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The Curse of Uncertainty in a Fishery*

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ABSTRACT

The performance heterogeneity in a fishery is analysed using an unbalanced panel data set for sealing. We analyse the relative importance of factors under the fishermen's control such as effort and different forms of uncertainty. We address the fishermen's possibility of forming well defined expectations by analysing the development in performance over time. The time series properties of the industry as a whole is also compared with the properties of the individual boats. The results indicate that the industry has a mean reverting technology, but that the individual boats are exposed to considerably more stochastics. In particular, a majority of the vessels demonstrate a non-stationary performance development; stochastics due to structural uncertainty about the size and the distribution of the stock dominates the performance development. This implies that regulation devices as ITQs no longer necessarily solves the efficiency problem.

1. INTRODUCTION

The introduction of ITQs appears to have solved the efficiency problem in fisheries. The idea is that by generating a market for quotas, an efficient allocation will be reached by having the fishermen bid according to their derived demand functions for quotas. However, the derived quota demand is conditioned on the fishermen's knowledge of the technology and the expectations of the level of outputs. If the expectation-formation on output is dominated by stochastics to the extent that the fishermen are unable to form well-defined expectations about output, the derived demand functions for quotas do not reflect the marginal value of quotas for the individual vessels. In this case the standard ITQs do not solve the efficiency problem. In this paper we address the fishermen's possibility of forming well-defined expectations by analyzing the development in performance over time.

Heterogeneity in performance between firms is a common feature in many industries and it has also been a topic in the fisheries economic literature (Wilen, 1979; 1985; Harper, 1989; Opaluch & Segerson, 1989; Weaver, 1989; Heaps, 1994). Factors endogenous to the firm such as the level and mix of inputs and outputs, and factors exogenous such as barriers to entry may explain the difference in performance. In fisheries, also a stochastic environment, the uncertainty of the size and distribution of the fish stocks, may be important in explaining the heterogeneity in performance within and between years or seasons (Salvanes and Steen, 1994).

Uncertainty in fisheries is commonly classified into three categories; *randomness, parameter uncertainty* and *structural uncertainty* (Walters and Hilborn, 1978, Charles, 1997). Randomness refers to processes were uncertainty is well defined in the sense that it has a well defined and generally known probability distribution.[1] Randomness is therefore possible to handle within the standard expectation framework. Parameter uncertainty, can also to a certain extent be reduced by research and learning over time. However, the third category «structural uncertainty» is a severe problem in fisheries management.[2] Structural uncertainty

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[1] In the finance literature randomness has its counterpart in the concept of *risk,* where an uncertain event occurs with a probability, but where the size of the event has a known probability distribution. Thus, agents can buy insurance to reduce uncertainty due to risk.

[2] Structural uncertainty has its counterparts in the finance literature in relation to market or price uncertainty. This uncertainty is closely related to the efficient market hypothesis. Samuelson (1965) showed that in efficient markets, the price reflects all available information, implying that prices follow a random walk over time, and are unpredictable. When investigating other aspects of stock prices, e.g. persistence in performance, it is therefore no accident that it is the returns that are analysed (e.g. Waring, 1996). The returns are the first difference of the price, and are stationary if the price follows a random walk.

refers to our ignorance about the nature of the fishery system as such; unknown stock recruitment relationships, unknown stock characteristics, spatial heterogeneity etc. Under structural uncertainty, there is no defined probability distribution for the possible outcomes, and the processes will be non-stationary. A non-stationary process has a changing mean, an infinite variance, and the autocorrelation coefficients will be near $|1|$ even for very long lags. Any innovation in such a process will leave a permanent effect on the variable; the process has an infinite memory and you obtain no mean-revertion. There is no deterministic effects that make these boats' performance levels move towards their historical means - as it is with uncertainty due to randomness. The fishermen's performance is dominated by the effects from structural uncertainty.

Because of structural uncertainty about the size and the distribution of the stock, luck might be important in determining performance. If so, the variation in performance would be dominated by some stochastic element caused by good or bad luck. Salvanes and Steen (1994) showed that if variation in performance is characterized by a non-stationary process, it is reasonable to believe that the stochastic element, i.e., luck, dominates in determining performance. We will refer to processes where structural uncertainty dominates as *"non-stationary stochastics*", as opposed to stationary stochastic processes where one also will have random elements (i.e. randomness and parameter uncertainty), but where the processes have well defined distributions with constant means and variances. The latter processes will be referred to as *"stationary stochastics*". By testing for stationarity we establish which of the boats have a performance development that is dominated by structural uncertainty and therefore are unable to form well-defined expectations of future performance.

The boats that have a stationary development and therefore a mean-reverting technology do not have this expectation problem. However, also in these cases the degree of uncertainty the fishermen face are of interest. A high degree of uncertainty will lead to a high noise to signal ratio, and it will be difficult to derive demand functions for quota with much precision. We decompose the efficiency score of these boats using so-called beta-coefficients. This enable us to measure each variable's importance in determining performance. In particular we compare the importance of factors that the fishermen can control with the importance of stationary stochastics; randomness and parameter uncertainty. Finally, we discuss the policy implications of the two forms of stochastics.

We analyze the Norwegian sealing off Newfoundland. A so-called "thick" production frontier based on estimated revenue functions for this industry will be used. Two revenue models are estimated, one for the total population, and one for the most efficient firms; the highest revenue quartile in terms of efficiency. An efficiency score measure (ES) calculated for each vessel for every year is established by comparing all vessels in the industry to the "thick" frontier. If the relative performance of vessels between seasons is predictable and well defined in terms of stochastics, we expect the variation in the individual vessel's ES over time to be systematic, i.e. to follow some pattern.

The issue of how different shocks affecting the level of the data series may affect the conclusions from unit root test has increasingly received more attention (Perron, 1989). In particular, it is often shown that data series which appear non-stationary become stationary when important shocks are controlled for. In our case, this issue might be important, as factors such as weather and stock size certainly may affect the sealers' productivity. Also changes in the level of factors that the sealers can control, such as crew size and the length of season may affect their productivity. Hence, controlling for these factors may be important when testing for stationarity. In addition to using standard Dickey-Fuller t-tests we will undertake three extensions. First we will extend the standard Dickey-Fuller test to account also for deterministic factors that might be important in the determination of performance. In our case, we have information about the crew size, the number of days at sea, the weather conditions and the stock size. If these deterministic factors are important we will anticipate non-stationary stochastics as measured by the unit-root tests to be less pronounced. Second, to ensure robustness against small-sample bias of our results we use Monte Carlo experiments to simulate exact distributions of the test statistics. Finally, we analyse the industry's development in performance to see whether the industry as a whole has different properties from the individual boats.

The paper is organized as follows. Section 2 presents the economic model of sealing, and how the revenue frontier is constructed. Section 3 presents the unit root test and the Monte Carlo simulations. In section 4 the decomposing of efficiency is undertaken, and in section 5 we discuss the policy implications. Section 6 concludes the paper.

2. THE ECONOMIC MODEL OF SEALING

This section presents the economic model and the estimation results that are used to test for performance heterogeneity. In the first subsection we define the short-run revenue function which is used to represent the technology and a hedonic input function which is used as a fixed composite effort function. In subsection two we describe the procedure for estimating a "thick" revenue frontier and compute the efficiency scores of the different boats that will be used in section 3. In subsection three we present the empirical results from the revenue estimations. Further details on the industry and the economic specification can be found in Salvanes & Steen.

2.1 A REVENUE MODEL WITH FIXED EFFECTS

The seal harvest can be described as a multiple output industry with two different products, young seals and adult seals. The harvest ratio of young to adult seals has changed over the period, due to changes in the demand for seal skins from young and adult seals. Since the Greenland seals are school animals and the seals were found and hunted on ice floes, it was possible for the fishermen to choose between young and adult seals when harvesting. Further, the prices of seals are determined in a spot market when landed, but information given by industry people clearly indicates that the fishermen formed specific price expectations before the season. Since each vessel had only a small fraction of the total landing of seals it is reasonable to consider them as pricetakers. Hence it is expected that the fishermen in order to maximize revenue, chose the optimal ratio of the two outputs. Effort variables such as boat characteristics and the length of the hunting season are typically fixed when the vessels have left the harbor, i.e. effort may be described as variable *ex ante* and given *ex post* (Johansen, 1972, Bjørndal, Conrad and Salvanes, 1993).[3] Further, every boat undertakes only one trip per season. Thus, the hold capacity (boat size) will restrict total take, unless the ice floes disappeared and the hunting season was over before the limit was reached or the vessel got stuck in the ice. We therefore choose a short-run revenue model where the fishing firm takes relative output prices, stock size and weather conditions as given, and is concerned with maximizing the value of production given its input endowment (Kirkley and Strand, 1988, and Squires and Kirkley, 1991).

The input endowment is characterized by a quasi-fixed input function and it will be represented by a composite input, the effort function, which will be estimated as a hedonic effort function. This is motivated by the fact that our main concern is the total revenue effect of effort, not the influence of the different effort variables on revenue. As shown by Salvanes & Steen, the main advantage of using a hedonic aggregate function as opposed to using calculated effort indices

[3] When referring to *ex post* throughout the paper we mean after the vessel has left the harbor and the season is started.

is that no prior restrictions on the relationship between the different effort variables are made. By substituting the effort function into the revenue function when estimating, the model itself weights the relationship between the effort variables.

The data have been collected from the Norwegian government archives and the Customs Service for each Norwegian sealing vessel which participated in the Newfoundland seal harvest from 1937 to 1984.[4] Specific information includes the number of days at sea, crew size, boat size (register tons), harvest and output prices of young and adult seals (in Norwegian kroner). Due to severe depletion of the seal stock, quotas on the seal harvest were introduced in 1971. The quota implies that the fishermen no longer are able to choose freely how much of each type to harvest. Thus, the rationale for our revenue model is no longer valid. Hence, we choose to omit observations after 1970.

To account for possible time trends and different weather conditions we include a linear time trend and two weather dummies in our revenue function. Further, we use boat dummies to account for firm-specific effects.[5] The revenue function is then defined as:

$$R\left[P_Y, P_O, t, W, B, \phi\ (X)\right] \tag{1}$$

where P_Y is the price of young seals, P_O is the price of adult seals, t is a linear time trend, W is a matrix of weather dummies, B is a matrix of boat dummies, and $\phi\ (X) = E$ is the hedonic effort function to be defined. As the data set contains the whole population, a fixed effect model is used (Hsiao, 1986; Greene, 1993). For a more comprehensive discussion of estimation issues and tests of technology characteristics as non-jointness-in-inputs, and input-output separability, see Salvanes & Steen.

The revenue function in (1) is estimated as a translog function:

$$\begin{aligned} \ln R &= \alpha_0 + \beta_Y \ln P_Y + \beta_O \ln P_O + \beta_E \ln E \\ &+ \tfrac{1}{2}\beta_{YY}(\ln P_Y)^2 + \tfrac{1}{2}\beta_{OO}(\ln P_O)^2 + \tfrac{1}{2}\beta_{EE}(\ln E)^2 \\ &+ \beta_{YE} \ln P_Y \ln E + \beta_{OE} \ln P_O \ln E + \beta_{YO} \ln P_Y \ln P_O \\ &+ \psi\ t + \gamma\ W + B + \varepsilon_R , \end{aligned} \tag{2}$$

[4] A total of 40 different vessels participated in this period, and we have 349 observations. Hence, most of the vessels only participated a few seasons.

where all exogenous variables are normalized to the point of approximation of the function, i.e. the sample mean. Symmetry of the Hessian matrix is imposed when formulating (2), $\beta_{YO} = \beta_{OY}$, and ε_R is a random error term. The revenue share of equation (3) is derived using the generalized Hotelling's lemma:

$$(3) \qquad S_i = \beta_i + \beta_{iY} \ln P_Y + \beta_{iO} \ln P_O + \beta_{iE} \ln E + \varepsilon_{S_i} \qquad i = Y, O$$

where S_i is the revenue share represented by the *i*th seal type, and ε_{S_i} are random error terms. To ensure efficient estimation, the revenue shares were estimated jointly with the revenue function. One of the revenue shares is deleted to overcome the problem of singularity in the covariance matrix. Efficient parameter estimates are obtained by iterating the Zellner's Seemingly Unrelated Regression (ZSUR) method. Prior to estimation, we impose homogeneity of degree one in prices by the following parameter restrictions:

$$(4) \qquad \sum_i \beta_i = 1, \ \sum_j \beta_{ij} = 0, \ \sum_i \beta_{ij} = 0, \ \sum_i \beta_{iE} = 0, \quad i = Y, O.$$

In order to estimate the restricted revenue function, an effort function to represent the fixed inputs has to be constructed. An effort function is in the fisheries literature defined as the composite input needed in order to harvest a particular amount of a species for a given stock. The effort function will then be the neoclassical part in the fisheries harvest function; $H = f\left[\phi\ (X), S\right]$, where f(·) is the harvest function with H as level of production, $\phi\ (X)$ is the effort function, X is a vector of input factors representing effort, and S is the biomass. The effort function cannot be estimated separately from the harvest function as we do not know the left-hand side of $E = \phi\ (X)$. This is solved in Salvanes & Steen in the case of revenue functions by representing the effort by a hedonic effort function that is substituted into the revenue function. We will use the same approach here and construct an effort aggregate and estimate it via the revenue model. The vessel size (N) will be used as the main physical input measure which is common in the empirical fisheries literature when constructing effort functions. In addition, the effects of other variables, the crew size (C) and

[5] It is common to also include a variable measuring the stock in the revenue function. We do have stock observations for the period from 1952 to 1970. However, since several of the analyzed boats fished in the

the total number of hunting days (D) are introduced, when constructing a Cobb-Douglas form hedonic effort function:

(5) $\ln E = \beta_N \ln N + \beta_C \ln C + \beta_D \ln D + \varepsilon_E$

2.2 HOW TO MEASURE EFFICIENCY - ESTIMATION OF A "THICK" REVENUE FRONTIER

Our estimated revenue frontier is based on a parametric technique developed by Berger and Humphrey (1991a,b) where they estimate so-called "thick" frontiers.[6] In this study frontiers are estimated by ranking observations according to cost/output ratios and using the observations of the most efficient quartile. The corresponding method for estimating revenue functions is to normalize revenue against effort. For the same reason we choose to use the composite effort function in (5) to represent effort; we normalize revenue against predicted effort, which is calculated by using the empirical estimated effort function (5) inserted for the actual crew and vessel size, and days at sea (the coefficient for $ß_N$, $ß_C$ and $ß_D$ used could be found in Table 1, Model 1). After having ranked the observations by the revenue/effort-ratio, we choose the upper quartile (the vessels with highest revenue relative to predicted effort, *n*=69) when estimating the "thick" revenue frontier. In estimating the frontier we use the same revenue model as presented earlier (equations 2, 3 and 5). The efficiency scores (ES) of every boat observation (*n*=274) are then computed as the ratio between actual revenue (AR) and the predicted revenue (PR) by the technology representing the revenue frontier (parameters presented in Table 1, Model 2), given the actual use of effort and the actual output prices, thus; ES=AR/PR. Because we are computing scores relative to a "thick" frontier, a number of boats will have efficiency scores above unity.

2.3. EMPIRICAL REVENUE RESULTS

In this subsection we present the results of our two revenue models in which the Zellner iteration procedure needed four iterations to converge. Model 1 is estimated using all

period previous to 1952, an inclusion of the stock variable would reduce our sample considerably.

[6] The main advantage of the parametric econometric approach is that it allows random components, e.g. differences in luck and measurement errors, when estimating the frontier. This is opposed to, for example, the DEA technique, which does not allow *any* random elements - all variations are treated as reflecting inefficiencies (Berger and Humphrey, 1991a). See Salvanes & Steen (1994) for a discussion of the frontier literature.

observations (n=274), and Model 2 is estimated over the upper revenue/effort quartile (n=69). The main parameters in the two revenue models are presented in Table 1.[7] The econometric package Shazam was used (White, 1978).

The statistical properties of both models are good. The overall explanatory power are 0.73 and 0.75, respectively. Boat-specific factors such as management and technological factors not accounted for in the effort variables seem to be important in explaining revenue in both models. Testing the null hypothesis of all boat dummies jointly equal to zero, we reject the null on all interesting significance levels using the log-of-likelihood test.[8]

Table 1. Estimated coefficients from the revenue models.

	Model 1		**Model 2**	
Parameter	*Coefficient*	*Standard error*	*Coefficient*	*Standard Error*
α_0	15.171 *	0.461	16.515 *	0.619
β_Y	0.398 *	0.019	0.552 *	0.028
β_O	0.602 *	0.019	0.448 *	0.028
β_C	0.901 **	0.409	-2.360 *	0.669
β_N	0.127	0.356	2.503 *	0.505
β_D	-0.264 **	0.153	0.071	0.363
β_{YY}	-0.077 **	0.038	0.306 *	0.054
β_{OO}	-0.077 **	0.038	0.306 *	0.054
β_{CC}	1.198	3.231	14.896 **	7.688
β_{NN}	-1.597	1.595	-4.662 **	2.434
β_{DD}	0.726 ***	0.501	-8.294 *	3.014
β_{DC}	-0.015	1.259	-12.366 *	4.118
β_{DN}	0.016	0.734	9.240 *	2.553
β_{CN}	1.049	1.423	-0.325	3.567
β_{YC}	0.329 *	0.135	0.603 **	0.266
β_{YD}	-0.032	0.083	-0.154	0.176
β_{YN}	-0.121 ***	0.078	-0.169	0.188
β_{OC}	-0.329 *	0.135	-0.603 **	0.266
β_{OD}	0.032	0.083	0.154	0.176
β_{ON}	0.121 ***	0.078	0.169	0.188
β_{YO}	0.077 **	0.038	-0.306 *	0.054
Ψ	-1.369 *	0.416	-2.591 *	0.558
γ_B	-0.492 *	0.07	-0.359 *	0.115
γ_G	0.243 *	0.075	0.163 *	0.06
R^2	0.732		0.754	

[7] The estimated coefficients representing the firm-specific effects are not presented, but are available upon request to the authors

[8] The l.o.l. test statistics for model 1 and 2 were 195.88 and 52.25 with 38 and 22 degrees of freedom, respectively.

l.o.l	-226.307	28.821

All first-order parameters in model 1 except $ß_D$, have the expected signs, which indicates that an increase in prices and effort variables has a positive influence on revenue.[9] However, the first-order effort coefficients have different signs and significance levels in the different models. The price coefficients ($ß_Y$ and $ß_O$) are significantly positive at a 5% significance level in both models. The coefficients representing the weather dummies (γ_B and γ_G) are significant at a 5% level, and both have the expected signs; in other words, bad weather has a negative influence on revenue and good weather has a positive influence on revenue. Both of the revenue models have, as expected due to the decrease in stock (Bjørndal, Conrad & Salvanes, 1993) a pronounced negative time trend (ψ) in revenue over the observation period; a result which also is significant at a 5% level. Homogeneity, separability, non-jointness, signs and significance of the input compensated own- and cross-price elasticities and the second-order conditions, are discussed in Salvanes & Steen (1994).. Since we are focusing on the importance of uncertainty we omit this discussion here.

Utilizing the results from our two revenue models we now calculate efficiency scores for all the boats. Furthermore, we calculate an aggregated performance index for the industry. These indices are used to analyze performance heterogeneity in the two next sections.

3 TESTING FOR THE IMPORTANCE OF NON-STATIONARY STOCHASTICS

Whether the harvest technology is dominated by the structural uncertainty about the size and the distribution of the stock can be tested by exploiting the time series properties of the efficiency scores of the different boats using unit-root tests. In the most extreme case - the *non-stationary-stochastics* situation - we will have that if the stochastic environment are sufficiently important, the efficiency scores will be non-stationary, while if the deterministic

[9]The variable harvesting days is relatively unstable as an explanatory variable. One way to interpret this is that the variable both includes days actually hunting and searching. According to industry people the split between days searching and days hunting varies considerably among vessels and between seasons caused by for instance weather conditions. Unfortunately we do not have data to split the variable into hunting and searching days.

factors represented by the technology together with stationary stochastics due to randomness determines the harvest, the efficiency score will be stationary (mean reverting).

Using Dickey-Fuller tests Salvanes & Steen (1994) found the majority of the boats development in performance to be non-stationary and therefore dominated by a stochastic trend (Dickey and Fuller, 1979; 1981). In addition to replicating their results using standard Dickey-Fuller t-tests we will undertake three extensions.[10] First we will extend the standard Dickey-Fuller test to account also for deterministic factors that might be important in the determination of performance. Several authors (Perron, 1989; Goodwin and Schroeder, 1991) have noted that if deterministic factors are not controlled for in the Dickey-Fuller test, the test may give misleading information. In our case, we have information about the crew size, the number of days at sea, the weather conditions and the stock size. All these factors may explain some of the movements in the efficiency scores. If these deterministic factors are important we will anticipate non-stationary stochastics as measured by the unit-root tests to be less pronounced than what Salvanes & Steen found. Second, to ensure robustness against small-sample bias of our results we use Monte Carlo experiments to simulate exact distributions of the test statistics. Finally, we analyse the industry's development in performance to see whether the industry as a whole has different properties from the individual boats.

3.1 UNIT-ROOT TESTS

We perform two sets of Dickey-Fuller tests, one in which no deterministic factors except a constant term is included, and one in which crew size, number of days at sea, weather conditions and stock size are included as regressors.

The equation used for the Dickey-Fuller test is

(6) $$ES_t = \alpha_0 + \delta ES_{t-1} + u_t$$

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[10] While Salvanes and Steen use the *F*-test version of the test, we will here use the *t*-test version of the test, as this test has become the common form of the test used in the literature when employing Dickey-Fuller tests. Furthermore, using the t-test we are able to use more precise test statistics generated for each sample size (MacKinnon, 1991)

where ES_t is the data series that is tested for stationarity, in our case the efficiency score, and u_t is a normally distributed error term. The null hypothesis of a unit root corresponds to a value of unity at the parameter δ, while the alternative of stationarity is that the parameter is less than unity. As the test statistics have a non standard distribution under the null, which is skewed to the left, ordinary inference theory does not apply. However, the distribution has been tabulated by Fuller (1976) for some sample sizes and MacKinnon (1991) provide a formula to compute the critical values for all sample sizes. An alternative formulation of the test which is more commonly used is

(7) $$\Delta ES_t = \alpha_0 + \rho ES_{t-1} + u_t$$

Here, Δ is the first difference operator. The null hypothesis is that the parameter ρ equals zero, while the alternative of stationarity is that the parameter is less than zero.[11]

When the crew size, number of days at sea, stock size and weather conditions are included as regressors, the equation used for the Dickey-Fuller test is;

(8) $$\mathrm{ES}_t = \alpha_0 + \alpha_1 \mathrm{C} + \alpha_2 \mathrm{D} + \alpha_3 \mathrm{S} + \alpha_4 \mathrm{W} + \delta \mathrm{ES}_{t-1} + \mathrm{u}_t,$$

and may alternatively be written;

(9) $$\Delta \mathrm{ES}_t = \alpha_0 + \alpha_1 \mathrm{C} + \alpha_2 \mathrm{D} + \alpha_3 \mathrm{S} + \alpha_4 \mathrm{W} + \rho \mathrm{ES}_{t-1} + \mathrm{u}_t.$$

Where S is stock size and W is a combination of the two weather dummies in the revenue function.[12] The data on stock size is taken from Bjørndal, Conrad and Salvanes (1992).[13] Again, it is respectively the parameters δ and ρ which are of interest. The critical value in the unit root tests is dependent on the number of deterministic variables in the test, as more

[11] There also exists a version of the test where a deterministic trend is included. However, as none of the efficiency scores reveal any trend and the results reported in Salvanes and Steen (1994) are the same independent of whether a trend is included or not, we do not include a trend here.

[12] When there was bad weather (γ_B equals 1), W takes the value -1, and when it was good weather (γ_G equals 1), W takes the value 1. Otherwise W takes the value 0. The main reason for introducing this new weather dummy is that it reduce the number of parameters to be estimated, saving degrees of freedom. Furthermore, in the next section we can decompose the total weather effect by doing this aggregation.

deterministic variables make the distribution more skewed. Hence, in our extended Dickey-Fuller tests, where crew, days, weather and stock are included the tests, the tabulated critical values for Dickey-Fuller tests cannot be used. Moreover, since the extra variables differs among the boats, the critical value may differ between the boats regardless of the sample size, e.g., the boat B14, which fished 14 periods starting in the year 1952, is exposed to different weather and stock conditions from the boat B13, which also fished for 14 seasons but started in the year 1957.

To obtain correct critical values, the distributions of the test statistics were simulated in Monte Carlo experiments. For each boat, 5,000 replications were performed. The data series in the experiments were generated using equation (8) but restricting δ to equal 1:

$$(10) \qquad \mathrm{ES_t} = \hat{\alpha}_0 + \hat{\alpha}_1\mathrm{C} + \hat{\alpha}_2\mathrm{D} + \hat{\alpha}_3\mathrm{S} + \hat{\alpha}_4\mathrm{W} + \mathrm{ES_{t-1}} + \mathrm{u_t},$$

where we by drawing an error term from the normal distribution, $u_t \sim N(0,5)$, together with the actual crew, days, weather and stock observations for each boat generated 5000 data series. The numbers used to represent the parameters; $\hat{\alpha}_0, \hat{\alpha}_1, \hat{\alpha}_2, \hat{\alpha}_3$ and $\hat{\alpha}_4$, where found by carrying out auxiliary regressions of (8) for each boat using the actual data, but allowing δ to be free. The correct critical values are reported in Table 3, together with the test statistics. As expected, all critical values are higher than in tables that tabulate the critical values from Dickey-Fuller tests, as the introduction of more variables in the Dickey-Fuller test makes the distribution more skewed to the left (Perron, 1989).

Parallel Monte Carlo experiments were carried out also for the aggregated industry series.

3.2 UNIT-ROOT RESULTS

The results from the standard Dickey-Fuller test in equation (7) are reported in Table 2. The tests conclude that at a 5% significance level, the efficiency score is non-stationary for six vessels, while the efficiency score is stationary for five vessels. This indicates that for the majority of the vessels, non-stationary stochastics dominates the harvest technology when evaluating the vessels performance. However, note that for the industry the efficiency score is

[13] We have of course also data on the boats' hold capacity, but it does not make sense to include this variable when analyzing the individual boats since it is fixed on this level and thus would enter only as a second

stationary. Hence, it seems like the non-stationary stochastics cancels out when aggregating over vessels.

The three vessels that were found to be stationary in Salvanes and Steen; B13, B21 and B23, were also found here to be stationary. However, the t-test and the critical values of the test statistics used here suggest that also the vessels B14 and B16 have a mean reverting technology.

TABLE 2 HERE (Missing)

Turning to the results from the extended Dickey-Fuller test (equation (8)) reported in Table 3 we read several things. The magnitude of the simulated test statistics is higher than in the standard Dickey-Fuller test. This highlights the importance of finding the correct critical values for the tests. In fact, if the ordinary critical values for the Dickey-Fuller test had been used, one would conclude that all the efficiency scores were stationary when including the deterministic variables. With the correct critical values, the test indicates that four vessels have a non-stationary efficiency score. Furthermore, except for the vessel B16, the test statistics increase in absolute value for all vessels. Hence, the inclusion of crew, days, weather and stock in the Dickey-Fuller test seems to be of importance as the non-stationary stochastics dominates the harvesting technology for fewer vessels when these factors are controlled for.

TABLE 3 HERE (Missing)

When testing the efficiency score for the industry, we performed two tests. In addition to the test in (8) where the same factors as for the individual vessels were included, we also performed a test where we include the average vessel size. In both tests, the efficiency scores are clearly stationary. Hence, also these extended tests do therefore indicate that the non-stationary stochastics cancels out over the industry.

Before we elaborate on the policy issues, we will concentrate on the stationary series to see whether we can decompose and thereby understand the performance development furthermore.

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constant term. However, in the aggregate industry analyses we also include the N variable.

4. DECOMPOSING THE EFFICIENCY SCORES

In this section we focus on the six boats that reveal a stationary development in efficiency scores, and the industry as a whole. These boats have a mean-reverting technology, and can therefore form well defined expectations. However, also in these cases the degree of uncertainty the fishermen face are of interest. A high degree of uncertainty will lead to a high noise to signal ratio, and it will be difficult to derive demand functions for quota with much precision. By decomposing the efficiency scores into factors as crew size, the length of the fishing season, stock, weather conditions and stationary stochastics we will measure the individual factors relative importance in determining efficiency.[14]

4.1 HOW TO DECOMPOSE THE EFFICIENCY SCORES

The coefficients of a regression model are affected by the units in which the variables are measured. For this reason a comparison of the magnitudes of individual regression coefficients is not very revealing. To overcome this problem one can transform the regression coefficients to obtain so-called "beta-coefficients". These standardized coefficients can then be compared (Kmenta, 1986). The idea is to measure all variables in terms of their respective sample standard deviation. The resulting coefficients measure the change in the dependent variable corresponding to a unit change in the respective explanatory variable, holding other explanatory variables constant, and measuring all changes in standard deviation units: $\hat{\beta}_{\mathrm{k}}^{*} = \hat{\beta}_{\mathrm{k}}\left(\mathrm{SE}(\mathrm{x}_{\mathrm{k}})/\mathrm{SE}(\mathrm{y})\right)$, where $\hat{\beta}_{\mathrm{k}}$ is the usual OLS coefficient and $\mathrm{SE}(\cdot)$ is the standard deviation. The main weakness with these coefficients is that they cannot be interpreted alone in a multiple model containing several explanatory variables. However, as long as we are interested in the relative importance of each variable these "beta-coefficients" provide us with a tool to measure the relative importance of each explanatory variable.

We start by estimating (8) but now excluding the lagged efficiency score; $\delta \mathrm{ES}_{t-1}$ from the regression, since we are only analyzing the stationary efficiency scores;

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[14] We denote both randomness and parameter uncertainty as stationary stochastics here. We are not modeling which part of the stationary stochastics that can be attributed to randomness and which part that can be attributed to parameter uncertainty.

(11) $$ES_t = \alpha_0 + \alpha_1 C + \alpha_2 D + \alpha_3 S + \alpha_4 W + u_t .$$

Then we compute the "beta-coefficients":

(12) $$\hat{\beta}^*_k = \hat{\alpha}_k \left(SE(x_k)/SE(y) \right)$$ where k=C,D,S,W.

Now we have a measure of the relative importance of crew size, the length of the fishing season, stock and weather conditions. However, the coefficients refer to what the model in (11) explain, i.e., there would still be some unexplained variation represented by the error term. We attribute this unexplained variation as *stationary stochastics*. Hence, by using the coefficients from (12) and interpreting these in terms of percentages shares of R^2 from the estimation of (11) we can decompose the efficiency score into five components, crew size, the length of the fishing season, stock, weather conditions and stationary stochastics.

4.2 THE DECOMPOSING RESULTS

Equation (11) is estimated for the six boats that reveal a stationary development in efficiency scores, and the industry as a whole. Then the "beta-coefficients" in (12) are calculated, and translated into percentages terms of R^2 for each regression. In Table 4 the results are presented.

TABLE 4 HERE (Missing)

For each boat the four first columns in Table 4 amount to the regression's R^2, and the figures in the stationary stochastics column are calculated as (1-R^2). Several things can be seen from Table 4. A large variation among the vessels together with relatively low R^2 indicates that the stochastic environment is important even for the boats with a mean reverting technology. When looking at the average boat as much as 44% of the variation in the efficiency score is ascribed to stationary stochastics, indicating a quite high noise to signal ratio. Accounting also for the weather effect - which also should be considered as a stochastic factor for the fisherman - as much as 53.6% of the variation in efficiency is due to stochastics. For the average boat, the length of the fishing season (days) seems to be the most important deterministic factor, accounting for nearly one fourth of the variation in efficiency.

When comparing the industry results with the average boat we find the industry considerable less exposed to stochastics. The stationary stochastics account for only 23.3% of the variation in efficiency, and the influence of the weather reduces even more, accounting now for only 2.7% of the variation in efficiency. Hence, at the boat level the stochastic factors (when also weather is included) is twice as important as at the industry level, where only 26% of the variation in performance can be ascribed to stochastic factors. Thus, the conclusions drawn from the unit-root tests, that the industry as a whole is less exposed to the stochastic environment - both stationary and non-stationary stochastics - are confirmed also by the decomposition undertaken in this section. The average boat results and the industry results are illustrated in Figure 1.

FIGURE 1 HERE (Missing)

The magnitudes of the industry figures seem reasonable, the importance of effort represented by crew size more than triples, and both the length of the fishing season and the stock size increase their importance. In particular, when looking at the industry, the fishermen now are in charge of the two factors that dominate their performance; the length of the fishing season and the crew size account for 58% of the variation of industry performance. At the boat level these accounted for only 32.2% of the fisherman's performance. The reduced weather effect is reasonable too; the individual boat is probably more affected by weather conditions than the industry as a whole since the vessels are distributed over a large geographical area and therefore exposed to different weather conditions.

When a vessel has a mean reverting technology, performance can be predicted by forming appropriate expectation models. From the decomposition in this section, we get information on which variables that is most important in predicting performance. Due to the size of the stationary stochastics - the noise to signal ratio - when compared to the factors endogenous to the fisherman, our results still suggest that it would be difficult to form proper expectations about future performance. Hence, even for the stationary vessels it is not straightforward to design an efficient regulation regime.

5. POLICY IMPLICATIONS AND POSSIBLE REGULATION DEVICES

The overall results suggest that both types of stochastics; the structural uncertainty and the well defined randomness and parameter uncertainty, are important for the individual boats' development of performance. Even when accounting properly for factors as the length of the fishing season, crew-size, weather and stock conditions we find four vessels where the non-stationary stochastics dominates the development in performance. For six vessels - when we decompose the efficiency scores for the stationary series - the analysis suggests that the stationary stochastics is the most important individual factor.

When comparing the individual boats with the industry as a whole, several interesting results appear. First, as opposed to several of the boats analyzed, the industry does have a mean reverting technology. Second, when decomposing the industry's efficiency score, the stationary stochastics are significantly less pronounced than what we can find on the individual boat level. Hence, it seems as the stochastics cancel out over the fishermen when we aggregate their overall performance. The regulator can accordingly find the optimal effort for the fishery. However, due to the lack of well defined expectations for the individual fishermen, achieving economic efficiency by regulation is more difficult since ITQs no longer is an appropriate regulation tool.

The results have important implications for how to regulate a fishery. In a fishery which is exposed to non-stationary stochastics, it is impossible to form well-defined expectations, since no well defined distribution exists. Hence, for the minority of vessels in this industry, standard regulation devices as ITQs would not work properly. Even for the majority of the vessels with a mean reverting technology, the large component of stationary stochastics makes the use of ITQs difficult. Furthermore, it seems difficult to regulate the individual fishing vessels using economic incentives directed towards input and outputs when these are less important for the performance than the stochastic environment. These issues must then be reckoned when designing regulation schemes.

The importance of the stochastic environment faced by the individual fishermen calls for new regulation devices where quotas may be distributed also *ex post*, as opposed to the traditional regulation devices as ITQs where quotas are distributed *ex ante*. Given a TAC, and using transferable quotas as a regulatory device to avoid rent dissipation in a fishery, the quotas are allocated and traded before the start of the fishery, where the inverse derived demand functions for quotas reflects the relative efficiency of the vessels (Salvanes and Squires, 1995). The efficiency gains are obtained by the reduction of the effort of less efficient vessels and the expansion of the effort of more efficient vessels. However, if the dominant part of the harvest technology is unknown to the vessel owner because of non-stationary stochastics (structural uncertainty), the inverse derived demand functions for quotas do not reflect properly the technology and performance parameters of the vessels and thus the resulting quota equilibrium will not reflect an efficient allocation of quotas.

Even for the vessels exposed to stationary stochastics the ITQs might be problematic. Expectations based on past performance have to be formed, and a large noise to signal ratio (44%) will lead to well-defined, but imprecise predictions about future performance. This may make the performance of the quota market more unstable. The result may be an outcome which is both inefficient and unstable.

The inverse demand functions (conditioned on the output which is stochastic), consist of deterministic and stochastic components which possibly may be exploited in designing a regulatory regime when the stochastics are stationary. One suggestion is to use a so-called two-part tariff where some part of the TAC can be traded *ex ante*, i.e., the deterministic part, and one part can be traded *ex post* to the opening of the fishing season.[15] The first part reflects the performance of vessels which is predictable and which depends on the factors endogenous to the vessel owners and thus is the standard part of the demand functions for vessels. The second part reflects the portion of the demand function for quotas which is due to the stochastics, and which is only known to the vessels *ex post*. This means that a part of the quotas should be traded *ex post,* when the uncertainty is revealed to the induvidual fishermen. A two-part tariff will also act as a risk-sharing device in that the fishermen will always be secured a certain amount of quota.

However, we still find four vessels to be non-stationary. The performance of these four vessels have changing means and infinite variances. Any innovation in these processes will leave a permanent effect on the performance development; the series has an infinite memory. Hence, for these vessels even a two-part-tariff scheme might be problematic, since their historical performance will not suffice for them to make predictions about their future performance. There is no deterministic effects that make these boats' performance levels move towards their historical means.

[15] For a more general treatment of two-part tariffs, see Schmalensee (1982), Tirole (1988) and Oi (1971).

When a vessel has a mean-reverting technology, performance can be predicted by forming appropriate expectation models. From the decomposition in section 5, we get information on which variables that is most important in predicting performance. Hence for the majority of the vessels, a two-part-tariff scheme might be used. Due to the size of the stationary stochastics - the noise to signal ratio - when compared to the factors endogenous to the fisherman, our results suggest that the largest part of the quota must be distributed *ex post*.

Finally, note that one of our results is that the industry has a mean reverting technology in the aggregate. This implies that the technology is well-defined - one may regulate total output - it is the individual quotas which requires particular attention.

6. CONCLUSIONS

The objective of the paper has been to test for the importance of uncertainty in a fishery. We find that the stochastic environment is important in explaining the performance development between seasons, more important than factors endogenous to the fishermen. First, many boats in this fishery have a performance development which is non-stationary. This means that the vessel's historical performance will not suffice in forming a well defined distribution to predict future performance - structural uncertainty dominates the performance development. This implies that in a regulatory scheme of ITQs, the demand for quotas has to be based on expected values which in this case are impossible to make since there is no deterministic effect that makes the vessels` performance level to move towards their historical mean.

Also for the boats which have a stationary process in performance, the importance of the stochastic factors (randomness and parameter uncertainty) dominate the factors controllable or endogenous to the fishermen. This implies that forming expectations are possible but difficult since the stochastic factors dominates the deterministic factors in explaining performance. If these results extends beyond the particular case of sealing which we have analyzed, the implications for the use of ITQs as a regulatory tool are potentially very important.

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