost associated with the design of flexible technology, varied vessels are likely to be technically less efficient in the short run. A lower technical efficiency for swordfish vessels than tuna or mixed vessels could be attributed to longer travel time involved for swordfish trips than for tuna or mixed trips. The travel time for swordfish trips is increasing every year, which may be one of the reasons why swordfish vessels have now shifted toward tuna or mixed species.

Owner-operated vessels tend to be more efficient than those operated by hired captains. As expected, both operator fishing experience and educational attainment have a positive influence on technical efficiency, but the effect of education is insignificant, indicating that experience is more important for vessel performance than the education level of the fishermen. Although not significant, vessel size has a positive influence, and vessel age has a negative influence on the technical efficiency of the longline fleet.

Elasticities and Returns to Scale

The estimates of output elasticities evaluated at means of relevant data points and defined by equation (5) are presented in table 5. As expected, the estimated values of output elasticities for all inputs are positive, suggesting that the estimated translog frontier production function is a well-behaved production technology. Furthermore, all elasticity estimates are significantly different from zero at the 0.01

Table 5
Output Elasticities for Longline Fishery Production in Hawaii

With Respect To:	Elasticity	Standard Error
Trip days	0.71*	0.15
Crew size	0.84*	0.32
Other input ($)	0.32*	0.12

Note: * statistically significant at the 0.01 level.

Table 6
Marginal Product of Inputs and Average and Marginal Crew Shares for the Longline Fishery in Hawaii ($/trip)

	Trip Days	Crew Size			Other Inputs
	Marginal Product	Marginal Product	Marginal Crew Share*	Average Crew Share*	Marginal Product
Mixed	2,023	7,436	1,906	1,744	0.81
Swordfish	1,821	12,730	2,957	2,605	0.86
Tuna	1,433	4,992	1,849	1,882	1.35
Varied	1,236	5,396	1,996	2,001	0.88
All	1,736	7,741	2,146	2,008	0.90

Note: * Crew shares denote the earnings per crew member, excluding captain and owner shares.

level of significance. Crew size is found to have the highest elasticity (0.84), followed by trip days (0.71) and other inputs (0.32).

To our knowledge, there exists few studies examining output elasticities in commercial fisheries. Although the authors did not present the estimates of output elasticities for the mid-Atlantic sea scallop fishery (Kirkley, Squires, and Strand 1995), based on their results we estimated elasticities of days at sea and crew size, in their case, to be 1.25 and 0.48, respectively. These values are quite different from our study. The returns to scale for Hawaii-based longline vessels, computed as the sum of output elasticities for all inputs, is estimated to be 1.87. Thus, based on 1993 data, longline fishery production can be characterized by increasing returns to scale. This is also confirmed by rejection of the constant returns to scale hypothesis (table 4). The output elasticities estimated for the mid-Atlantic sea scallop fishery also indicate the presence of increasing returns to scale.

Table 6 provides estimates of the marginal contribution of each input to gross earnings by target, derived from equation (6). Overall, fishermen could increase their per-trip gross earnings by more than $1,700 by adding a fishing day. Similarly, by adding a crew member, they could increase their per-trip gross earnings by more than $7,700. Of this, approximately 50% goes to the owner of the vessel, 15% to the captain, and the remaining 35% is shared among other crew members. The addition of an extra crew member could increase per-trip earnings of each crew member (excluding the captain) by about $140 (table 6). Except for tuna vessels, the marginal gain from increasing other inputs is not large enough to cover the actual expenses involved, indicating the super-optimal (over) use of these inputs.

The results show substantial variation in marginal productivities of inputs among different target groups. For example, mixed vessels may benefit most by fishing an extra day, but low marginal productivity of other inputs suggests shorter trips, as longer trips are associated with higher levels of these inputs. Comparing marginal productivity of crew size with average earnings received by each crew member, swordfish vessels may benefit most by increasing crew size. Among other target groups, mixed vessels could also benefit slightly by expanding crew size, while varied and tuna vessels are probably at or above optimal crew size already. Only tuna vessels are found to be highly efficient in using the other inputs.

Table 7
Average Technical Efficiency, Input Use, and Revenue by Target in 1993

	Mixed	Swordfish	Tuna	Varied
Number of vessels analyzed	30	21	31	9
Average number of trips	10.7	7.7	13.0	11.2
Technical efficiency	0.86	0.80	0.89	0.89
Inputs				
Trip days (days/trip)	18.8	32.1	13.8	19.8
Crew size (no. of people)	6.0	5.4	4.7	5.3
Other inputs ($/trip)	21,250	30,434	6,589	12,566
Revenue				
Actual revenue ($/trip)	53,721	82,386	27,958	34,463
Frontier revenue ($/trip)	61,870	100,790	31,195	47,775
Difference (%)	15.2	22.3	11.6	38.6

Implications

Given the stock availability and fishing practices of the sample vessels in 1993, results indicate that the majority of mixed and tuna vessels operate close to the efficient frontier, while there still exists potential for improving performance among varied and swordfish vessels. On average, the sample vessels could have increased their 1993 per-trip gross earnings by about 19% by operating at full technical efficiency.[10] Table 7 shows the mean levels of actual and frontier revenues, as well as average input levels by target. Based on these results, varied vessels could, on average, increase their gross earnings by 39%, swordfish vessels by approximately 22%, mixed vessels by 15%, and tuna vessels by 12% if operated at full technical efficiency. If these results were extrapolated for the entire longline fleet in Hawaii, the 1993 total annual gross earnings at full efficiency would have been nearly $12 million higher than actual total earnings. Due to their large size, capacity to take longer trips, and hold more catch, swordfish vessels could capture more than two-fifths of these increased earnings at full technical efficiency, followed by mixed vessels. Because of the decline in longline effort toward swordfish, the share of swordfish vessels in total efficiency gains would be smaller after 1993, but it would still be the largest.

The model for technical inefficiency effects provides some helpful clues to improve performance of the longline fleet. For instance, the results indicate

[10] Although the output is measured in value, increased revenue at a higher level of technical efficiency has to come mainly from increases in landings, as fishermen have little control over prices they get. There may exist potential for increasing revenue without increasing the total quantities of fish harvested through an increase in allocative efficiency; *i.e.*, increasing the effort toward targeting high-value instead of low-value species. Either way, increases in efficiency will contribute to a decline in stocks. Despite a decline in swordfish catch in last 3–4 years, there is no evidence that increased longline activities have led to this decline. In fact, the longline landings of tuna and mixed species, especially sharks, have increased as vessels previously targeting swordfish have shifted toward tuna and mixed species. It is still not clear whether the recent decline in swordfish catches by Hawaii-based longliners is due to a decline in swordfish abundance or due to the decline in longline effort toward swordfish.

that, holding everything else constant, varied vessels could benefit by changing their targeting strategies in the short-run, but as mentioned previously, the application of varying technology can be advantageous in the long-term. Similarly, vessel owners may increase the rate of return by operating the vessel by themselves or by using more experienced captains. If the current trend of using newer and larger vessels continues, and everything else remains the same, vessel efficiency of the longline fleet is expected to improve over time.

The analysis of marginal productivities of inputs also provides some useful information for the longliners, although they might have changed over the past 3–4 years. Except for tuna vessels, smaller marginal benefits of inputs other than their actual expenses, indicate that fishermen will not gain by increasing the levels of these inputs. For the same reason, they will also not benefit by prolonging fishing trips, as this increases the levels of operating inputs. The results also indicate that swordfish vessels and, to some extent, mixed vessels could benefit by increasing their crew size.

Conclusions

This paper provides an assessment of technical efficiency for a sample of Hawaii-based domestic longline vessels based on their 1993 catch performance and cost data. Average per-trip inputs and revenues, as well as vessel- and operator-specific information are analyzed by estimating a translog stochastic production frontier, including a model for technical efficiency effects. Besides technical efficiency, output elasticities and marginal products of trip days, crew size and other inputs, and returns to scale are also examined.

The results reveal that technical inefficiency effects are significant in explaining the level and variation in per-trip vessel revenues. The mean technical efficiency for the sample longliners is estimated to be 84%. Various vessel- and operator-specific factors influence technical efficiency, particularly vessel ownership, experience of fishermen, and the choice of targets. Owner-operated vessels seem to operate more efficiently than those operated by hired captains. Fishing experience has a strong positive effect on technical efficiency. Mixed and tuna vessels tend to be relatively more efficient than varied and swordfish vessels. Results indicate the presence of increasing returns to scale in longline fishery production. The estimates of marginal productivities of inputs suggest that, except for tuna vessels, it is not economical for longliners to extend their trip days or to increase the level of other inputs. Swordfish vessels have the most potential for expanding crew size.

Based on 1993 data, sample vessels, on average, could increase their per-trip gross earnings by 19% if all vessels operate at full technical efficiency. This would amount to an additional $12 million annual revenue for the entire longline fleet.

Because of the use of average per-trip data, we cannot examine the seasonal variation in performance of the longline fleet. Similarly, due to the lack of adequate observations in the sample, the frontier analysis could not be conducted separately for each target group to examine the presence of different production technologies under different targeting strategies. Although the availability of fish stocks can have a significant impact on the level and efficiency of fishery production, this information was not available. Despite the importance of allocative and scale efficiencies, again, due to data constraints, our analysis focused only on technical efficiency. Therefore, further study is recommended to analyze the seasonal effects on efficiency by collecting trip-level production data (including trip days, crew size, and other inputs), to estimate the separate production frontier for each target by increasing the sample size, and to extend the analysis to allocative and scale efficiencies. Finally, due to the migratory nature of pelagic species, collecting direct information on the abundance of fish stocks will continue to be a challenge.

References

Aigner, D., C.A.K. Lovell, and P. Schmidt. 1977. Formulation and Estimation of Stochastic Frontier Production Function Models. *Journal of Econometrics* 6(1):21–37.

Battese, G.E., and T.J. Coelli. 1988. Prediction of Firm-level Technical Efficiencies with a Generalized Frontier Production Function and Panel Data. *Journal of Econometrics* 38(3):387–99.

___. 1995. A Model for Technical Inefficiency Effects in a Stochastic Frontier Production Function for Panel Data. *Empirical Economics* 20:325–32.

Battese, G.E., T.J. Coelli, and T.C. Colby. 1989. Estimation of Frontier Production and Efficiencies of Indian Farms Using Panel Data From ICRISAT's Village Level Studies. *Journal of Quantitative Economics* 5(2):327–48.

Boggs, C.H., and R.Y. Ito. 1993. Hawaii's Pelagic Fisheries. *Marine Fisheries Review* 55(2):69–82.

Boisvert, R.N. 1982. The Translog Production Function: Its Properties, its Several Interpretations and Estimation Problems. *Agricultural Economics Research 82–28*. Cornell University, Ithaca, NY.

Campbell, H.F., and J. Hand. 1997. *Joint Ventures and Technology Transfer: The Solomon Islands Pole-and-Line Fishery. Technical Paper* No. 5, University of Queensland.

Campbell, H.F., and R.B. Nicholl. 1994. Can Purse Seiners Target Yellowfin Tuna? *Land Economics* 70(3):345–54.

Coelli, T.J. 1994. A Guide to FRONTIER Version 4.1: A Computer Program for Stochastic Frontier Production and Cost function Estimation, Department of Econometrics, University of New England, Armidale, Australia.

___. 1995a. Recent Developments in Frontier Modeling and Efficiency Measurement. *Australian Journal of Agricultural Economics* 39(3):219-45.

___. 1995b. A Monte Carlo Analysis of the Stochastic Frontier Production Function. *Journal of Productivity Analysis* 6:247–68.

Coelli, T.J., and G.E. Battese. 1996. Identification of Factors Which Influence the Technical Inefficiency of Indian Farmers. *Australian Journal of Agricultural Economics* 40(2):103–28.

Dollar, R.A. 1994. *Annual Report of the 1993 Western Pacific Longline Fishery*. Administrative Report H-94-06 (August): Honolulu Laboratory, National Marine Fisheries Service.

Dupont, D.P. 1990. Rent Dissipation in Restricted Access Fisheries. *Journal of Environmental Economics and Management* 19(1):26–44.

___. 1991. Testing for Input Substitution in a Regulated Fishery. *American Journal of Agricultural Economics* 73(1):155–64.

Hamilton, M.S., R.E. Curtis, and M.D. Travis. 1996. Cost-Earnings Study of the Hawaii-Based Domestic Longline Fleet. Pelagic Fisheries Research Program, Joint Institute of Marine and Atmospheric Research, University of Hawaii at Manoa.

Huang, C.J., and J.-T. Liu. 1994. Estimation of a Non-neutral Stochastic Frontier Production Function. *Journal of Productivity Analysis* 5:171–80.

Ito, R.Y. 1995. Annual Report of the Hawaii-Based Longline Fishery for 1994. National Marine Fishery Service, Honolulu Laboratory.

Ito, R.Y., and W.A. Machado. 1996. Annual Report of the Hawaii-Based Longline Fishery for 1995. National Marine Fishery Service, Honolulu Laboratory.

___. 1997. Annual Report of the Hawaii-Based Longline Fishery for 1996. National Marine Fishery Service, Honolulu Laboratory.

Kirkley, J.E., D. Squires, and I.E. Strand. 1995. Assessing Technical Efficiency in Commercial Fisheries: The Mid-Atlantic Sea Scallop Fishery. *American Journal of Agricultural Economics* 77(3):686–97.

Kirkley, J.E., and I.E. Strand. 1988. The Technology and Management of Multi-species Fisheries. *Applied Economics* 20(10):1279–92.

Kodde, D.A., and F.C. Palm. 1986. Wald Criteria for Jointly Testing Equality and Inequality Restrictions. *Econometrica* 54(5):1243–48.

Kumbhakar, S.C. 1996. Efficiency Measurement with Multiple Outputs and Multiple Inputs. *Journal of Productivity Analysis* 7:225–55.

Kumbhakar, S.C., S. Ghosh, and T. McGuckin. 1991. A Generalized Production Frontier Approach for Estimating Determinants of Inefficiency in U.S. Dairy Farms. *Journal of Business and Economic Statistics* 9(3):279–86.

Meeusen, W., and J. van den Broeck. 1977. Efficiency Estimation from Cobb-Douglas Production Functions With Composite Error. *International Economic Review* 18(2):435–44.

Pascoe, S., and C. Robinson. 1998. Input Controls, Input Substitution and Profit Maximization in the English Channel Beam Trawl Fishery. *Journal of Agricultural Economics* 49(1):16–33.

Pooley, S.G. 1990. Hawaii Longline Fishing Controversy. *Tuna Newsletter* 97:6–9.

Squires, D. 1987a. Public Regulation and Structure of Production in Multiproduct Industries: An Application to the New England Trawl Industry. *Rand Journal of Economics* 18(2):232–48.

___. 1987b. Fishing Effort: Its Testing, Specification, and Internal Structure in Fisheries Economics and Management. *Journal of Environmental Economics and Management* 14(3):268–82.

WPRFMC (Western Pacific Regional Fishery Management Council). 1995. *Pelagic Fishing Methods in the Pacific.*

___. 1994a. Pelagic Fisheries of the Western Pacific Region 1993 Annual Report. Prepared by the Pelagic Plan Team and Council Staff: Honolulu, Hawaii.

___. 1994b. *Management of U.S. Pacific Pelagic Fisheries: Single Council Designations.*

Zellner, A., J. Kmenta, and J. Drèz. 1966. Specification and Estimation of Cobb-Douglas Production Function Models. *Econometrica* 34(4):785–95.