A Stochastic Production Frontier Model of the Newfoundland Snow Crab Fishery

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Abstract. Since the collapse of the Newfoundland groundfishery in 1992, the snow crab fishery has become Newfoundland's largest fishery, accounting for approximately half the value of total landings. This study uses trip log data to estimate the production frontier and the technical efficiency of this fishery using a Stochastic Frontier Analysis (SFA) methodology. The analysis is based on over 11,000 observations taken over a five-year period. The technical efficiency of the fishery is estimated to be at a level of fifty percent or less.

Keywords: Stochastic Frontier Analysis, technical efficiency, production frontier, Newfoundland snow crab.

1. INTRODUCTION

The collapse of the groundfish fishery in Newfoundland beginning in 1992 is well known (see, for example, Gordon and Munro, 1996; Roy, 1996; Ruitenbeek, 1996; Schrank, 1995). The most recent stock status report on Northern cod by Canadian fisheries scientists has concluded that the stock continues to decline despite the virtually complete closure of the fishery (Fisheries and Oceans Canada, 2002).

Notwithstanding the collapse in groundfish stocks, shellfish catches have more than offset the near-closure of the ground fishery. While total landings in Newfoundland valued $262 million in the year before the cod moratorium was instituted (1991), they had increased to $587 million by 2000. Almost all of this increase was in shellfish, predominantly crab and shrimp.

However, these fisheries are not performing the economic role that cod used to play in the rural economy of Newfoundland. Neither harvesting nor processing of shellfish is as labour-intensive as that of groundfish, and so employment in the industry is still low compared to pre-moratorium levels. Nonetheless, many former cod fishers have been able to use existing and newly issued crab and shrimp licenses to replace the revenues that groundfish previously generated. As a result, landings of snow crab (*Chionecetes opilio*) increased from 16,441 tonnes in 1992 to 69,121 tonnes in 1999. Shrimp landings show a similar increase.

The radical change in the operating circumstances of this relatively homogeneous fishery provides a basis on which the impact of this major expansion on the economic productivity of the fishery can be assessed. Accordingly, this paper utilizes trip log data on crab catches over the period 1993-1997 to estimate a frontier productivity model of the crab fishery. These data are utilized to estimate a technically-efficient production frontier for this fishery, and to estimate measures of the technical efficiency of firms exploiting this fishery. It is clearly of interest to establish whether technical efficiency varies systematically with characteristics of the firm, and an attempt is made to determine whether this is the case.

The Newfoundland snow crab fishery is described in the next section, while the stochastic frontier model is briefly outlined in Section 3. The next three sections present three empirical analyses of the snow crab fishery that are based on the stochastic frontier model. Section 4 estimates the production frontier and the associated technical inefficiencies of the observed data using a cross-section analysis of the trip log data. Section 5 groups the trip data by vessel in order to estimate a panel model of the production frontier; here the technical efficiency of each vessel is assumed to remain stable through the sample. Finally, Section 6 examines the possibility that the technical efficiency of a vessel may be related to certain characteristics. Section 7 concludes the paper.

2. THE NEWFOUNDLAND SNOW CRAB FISHERY

Snow crab are distributed widely over the Northwest Atlantic from Greenland to the Gulf of Maine. Total Allowable Catches are set for three distinct areas off Newfoundland and Labrador, corresponding roughly to the Northeast, South, and West coasts. Only males with carapace length in excess of 95 mm may legally be caught.

The fishery initially began in 1968 in inshore waters as gillnet bycatch. However, within several years a directed trap ("pot") fishery had become established along the northeast coast of the island. As catches declined in these traditional areas, the fishery expanded offshore and to other inshore areas off Newfoundland and Labrador.

Initially the fishery was prosecuted full-time by approximately 50 vessels subject to trap limits. Beginning in 1985, because of the failing inshore groundfish fishery, groundfish enterprises were granted "supplementary" licenses to harvest crab during that part of the fishing season during which cod were no longer available. The number of these supplementary licenses eventually rose to exceed 700, and the original "full-time" licenses are now restricted to offshore waters. Finally, in 1995 "temporary" seasonal permits were granted to enterprises fishing in vessels less than 35 ft.(10.6m.), who had been ineligible to acquire supplementary licenses. By 1997, 2300 such permits had been issued.

The fishery is now managed on the basis of four fleet sectors: full-time (offshore), supplementary larger than 40 gross tons, supplementary less than 40 gross tons (but 35 feet in length or greater), and seasonal permits for vessels less than 35 feet in length. All fleet sectors have designated trap limits, trip limits, fishing areas, and differing seasons. As well, all license and permit holders work under an individual but non-transferable quota.

3. THE PRODUCTION FRONTIER FUNCTION

Broadly speaking, production possibility frontiers are estimated through two distinct approaches. Data Envelopment Analysis (DEA) is a non-parametric method whose main weakness is an inability to allow for stochastic shocks to the frontier[1]. It is arguable that this characteristic of DEA renders it an unsuitable instrument for investigating production frontiers in noisy environments such as fisheries. Stochastic Frontier Analysis (SFA), in contrast, is designed to incorporate stochastic disturbances, but requires strong parametric specifications in its implementation.[2]

Stochastic Frontier Analysis was developed independently by Aigner *et al.* (1977) and Meeusen and van den Broeck (1977), and is based on an econometric specification of a production *frontier*. For example, if a double-log (Cobb-Douglas) specification is adopted, as we shall do, then the production frontier of a group of N firms would be specified as

$$\ln y_i^{\max} = \beta_0 + \Sigma_k \beta_k \ln X_{ki} + v_i \,, \quad i = 1, \ldots, N \tag{1}$$

where y_i is output of the i^{th} firm, the X_{ki} are k factors determining the production frontier, and v_i is a random variable reflecting noise and other stochastic shocks entering into the definition of the frontier — factors such as luck, bad weather, and so on. It is almost universal to specify this random variable as independent normally distributed with zero mean, constant unknown variance σ_v^2, and independent of the X_{ki}.

$$v_i \sim \text{iid } N(0,\sigma_v^2) \,, \quad i = 1, \ldots, N \tag{2}$$

The difference between $\ln y_i^{\max}$ and observed $\ln y_i$ is a (logarithmic) measure of the *technical inefficiency* of firm i, and is modelled as an unobserved non-negative random variable u_i, which is assumed to be distributed independently of v_t and the X_{kt}.

$$u_i = \ln y_i^{\max} - \ln y_i \geq 0 \,, \quad i = 1, \ldots, N \tag{3}$$

In the original formulations of the model, Meeusen and van den Broeck modelled u_i as having an exponential distribution, which has the density function $\theta \exp\{-\theta u\}$, while Aigner *et al.* used the half-normal distribution (a zero-mean normal distribution truncated at zero) as well. These remain the two most common specifications for the distribution of u_i in the SFA literature.

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[1]For a recent survey see Seiford (1996). Recently Cazals *et al.* (2002) have proposed a DEA-type estimator which is more robust to shocks.

[2]Several surveys of Stochastic Frontier Analysis are available, most recently Kumbakhar and Lovell (2000). Recently, Park *et al.* (1998) have developed semiparametric estimators of stochastic frontiers.

Substituting (3) into (1) gives a regression equation

$$\ln y_i = \beta_0 + \Sigma_k \beta_k \ln X_{ki} + v_i - u_i, \quad i = 1, \ldots, N \tag{4}$$

which can be estimated by maximum likelihood once a density function for u_i is specified. Further, estimation of the u_i's provides a measure of the technical efficiency of the firms in the sample.

Technical efficiency in the context of a fishery is generally considered to be an indicator of the capability of the skipper (Kirkley *et al.* 1998). What constitutes 'skipper skill' is not well understood, but navigational ability, knowledge of the ocean, ability to adapt to changing circumstances, and understanding of species behaviour are cited as relevant factors (Squires and Kirkley 1999 survey the current state of understanding about 'skipper skill'). 'Skipper skill' is widely believed to be a highly variable attribute in at least some fisheries, with a small number of 'highliners' often accounting for a major share of landings in the fishery. In modelling such fisheries, it is obviously important to allow and account for technical inefficiency among firms in the fishery.

4. STOCHASTIC FRONTIER ESTIMATION

The model is estimated with trip log data for crab catches off the coast of Newfoundland over the period 1993-1997. We use for the X_{ki} variables defining the production frontier the length of the vessel, engine horsepower, gross tonnage, and number of days fished. We also include dummy variables for each year in the sample, primarily to capture annual differences in resource abundance. Once log entries with missing observations on any of these variables are removed from the sample, we are left with 11,894 observations.

The variables used here are not conventional economic inputs, and no doubt embody the standard capital, labour, energy and materials inputs only imperfectly. On the other hand, it is fairly common for analysis of production in a fishery to be based on variables of this kind because of data limitations; see for example, Kirkley *et al.* (1998). However, one implication should be noted: if the included variables do not fully capture the effects of all factor inputs, and if the use of these omitted factors varies systematically from firm to firm, then the effect of these factors will likely be captured by that portion of the disturbance u_i that we are identifying with technical inefficiency. Therefore, what we are measuring as technical inefficiency could be the effect of differences in the use of these omitted factors — differences that may be entirely appropriate for the firms in question.

Maximum likelihood estimation of equation (4) requires a specification of the distribution of the error components v_i and u_i. The former is universally assumed to be normally distributed, but the latter requires special treatment because it is constrained to be non-negative. As noted above, the two most common specifications are the half-normal distribution and the exponential distribution. Fortunately, these two specifications produce similar estimates of (4) with our data set, and both seem broadly consistent with the data, although the half-normal appears to be a little better fit. Neither of the specifications nest into the other, but the likelihood ratio test proposed by Vuong (1989) is available to test one hypothesis against the other. When testing the half-normal model against the exponential using our data, the test statistic, which is distributed as standard normal under the null hypothesis that the two models are equivalent, has a value of 1.35 (p-value=0.09). Therefore, for a two-tail test at a 20% level of significance, the half-normal distribution can be accepted against the exponential. At a lower level of significance, one cannot discriminate between the two hypotheses given the data.

One point of contention with both specifications is that these density functions are monotone decreasing for $u_i \geq 0$. The implication is that technically efficient data are observed more frequently than less technically efficient data, because the density function specifies how frequently a particular value of u_i, and therefore a particular level of technical inefficiency, is to be observed in the sample. This implication imposes strong requirements on the data that may not be satisfied in fisheries having only a small number of technically efficient 'highliners', as described above.

Both the half-normal and the exponential densities can be generalized to permit this possibility. For example, suppose that u_i is distributed as a normal density with mean μ but truncated at zero, as first proposed by Stevenson (1980), so that

$$u_i \sim \text{iid } N^+(\mu, \sigma_u^2), \quad i = 1, \ldots, N \tag{5}$$

Essentially the half-normal distribution is displaced horizontally by μ, and truncated at the origin so that the requirement that $u_i \geq 0$ remains satisfied. Our estimates of equation (4) based on this truncated-normal model (which are reported in Table 2) do not differ materially from those generated by the half-normal specification, but do enable us to reject statistically the half-normal model that nests into it.[3] Therefore, it appears that the truncated-normal specification has more explanatory power in our sample than the half-normal or exponential distributions, and so will be used in the remainder of this paper.[4]

The results of this cross-section estimation are presented in column 2 of Table 2. The Ordinary Least Squares estimates are also presented for comparison. Except for the constant term, the results do not differ materially from the OLS estimates, but the greater efficiency of the maximum-likelihood estimator is reflected in the generally smaller standard errors associated with these estimates, which are all significant at the five percent level. The most important variable defining the production frontier is the length of the vessel, with a production elasticity a little larger than unity (because the variables are transformed into logarithms, the estimated parameters can be interpreted as elasticities). The importance of vessel length may be a reflection of the fact that on-board storage capacity (and so maximum catch) is closely related to the length of the vessel. Motor horsepower, vessel tonnage, and the length of the trip all have only a modest effect (elasticities around 0.2-0.3) in production capacity. The small effect of the number of days fishing is especially surprising, and may reflect the effect of trip limits. The year dummy variables, with the exception of that pertaining to 1994, show only a small difference from the 1997 datum.

Also reported are estimates of the parameters μ, σ_u^2, and σ_v^2 of the composite error term, along with estimates of the mean and variance of the distribution of the technical efficiency term u_i (because the normal distribution is truncated, the mean and variance of the *truncated* distribution are no longer identical to μ and σ_u^2 respectively, and in fact depend on both parameters).[5] We estimate that most of the composite error can be ascribed to variation is technical inefficiency u_i rather than random variation which is not associated with differences in technical efficiency v_i. Specifically, the variance in the u_i part of the composite error is 0.67, while that of the v_i part is only 0.14. A likelihood-ratio test of the hypothesis that $\mu = \sigma_u^2 = 0$, so that there is no variation in technical efficiency in the sample (and so no skipper effect), decisively rejects the null hypothesis; the value of the test statistic is 1636, which far exceeds the critical value of 5.138 at a five percent level of significance.[6]

Consistent estimation of equation (4) would enable retrieval of a point consistent estimate of the composite error $v_i - u_i$. Separating this estimate into its two components is more difficult. However, Jondrow *et al.* (1982) were able to derive an unbiased estimate of the technical inefficiency component u_i, which is conditional on the value of the composite error which can in turn be estimated by the equation residual. From this estimate, estimates of the technical efficiency of each observation can be derived. A measure of technical efficiency that is consistent with a definition of technical efficiency originally proposed by Farrell (1957) would be the ratio of actual to frontier production y_i / y_i^{max}, which by equations (1) and (4) must equal $\exp(-u_i)$. Battese and Coelli (1988) derived an unbiased estimate of this measure,[7] the summary statistics for which are also reported in Table 2.

These estimates of technical efficiency range from a maximum of 0.92 to a minimum of just above zero, and the mean level is 0.47 (standard deviation=0.24). A histogram (Figure 1(a)) reveals a distribution that is skewed to the

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[3]Specifically, the estimate of μ has a t-statistic of -3.22 (p-value=0.0006), so that the null hypothesis of $\mu = 0$ can be safely rejected. Similarly, a likelihood ratio test of the half-normal against the truncated normal model, which is asymptotically distributed as $\chi^2(1)$, has a value of 22.962 (p-value=10^{-5}).

[4]Note, however, that the estimate of μ is negative, and so the density function of u_i remains monotone decreasing. The reason, as discussed below, is that the distribution of technical efficiencies is strongly skewed to the right (see Figure 1(a)), and this distribution is best captured by a truncated normal with negative μ. While highliner effects are present, these are dominated by the skew in the distribution.

[5]Writing $\lambda=\phi[\mu/\sigma_u]/\Phi[\mu/\sigma_u]$, where ϕ and Φ are the standard normal probability density and cumulative distribution functions respectively, $E[u] = \mu + \sigma_u\lambda$ and $Var[u] = \sigma_u^2 [1 - \lambda(\mu/\sigma_u + \lambda)]$.

[6]The test is implemented using the values of the log-likelihoods of the OLS and Maximum-Likelihood estimates respectively, these two estimates being equivalent under the null hypothesis $\mu = \sigma_u^2 = 0$. Under the null hypothesis, the test statistic is asymptotically distributed as the weighted chi-square variable $0.5\chi^2(1) + 0.5\chi^2(2)$, rather than as a simple $\chi^2(2)$, because the value of σ_u^2 under the null hypothesis is on the boundary of the admissible parameter space, and so a two-sided test is inappropriate. See Gouriéroux *et al.* (1982), Kodde and Palm (1986), and Coelli (1995).

[7]If we write $\varepsilon_i = v_i - u_i$, $\gamma = \sigma_u^2 / (\sigma_u^2 + \sigma_v^2)$, and $\zeta^2 = \gamma\sigma_v^2$ then the technical efficiency of the i^{th} observation can be estimated as

$$E[u_i \mid \varepsilon_i] = [1 - \Phi(\zeta + \gamma\varepsilon_i / \zeta)] \exp(\gamma\varepsilon_i + \zeta^2/2) / [1 - \Phi(\gamma\varepsilon_i / \zeta)]$$

where Φ is the standard normal cumulative probability function. While unbiased by construction, it is not consistent because it does not converge with probability one to the true value of u_i as the sample increases.

right, with a mode at around 0.75 but with only a few observations in excess of around 0.85. These estimates are consistent with the characterization of skipper skill described above, as an attribute that is highly variable and with only a few observations consistent with a high level of technical efficiency. They suggest that on average a fishing trip was conducted at less than 50 percent efficiency — or, looking at it from another perspective, the same catch could have been obtained with half the trips if these had been conducted in a technically efficient manner. Even in comparison to most artisanal industries that have been studied using this method,[8] this is a dismal performance.

5. A PANEL MODEL OF THE STOCHASTIC PRODUCTION FRONTIER

The specification outlined in the previous section permits, for each trip in the sample, a decomposition in the stochastic error between technical inefficiency $-u_i$ and other random factors v_i. However, it can be argued that technical inefficiency is a characteristic of the firm, and should be roughly the same for all trips taken by a particular enterprise. In fact, an analysis of variance of the trip technical efficiency measures estimated in the previous section shows that when these technical efficiency estimates are grouped by vessel, the mean square variation between groups is 0.421, as compared with a mean square variation within groups of only 0.033. Therefore, the measured variation in technical efficiency from trip to trip by the same vessel is minuscule in comparison to the differences between vessels.[9] This finding supports the interpretation of technical efficiency as being largely a function of 'skipper skill.'

If the assumption that technical inefficiency u_i is the same for all observations on a particular vessel is valid (we present some evidence in the next section that it may not be), increased efficiency can be achieved by reestimating the production frontier as a panel subject to this restriction, an approach first implemented by Pitt and Lee (1981). The regression equation then becomes

$$\begin{gathered} \ln y_{it} = \beta_0 + \Sigma_k \beta_k \ln X_{kit} + v_{it} - u_i, \\ v_{it} \sim \text{iid } N(0,\sigma_v^2) \end{gathered} \qquad i = 1, \ldots, N;\ t = 1,\ldots,T_i \qquad (6)$$

so that all variables except technical inefficiency u_i are subject to two subscripts: i for each vessel and t for each observation (trip) on the vessel. Our database consists of 11,894 observations on 848 vessels.

Applying the truncated normal specification (5) for u_i in equation (6), as in Kumbhakar (1987) and Battese and Coelli (1988), produces the estimates reported in the third column of Table 2 and labelled as the Panel Data Model. These results can be profitably compared with those of the Cross-Section Model, also reported in Table 2. First consider the estimates of the stochastic parameters μ, σ_u^2, and σ_v^2. The panel specification implies that the value of u_i, is the same for all observations on firm i. While in the Cross-Section Model the random variable u_i captures both between-group and within-group variation in technical efficiency, in the Panel Model only between-group variation is captured, leaving within-group variation to be captured by other elements of the model, including the random variable v_{it}. It can be expected then that u_i becomes less important relative to v_{it} in the Panel Model. This is exactly what happens; the variance of u_i is cut in half, while that of v_{it} increases threefold. Notwithstanding the reduced importance of the technical inefficiency term, we continue to reject the null hypothesis that $\mu = \sigma_u^2 = 0$, which would have implied that technical efficiency effects are absent from the data.[10]

In general terms, the parameters of the production frontier do not change in a major way, but the differences are not negligible. The finding of considerable technical inefficiency remains, the technical efficiency measures averaging 0.5. The histogram (see Figure 1(b)) of the technical efficiency measures (now based on that of the vessel rather than the

[8]Some representative examples are Australian diary farmers (Battese and Coelli 1988), with technical efficiency measures in the range 0.63-0.77; Indian paddy farmers (Battese and Coelli 1992), in the range 0.82-0.94; Japanese rice farmers (Ajibefun *et al.* 1996), 0.74; mid-Atlantic scallop dredgers (Kirkley *et al.* 1998), 0.75; and Hawaii longline fishers (Sharma and Leung 1998), 0.69-0.89. An exception is Kuperan *et al.* (2001), who measured the average technical efficiency of a Malaysian trawl fishery at 0.49. For an earlier survey, see Bravo-Ureta and Pinheiro (1993).

[9]The value of the F statistic, with 847 and 11893 degrees of freedom, is 12.7, clearly rejecting the null hypothesis that all measures of technical efficiency are drawn from the same population. At the same time, since there are many more trips than there are vessels, the total amount of variation in technical efficiency is about equally split between between-group and within-group variability.

[10]A likelihood-ratio test, implementing the log-likelihoods of the Ordinary Least Squares and Panel Maximum Likelihood estimates respectively, gives a test statistic of 4898, while the critical value at a five percent level of significance is 5.138. The rejection is even stronger than in the Cross-Section Model, because in the Panel Model the maintained hypothesis specifies firm-specific values for the u_i, which can be estimated more precisely since they are based on observations from several trips instead of just one.

trip) is more symmetrical than in the previous section, with a model value around 0.42. Only a small number of vessels (14 out of 848) have technical efficiency in excess of 0.9. However, the characteristics of these vessels are broadly representative of the sample, perhaps with a tendency for gross tonnage to be *below* average. Two of the 14 are temporary seasonal permit holders.

6. A MODEL OF TECHNICAL EFFICIENCY

The consistency of both the Cross-Section and Panel Model estimates depend on the assumption that the disturbance term v_{it} - u_i is uncorrelated with the X_k variables. If this is untrue, some of the disturbance will be incorrectly ascribed to the X_k variables. The model of Zellner *et al.* (1966) is often cited (e.g., by Kirkley *et al.* 1998) to justify the argument that if the disturbance term is unknown to the firm at the time that the input decision is made, this decision will be made on the basis of *expected* profit maximization, and so will be uncorrelated with the disturbance term. While this argument has some compelling logic where the random component v_{it} of the disturbance term is concerned, its relevance to the technical inefficiency term u_i is less apparent. It would appear to depend on whether the technical efficiency of a firm affects its decisions about factor inputs.

Some evidence on this point can be obtained from using a Hausman test comparing the fixed-effect and random-effects estimators of the panel model (see, for example, Greene 2000, pp. 576-577). If the null hypothesis that u_i is uncorrelated with the X_k is true, there would be no significant difference between the two estimates. In fact, the Hausman test, which is asymptotically distributed as $\chi^2(8)$, has a value of 40.7 (*p*-value=0.000002), suggesting that the null hypothesis is false and that the technical efficiency effects are related to at least some of the explanatory variables in the production frontier equation.

Under these conditions, the fixed effect model is often recommended as the estimator of choice in the panel model literature. However, there is a growing consensus (see however Gong and Sickles 1989) that the fixed-effects estimator does not perform well in stochastic frontier models. As Greene (2001) puts it, "In the context of the stochastic frontier model, there is a particular ambiguity about the use of the fixed effects model. The term picks up all firm specific heterogeneity, whether it is in the production frontier or in the inefficiency term, and lumps it all into the single 'effect'." (See also Simar 1992). With our data, most of the variation (except for the days fished variable) is predominantly between groups rather than within groups, and so the fixed-effect estimator (sometimes called the within-groups estimator) fails to utilize most of the information in this data set.

Another approach is to specify a model of technical efficiency that depends on a set of variables which may include some or all of the X_k variables defining the production frontier. In this way, the effects of a set of variables on the production frontier can be separated from the effect of a (possibly overlapping) set of variables on the placement of a particular observation inside the frontier. The easiest way of doing this, while retaining use of the truncated normal specification, is to specify one of the parameters of the distribution as a linear function of several variables; for example, as in Battese and Coelli (1995),

$$u_{it} \sim \text{iid } N^{+}(\mu_{it}, \sigma_u^2) \qquad i = 1, \ldots, N; \; t = 1, \ldots, T_i \qquad (7)$$
$$\mu_{it} = \delta_0 + \Sigma_j \, \delta_j \ln Z_{jit}$$

In such a model, the Z variables affect technical efficiency e^{-u} in a log-linear way, and so the δ_j can be interpreted as the *negative* of the elasticity of technical efficiency with respect to Z_j.

Such a model would serve two useful purposes. First, it enables us to separate the effects of production variables on the production frontier from the effect of these variables on technical efficiency, and thereby ensure that the parameter estimates are consistent. We can do that by including in the Z variables those production variables that enter the production frontier which we think may also affect technical efficiency. Second, such a model would also enable us to shed some light on whether recent regulatory changes in this fishery, and in particularly the issuance of temporary seasonal permits to smaller vessels, have implications for technical efficiency in this fishery.[11]

We include in the Z variables all variables (except for the year dummies) that enter into the production frontier. The resultant model as specified by equations (6) and (7) was estimated. The estimates of the technical efficiency effects are presented in Table 1, while those of the production frontier are presented in column 4 of Table 2 and labelled the Technical Efficiency Model.

The technical efficiency model is statistically significant, with the null hypothesis that $\delta_1 = \delta_2 = \delta_3 = \delta_4 = 0$ rejected

[11] Such a model can also potentially shed light on factors entering into 'skipper skill', as in Kirkley *at al.* 1998 and Kuperan *et al.* 2001. Unfortunately, trip log data do not contain much information on the characteristics of the skipper to be useful for this purpose.

by a likelihood-ratio test with a value of 232.4, as contrasted with a critical value for the $\chi^2(4)$ distribution of 9.49 at the five percent level of significance. Of the individual effects, length of vessel, perhaps surprisingly, is not statistically significant, so that the idea that small vessels are associated with technical inefficiency receives no support from the data. However, both tonnage and days per fishing trip are associated with technical efficiency, while horsepower shows a modest but statistically significant *negative* association with technical efficiency. One implication is that trip limits can reduce technical efficiency if they lead to trips that are artificially shortened because of the imposition of the limit.

Allowing for these technical efficiency effects modifies the estimates of the production frontier somewhat. Length of vessel remains important, and vessel horsepower has some effect as well. But the effect of vessel tonnage is no longer statistically significant, and the length of the fishing trip becomes even less important (although still statistically significant). The year dummies become less important, and two become statistically insignificant. The estimates of technical efficiency at the firm level are even lower than before; technical efficiency is estimated to average 0.41 in our sample.[12]

7. CONCLUSION

While the three models estimated in this paper differ in detail, they all highlight the importance of allowing explicitly for technical efficiency in modelling productivity in this fishery. The consistent finding of an average level of technical efficiency in this fishery that is at or below fifty percent is a matter that should be of considerable concern to those responsible for developing licensing policy in this and similar fisheries.

[12]These results are consistent with the finding of Wang and Schmidt (2002), based on Monte Carlo evidence, that if the dependency of inefficiency on the Z variables is ignored, the estimated firm-level efficiencies are spuriously underdispersed. Since the technical inefficiency random variable u_{it} is now a function of the Z_{it}, and the parameter μ is no longer fixed, the mean and variance of this random variable is now conditional on the value of the Z_{it},; the values of μ and of the moments of u that are reported in Table 2 are those applicable to Z_{it},'s equal to the sample mean.

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REFERENCES

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

Ajibefun, I.A., G.E. Battese, and R. Kada. Technical Efficiency and Technological Change in the Japanese Rice Industry: a Stochastic Frontier Analysis, Centre for Efficiency and Productivity Analysis (CEPA) Working Paper 9/96. University of New England, 1996.

Battese, G.E., and T.J. Coelli. Prediction of Firm-Level Technical Efficiencies with a Generalized Frontier Production Function, *Journal of Econometrics* 38, 387-399, 1988.

Battese, G.E., and T.J. Coelli. Frontier Production Functions, Technical Efficiency and Panel Data: with Application to Paddy Farmers in India, *Journal of Productivity Analysis* 3:1/2, 153-169, 1992.

Battese, G.E., and T.J. Coelli. A Model for Technical Inefficiency Effects in a Stochastic Frontier Production Function for Panel Data, *Empirical Economics* 20, 325-332, 1995.

Bravo-Ureta, B., amd A. Pinheiro. Efficiency Analysis of Developing Country Agriculture: a Review of the Frontier Function Literature, *Agricultural and Resource Economics Review* 22(1), 88-101, 1993.

Cazals, C., J.-P. Florens, and L. Simar. Nonparametric frontier estimation: a robust approach, *Journal of Econometrics* 106, 1-25, 2002.

Coelli, T.J. A computer program for frontier production function estimation. *Economics Letters* 39, 29-32, 1992.

Coelli, T. Estimators and Hypothesis Tests for a Stochastic Frontier Function: A Monte Carlo Analysis, *Journal of Productivity Analysis* 6:4, 247-268, 1995.

Farrell, M.J. The Measurement of Productive Efficiency, *Journal of the Royal Statistical Society, Series A*, CXX, Part 3, 253-290, 1957.

Fisheries and Oceans Canada. Northern (2J+3KL) cod Stock Status Update. DFO Science Stock Status Report A2-01(2002).

Gong, B.-H., and R.C. Sickles. Finite Sample Evidence on the Performance of Stochastic Frontier Models Ising Panel Data, *Journal of Productivity Analysis* 1, 229-261, 1989.

Gordon, D.and G. Munro, eds. *Fisheries and Uncertainty: A Precautionary Approach to Resource Management*, University of Calgary Press, 1996.

Gouriéroux, C., A. Holly, and A. Monfort. Likelihood Ratio Test, Wald Test, and Kuhn-Tucker Test in Linear Models with Inequality Constraints on the Regression Parameters, *Econometrica* 50(1), 63-80, 1982

Greene, W.H. *Econometric Analysis*. Fourth Edition. Prentice Hall, 2000.

Greene, W. H. New Developments in the Estimation of Stochastic Frontier Models with Panel Data. 7th European Workshop on Efficiency and Productivity analysis, University of Oviedo, Spain, September 2001.

Jondrow, J., C.A.K. Lovell, I.S. Materov, and P. Schmidt. On Estimation of Technical Inefficiency in the Stochastic Frontier Production Function Model, *Journal of Econometrics* 19:2/3, 233-238, 1982.

Kodde, D.A., and F.C. Palm. Wald criteria for jointly testing equality and inequality restrictions, *Econometrica* 54(5), 1243-1248, 1986.

Kirkley, J., D. Squires, and I.E. Strand. Characterizing Managerial Skill and Technical Efficiency in a Fishery, *Journal of Productivity Analysis* 9, 145-160, 1998.

Kumbhakar, S. C. The Specification of Technical and Allocative Inefficiency in Stochastic Production and Profit Frontiers, *Journal of Econometrics* 34, 335-348, 1987.

Kumbhakar, S. C., and C.A. Knox Lovell. *Stochastic Frontier Analysis.* Cambridge University Press, 2002.

Kuperan V., K., I.H. Omar, Y. Jeon, J. Kirkley, D. Squires, and I. Susilowati, "Fishing Skill in Developing Country Fisheries: the Kedah, Malaysia Trawl Fishery," *Marine Resource Economics* 16(4), 293-314, 2001.

Meeusen, W., and J. van den Broeck. Efficiency Estimation from Cobb-Douglas Production Functions with Composed Error, *International Economic Review* 18:2, 435-444, 1977.

Park, B.U., R.C. Sickles, and L. Simar. Stochastic Panel Frontiers: a Semiparametric Approach, *Journal of Econometrics* 84:2, 273-301, 1998.

Pitt, M., and L.F. Lee. The Measurement and Sources of Technical Inefficiency in the Indonesian Weaving Industry, *Journal of Development Economics* 9, 43-64, 1981.

Roy, N. The Atlantic Canada Resource Management Catastrophe, *Canadian Journal of Economics*, XXIX, S139-S144, 1996.

Ruitenbeek, H.J. The great Canadian fishery collapse: some policy lessons, *Ecological Economics* 19, 103-106, 1996.

Schrank, W.E. Extended Fisheries Jurisdiction: origins of the current crisis in Atlantic Canada's fisheries, *Marine Policy* 19(4), 285-199, 1995.

Seiford, L.M. Data Envelopment Analysis: The Evolution of the State of the Art (1978-1995), *Journal of Productivity Analysis* 7, 99-137, 1996.

Sharma, K.R. and P.S. Leung. Technical Efficiency of Hawaii's Longline Fishery, *Marine Resource Economics* 13(4), 259-274, 1998.

Simar, L. Estimating efficiencies from frontier models with panel data: a comparison of parametric, non-parametric and semi-parametric methods with bootstrapping, *Journal of Productivity Analysis* 3, 1171-203, 1992.

Squires, D., and J. Kirkley. Skipper skill and panel data in fishing industries, *Canadian Journal of fisheries and Aquatic Sciences* 56, 2011-2018, 1999.

Stevenson, Rodney E. Likelihood Functions for Generalized Stochastic Frontier Estimation, *Journal of Econometrics* 13:1, 57-66, 1980.

Vuong, Q. H. Likelihood Ratio Tests for Model Selection and Non-Nested Hypotheses, *Econometrica* 57(2), 307-333, 1989.

Wang, H.-J., and P. Schmidt. One-Step and Two-Step Estimation of the Effects of Exogenous Variables on Technical Efficiency Levels, *Journal of Productivity Analysis* 18, 129-144, 2002.

Zellner, A., J. Kmenta, and J. Drèze. Specification and Estimation of Cobb-Douglas Production Function Models, *Econometrica* 34(4), 784-796, 1966.