Aggregation Level and Prediction of Fishing Vessel Behavior and Productivity

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Abstract: Fishing overcapacity has lead to unsustainable harvesting and rent dissipation in global fisheries. Only government intervention of some kind can lead to a reduction in capacity. If efficiency is the primary objective for the regulator, then the least efficient vessels should be decommissioned. Here we analyze the Swedish fishery using a panel of individual fishing trip observations. Trip data provide some additional information compared to annual vessel data that could be exploited at both aggregation levels. The effect of data aggregation choice on estimated vessel behavior and productivity is examined. Productivity estimates are utilized in a Probit model of exit from the fishery. We also estimate returns to diversification and obtain some interesting results on the tradeoff between trip length and number of trips.

Keywords: Aggregation, fishing vessels, productivity, exit.

1. INTRODUCTION

Globally, fisheries are characterized by poor profitability, large government subsidies, and overexploitation of fish stocks. The open access nature of fisheries is the root cause for this situation (Gordon 1954). Today, pure open-access rarely exist in fisheries but most attempts by government to regulate fisheries have not been successful in generating rent. There are several reasons for this failure: Input substitution, fleet redundancy, and fleet composition. In other words, fishers may substitute unrestricted inputs for restricted inputs, more than the optimal number of vessels may participate in the fishery, and there may be a suboptimal mix of vessels in the fishery. In general, overinvestments in vessels and fishing gear, leading to excess capacity, is the main cause of the current state of global fisheries. This has taken place because governments have failed to introduce and enforce regulations. It has become increasingly clear that government interventions that can reduce fishing capacity are necessary. Given the political climate, decommissioning of fishing vessels in combination with limited access (fishing licenses) is an interesting second-best option. EU has for some years had buy-back programs with an economic compensation per gross register ton. The nature of these programs is such that exit is the result of vessel owners' self-section.

According to empirical evidence, fishing vessels (or fishers) are heterogeneous in terms of productivity (Pascoe and Coglan, 2002). If efficiency is the primary objective of the regulator, then measures to reduce fishing capacity should ensure that only the most efficient vessels remain in the fishery. Regulators that decide to use buy-back programs to reduce capacity could potentially need information on the productivity of fishing vessels. One question is whether econometric analysis of vessel data can provide useful information to policy makers on the productivity of fishing vessels. Another question is if current decommissioning schemes which includes economic compensation for scrapping of vessels, lead to a self-selection where the least efficient exit. One should be aware that skipper skill may be an important determinant of the efficiency of a vessel.

In this article we demonstrate how use of different levels of data aggregation allows one to test different hypotheses on firm behavior and productivity. Furthermore, although the sign of a variable or elasticity to be tested may be the same at different aggregation levels, the level of statistical significance may not. Hence, the outcome of a hypothesis test may depend on the level of aggregation. Here, we compare estimates from trip level data with annual vessel data. A large number of empirical studies use annual data, e.g. Kirkley and Strand (1988) and Salvanes and Steen (1994). One potential source of bias in estimates based on annual data, unlike trip data, is that they do not capture price and fish stock variations through the year.

We are also interested in fishers' gear choices in response to changes in relative earnings from different species. The data set provides information on the type of fishing gear used on each trip. We examine the relationship between gear choice and productivity. Furthermore, the returns to gear (i.e. target species) specialization or diversification are also examined using a Herfindahl type index. Specialized vessels may be more efficient in their particular fishery, but are on the other hand not able to respond to revenue opportunities in other fisheries (McKelvey, 1983). The trade-off between trip lengts and number of trips is also investigated.

Finally, the relationship between vessel efficiency and exit from the fishery is analyzed. Less productive vessels or skippers should have a higher probability of exit. We utilize the estimated vessel-specific effects from the revenue functions in a Probit model framework to test if exit is related to productivity realizations. Other variables are included to account for, e.g., vintage effects. Public programs that provide economic incentives for decommissioning of vessels have been in place for several years, although with varying rates of compensation. Here, the estimated exit model gives us some indication whether self-selection leads to exit of the most inefficient vessels (or skippers).

2. DEMERSAL TRAWL FISHERY

The Swedish West Coast demersal trawl fleet targets several species of which Norway lobster (hereafter *Nephrops*), shrimp and cod are the most important. The fleet, consisting of almost 300 vessels, produced an ex-vessel landing value of SEK[1] 430 million or more than 40% of total Swedish landings in 1998. The absolute figures have been pretty stable in real SEK, while the relative figures declined from 1995 to 1998 due to major increases in the pelagic landings during that period.

Each commercially important species has an overall total allowable catch (TAC) quota and a specific gear regulation. The gear regulations include different minimum sizes of the trawl mesh and a general upper limit of 70% by-catch of other species. The Swedish fisheries are managed under the Council of the EU since Swedish membership in January 1, 1995, but the Swedish Board of Fisheries and the Swedish Coastguard carry out the monitoring and enforcement. Commercial fishing requires a vessel license, which in turn requires a personal license held by a minimum of one crew member. The enforced and restrictive regulations are; a) the maximum 70% by-catch rule, b) a minimum landing size for shrimp, Norway lobster, and cod, c) a minimum trawl mesh size of 60, 70, and 90 mm, respectively, and d) a TAC for the commercially important species. The TACs for Norway lobster, shrimp, and demersal fish have not been binding during the 1990s. In broader terms, the Swedish West Coast demersal trawl fishery in 1995 can be characterized as a regulated open access fishery, which suffers from over-capitalization and low profitability (Eggert and Ulmestrand, 1999; Eggert, 2000). The Swedish fishermen organization has an agreement of vessel quotas on a weekly basis for shrimp. The objective is to avoid price fall in case of too successful landings. The quota is just a division of the Swedish shrimp TAC by vessels and weeks, anyone is free to enter. This rationing is, from a legal perspective, voluntary and not enforced by the Coastguard.

3. METHODOLOGY, MODEL AND DATA

3.1. ECONOMETRIC REVENUE MODEL SPECIFICATIONS

A revenue function is used here (Diewert, 1974). Several studies of behavior and performance in fisheries have used this approach, e.g., Kirkley and Strand (1988), Squires and Kirkley (1991), Salvanes and Steen (1994).[2] Revenue functions will be estimated at two different aggregation levels, individual trip data, and annual vessel data. The general specification of the revenue function to be estimated on trip level data is $R_{it} = R(P_{it}, T_i, G_{it}, S_t, H_{it}, V_i)$, where i is the vessel subscript, t is the trip subscript (or the time period in which the trip takes place, e.g. month), P is a vector of fish output prices, T is gross registered tonnes, G is a vector of fishing gear dummy variables, S is a vector of fish stocks, H is the hours of fishing, and V is a vector of vessel dummies.[3] Strictly speaking, H is a variable input, which is inconsistent with the theoretical revenue model, and which may also give rise to econometric problems in the form of endogeneity.[4] It is common in the fisheries literature

[1] Euro 1 = SEK 8,90 (April, 2002)

[2] Price and quantity data are not available to us for variable inputs such as fuel and labor, so we cannot use a profit function.

[3] Vessel age was included in some econometric specifications not reported here, but turned out to be insignificant and was consequently dropped.

[4] Inclusion of a variable input calls for the use of a profit function model framework. However, we do not have data on the variable costs associated with an hour of fishing, and therefore stick with the revenue function model framework. An additional problem is the possible simultaneity between fishing hours and revenue, leading to an endogenous left-hand side variable. However, Zellner, Kmenta and Dreze (1966) and Blair & Lusky (1975) have demonstrated for expected profit maximization and expected utility maximization, respectively, that input

to estimate production functions with the output measured by revenue. However, the input endogeneity problem still remains in a production function framework. Advantages of a revenue function approach compared to a production function, is that the former controls for the effects of output prices, and that one can improve parameter efficiency by estimating it in a SURE type system together with output supply equations (or output shares in a translog).

The Swedish National Board of Fisheries collected the data used in this study. Data were provided for 101 vessels. Note that the vessel characteristic that is used in the model, gross register tonnes (GRT), is not time-invariant. Various vessel modifications lead to changes in GRT for 31 vessels during the data period. Nevertheless, there is a high degree of multicollinearity between vessel size and vessel-specific effects.[5]

Here we estimate models both on trip data and on annual aggregated data for each vessel. When we aggregate from trip to annual vessel data, the number of observations is reduced from 54195 to 557. The models estimated on trip data can be regarded as short-term response models, while the models estimated on annual data provide information on average or more long-term response.

The species harvested by the fishing vessels in the data set were grouped into four outputs; shrimp, nephrops, cod and 'other species'. The sample mean trip revenue from these species is of the same magnitude, ranging from 2443 SEK for shrimp to 4904 SEK for nephrops. Unfortunately, trip level data are not available for output prices. We obtained monthly average prices from the National Board of Fisheries, and used these to create revenues and the composite price for other species for each trip.

An index of fish stock availability (S) was constructed for each of the four species groups by dividing the total monthly catch of the species group by the vessels in the sample by the total number of fishing hours for these vessels in the same month (Kirkley, Squires and Strand, 1998).[6] Because of the large number of vessels and observations in the sample, the stock index should be an exogenous variable when estimated on individual trip or vessel observations.

One advantage associated with trip level data is the possibility to estimate the effect of gear choice on revenue. For each trip the data set has information on the type of fishing gear used. Some specifications estimated on trip data will include gear dummy variables: One dummy variable for fishing gears targeting cod, one dummy for shrimp gear, and two dummies for nephrops gears (*single* and *twin* nephrops trawl), leaving gears targeting other species as the base category. The model is then specified as:

$$\begin{aligned}
\ln R_{it} = {} & \Sigma_{s=1,4}\alpha_s \ln P_{st} + \Sigma_r\Sigma_s 0.5\alpha_{rs}\ln P_{rt}\ln P_{st} + \alpha_H \ln H_{it} + 0.5\alpha_{HH}(\ln H_{it})^2 \\
& + \alpha_T \ln T_i + 0.5\alpha_{TT}(\ln T_i)^2 + \alpha_{HT}\ln H_{it}\ln T_i \\
& + \Sigma_{s=1,4}\alpha_{st}\ln S_{st} + \Sigma_r\Sigma_s 0.5\alpha_{rs}\ln S_{rt}\ln S_{st} + \Sigma_{g=1,4}\alpha_g G_{git} \\
& + \Sigma_{s=1,4}\Sigma_{g=1,4}\alpha_{pg}\ln P_{st}G_{git} + \Sigma_{s=1,4}\Sigma_{g=1,4}\alpha_{pg}\ln S_{st}G_{git} + \Sigma_{i=1,100}\alpha_i V_i + u_{it}.
\end{aligned} \tag{1}$$

In some specifications the vessels are assumed to be homogeneous, i.e. the vessels specific effects are restricted to be equal ($\alpha_1 = \alpha_2 = \ldots = \alpha_{101}$). The translog revenue function is estimated together with s-1 revenue share equations, $y_s{\cdot}p_s/R = \partial\ln R/\partial\ln p_s$, using Zellner's seemingly unrelated regression technique (Zellner 1962).[7]

In principle, vessels can switch between the five different gear types in response to changes in relative profitability. However, one should expect some degree of inertia in gear choices, since (a) investments in fishing gear and gear switching are costly, (b) some smaller vessels may not be able to use certain gear types, and (c) there may be information costs and uncertainties associated with switching target species. The physical characteristics of the vessel determine whether all types of gear considered here can be used, and some vessels may consequently have invested only in one or two gears. Gear switching can be time-consuming and thus

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endogeneity is a smaller problem under risk, since optimal input decisions are uncorrelated with the stochastic error term.

[5] There are both empirical and statistical (i.e. test based) arguments for including terms with GRT, but also for including vessel-specific fixed effects (FE). The revenue elasticity wrt. GRT declines compared to a specification with homogeneous FE. However, it is well known that most elasticities tend to decline when fixed effects are introduced in production models.

[6] An alternative measure could for each species group divide by the number of fishing hours from trip observations were a gear that target that species is used. These two alternative measures are highly correlated, with a correlation coefficient of 0.97 or higher for all species groups except shrimp (0.67).

[7] One of the share equations has to be deleted to obtain a nonsingular covariance matrix. The estimates are then asymptotically equivalent to maximum likelihood estimates and invariant to which equation is deleted (Barten 1969).

costly, since time is lost that could have been spent on the fishing grounds or in other activities. Some fishers may also have acquired knowledge and developed skills for particular fishing grounds where a certain species dominate, and thus be reluctant to target other species despite small catches on recent trips. However, since the relative abundance of different species and thus the revenue potential change over the season, there should be incentives to switch gear.

An examination of the number of gears used by the sample vessels on an annual basis reveals that for 123 of the 557 vessel observations only one gear was used throughout the year (22.08%). Furthermore, two gears were used in 244 (43.81%) of the vessel observations, three gears in 165 (29.62%) of the observations, four gears in 25 (4.49%) of the observations, and no vessels used five gears in any year.

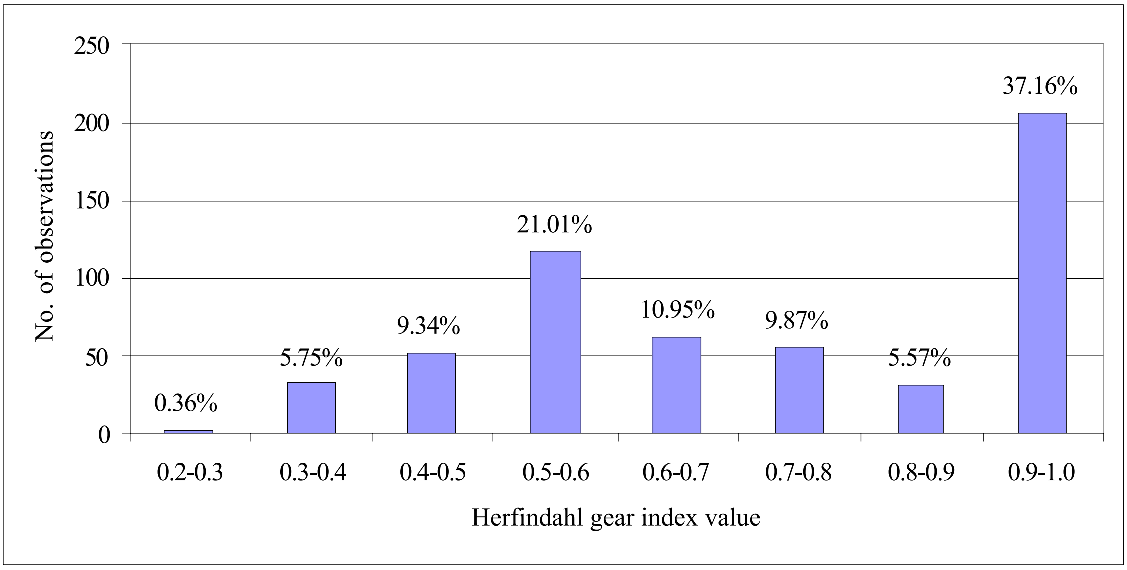

Figure 1. Distribution of Fishing Gear Choice Herfindahl Index for Annual Data (557 obs.)

A potentially useful measure of vessels' target species (or gear) specialization (diversification) is a Herfindahl type measure:

$$H_g = \Sigma_g s_g^2,$$

where s_g is the relative share of the trips where gear g is used (i.e., $0 \geq s_g \geq 1$, and $\Sigma_g s_g = 1$). This measure provides additional information compared to, as above, a simple count of the number of gears used, because the index value changes with the relative distribution of the gears. With five gears, the minimum value of this specialization index, corresponding to a perfectly even distribution of gear use, is $H_g = 0.2$. The maximum value, corresponding to a vessel that specializes in only one gear (target species), is $H_g = 1$. In one of the models that we estimate on annual data, we include the H_g index to examine the returns to specialization/diversification. The mean value of the Herfindahl specialization index is 0.73, with minimum and maximum values of 0.27 and 1.00, respectively. Figure 1 provides some more information on the distribution of the index. We see that around 37% of the vessels are highly specialized each year, with an index higher than 0.9. Fewer vessels are highly diversified. Only 15% of the annual observations have a Herfindahl index lower than 0.5.

Next, we examine the correlations between annual vessel observations of central variables. Vessel size characteristics motor power (kw), vessel length (loa) and gross register tonnes (GRT) are highly correlated, with corr(kw, loa) = 0.76, corr(kw, GRT) = 0.85, and corr(loa, GRT) = 0.92. The correlation between vessel's age and other vessel characteristics are much smaller, and have different signs. There are no strong correlations between the Herfindahl gear specialization index and other vessel characteristics, such as vessel size measures. Hence, we do not find any strong support for the hypothesis that larger vessels diversify more with respect to target species. Not unexpectedly, larger vessels tend to have larger catches and catch revenues, as indicated by the correlations between vessel size characteristics (kw, loa and GRT) and catch and rev.

Vessels may substitute between the length of each fishing trip and the number of trips each season. For the fishers the marginal utility probably decreases in fishing time after a certain number of hours. The quality of the fish may also deteriorate with increasing fishing time, depending on the onboard storage technology and type of species harvested. Furthermore, the vessel may have binding capacity restrictions with respect to storage, fuel, etc. Finally, trips to the home port represent opportunities to switch gear. On the other hand, trips to shore also have an opportunity cost in terms of lost fishing time (revenues) and expenditures on fuel and labor. There is a negative correlation between average fishing time and the number of fishing trips (-0.40), suggesting that vessels which fish shorter periods on each trip tend to compensate for this by making more trips during the year. Furthermore, there is a positive relationship between vessel size characteristics (kw, loa and GRT) and average and total fishing time, according to the estimated correlations. On the other hand, the correlations between vessel size characteristics (kw, loa and GRT) and total number of trips are all around zero. Hence, it seems as larger vessels tend to fish for longer periods on each trip, but do not make more trips during the year. In the model specifications estimated on the annual data we include terms with the number of trips to account for the effect of trip numbers on revenues.

3.2. ECONOMETRIC VESSEL EXIT MODEL

In a second stage we estimate the determinants of vessel exit in the Swedish fishery. Several theories exist for firm exit. The selection model or passive learning model due to Jovanovic (1982) predicts that firms gradually learn about their relative abilities from the date of entry and exit if they receive unfavorable information. In another model, the active learning or evolutionary learning model, the firms' initial ability is not as important as their ability to improve (e.g. by increasing productivity) and reduce the gap between themselves and the incumbents (Pakes and Ericson, 1992). Both these theories predict that the exit rate declines with the age of the plant, which is positively correlated with the firms' productivity. A third theoretical explanation, the vintage model, predicts that the exit rate of firms increases in the age of capital, where capital age is generally assumed to be positively correlated with firm age (Johansen, 1959, 1972; Solow, 1956, 1960). The main point is that new technology is embodied in the latest vintages of capital. Thus new capital is better or more productive than old capital not only because of wear and tear but because new capital was more productive than old capital even when the old capital was new.

We employ a Probit model as the parametric specification of our exit model. The model is given by

$$EXIT_{it}^{*} = \beta\,\mathbf{x}_{it} + u_{it}\,, \qquad u_{it} \sim \text{IN}(0, \sigma_u^2),\ i = 1,2,\ldots, N,\ t = 1,2,\ldots, T,$$

with $EXIT_{it} = 1$ if $EXIT_{it}^{*} > 0$, and $EXIT_{it} = 0$ otherwise. In the Probit model the probability that firm i will exit in year t is (Maddala, 1983):

$$\begin{aligned}\text{Prob}\left[EXIT_{it} = 1\right] &= \int_{-\infty}^{\beta'\mathbf{x}_{it}} \phi(u)\,du \\ &= \Phi\left(\beta'\,\mathbf{x}_{it}\right)\end{aligned}.$$

In words, the probability of exit is equal to the area under the standard normal distribution from $-\infty$ to $\beta'\mathbf{x}$. As the value of $\beta'\mathbf{x}$ increases the likelihood of exit also increases. We define as exit those vessels that were scrapped or sold during the data period. Scrapping represents a revenue opportunity for the vessel owner. The EU scrap premium was SEK 12 000 per GRT in 1995, then lowered to 8000 SEK/GRT in 1996, and was increased in 2000 to 18 000 SEK/GRT.

In the vector of explanatory variables, $\mathbf{x}$, we include the predicted vessel-specific fixed effect (V), vessel size as measured by GRT (T), and vessel's construction year, which coulde capture vintage effects. In one specification we also test, by employing the Herfindahl index, whether it is vessels that diversify to several species or specialized vessels that are most likely to exit.

4. EMPIRICAL RESULTS

4.1. REVENUE FUNCTION RESULTS

With the large number of parameters in the models a meaningful discussion requires that the empirical results are presented in terms of elasticities. Due to space considerations we have not presented (the large number of) estimated parameters of each model.[8] Table 1 presents elasticity estimates and some other key statistics from the models estimated on trip data, while Table 2 presents similar figures for models estimated on annual vessel data.

We first estimated the revenue model without revenue share equations on trip level data, specifying the vessel-specific effects as both random and fixed (not presented here). A Hausman specification test firmly rejected

[8] Available upon request from the authors.

random effects specification in favor of fixed effects. Hence, we hereafter only present models with vessel effects specified as fixed.

A comparison of the parameter estimates of econometric model when we go from trip level data to annual vessel data reveals a large reduction in the number of statistically significant parameters. For the model with homogeneous constant term, the number of parameters that are statistically significant at the 10% (1%) level are reduced from 30 to 12 (27 to 8). Similar reductions are found for the model with vessel-specific intercepts, where the number of parameters that are statistically significant at the 10% (1%) level are reduced from 28 to 14 (25 to 6).

An important difference between using trip data and annual data is the ability to control for seasonal price and stock variations. The stock of all four target species groups exhibit substantial variation throughout the year. When we compare the trip data models, which accounts for seasonal variation, with the annual data models, we find that some elasticities are very similar while others are dramatically different. For example, the sample mean elasticity of revenue w.r.t. the price of other species, ε_{Pother}, lies between 0.03 and 0.11 across trip data models, and between 0.44 and 0.55 across annual data models. The estimates of the elasticities ε_{Pcod} and $\varepsilon_{Pnephrops}$, on the other hand, are very similar between the trip data models and annual data models.

How elastic is revenue in fishing time? According to Table 1,the mean value of ε_H ranges from 0.86 to 0.92 across models estimated on trip data. The elasticities are, however, substantially lower for the models estimated on annual vessel data (c.f. Table 2), ranging from 0.58 to 0.72. It is interesting to note from Table 2 the high mean elasticity of revenue w.r.t. number of trips during the year, ε_{ntrips}, which ranges from 0.78 to 2.02. These high figures probably reflect the marginal costs of increasing the number of trips.

Next, we examine the returns to vessel size, as measured by gross register tonnes (T). The calculated mean elasticity of revenue w.r.t. vessel size, ε_T, from the models estimated on trip data range from 0.04 to 0.48 across models. For the models estimated on annual vessel data, the figures are somewhat higher, with mean elasticity estimates in the range 0.26-0.44 across models.

Table 1. Revenue Model Estimates Trip Level Data (54195 obs)

Model	I		II		III	
Variable	Mean	St.dev.	Mean	St.dev.	Mean	St.dev.
ε_{Pcod}	0.213	0.052	0.213	0.052	0.213	0.207
$\varepsilon_{Pnephrops}$	0.453	0.079	0.453	0.078	0.453	0.314
$\varepsilon_{Pshrimp}$	0.150	0.008	0.149	0.008	0.149	0.340
ε_{Pother}	0.030	0.031	0.035	0.023	0.041	0.097
ε_{Scod}	0.232	0.095	0.231	0.075	0.249	0.155
$\varepsilon_{\text{Snephrops}}$	0.355	0.130	0.345	0.129	0.339	0.140
$\varepsilon_{Sshrimp}$	0.172	0.053	0.157	0.048	0.168	0.171
ε_{Sother}	0.022	0.017	0.024	0.022	0.023	0.050
ε_T	0.478	0.408	0.262	0.181	0.331	0.161
ε_H	0.860	0.091	0.908	0.061	0.917	0.041
$\varepsilon_{Gshrimp}$					-0.647	0.194
$\varepsilon_{Gnephrops}$					-0.463	0.201
ε_{Gtwin}					-0.239	0.222
ε_{Gcod}					-0.344	0.248
R^2	0.48		0.99		0.99	
Vessel effects	No		Fixed		Fixed	
Vessel-specific effect:						
Mean			5.221		10.216	
St.dev.			0.360		0.299	
Min			4.414		9.426	

Max	6.438	10.909

Table 2. Revenue Model Estimates Annual Vessel Data (557 obs)

Model	IV		V		VI		VII	
Variable	Mean	St.dev.	Mean	St.dev.	Mean	St.dev.	Mean	St.dev.
ε_{Pcod}	0.201	0.042	0.200	0.043	0.201	0.043	0.201	0.043
$\varepsilon_{Pnephrops}$	0.454	0.053	0.453	0.051	0.454	0.052	0.454	0.052
$\varepsilon_{Pshrimp}$	0.184	0.024	0.186	0.025	0.184	0.024	0.184	0.025
ε_{Pother}	0.526	0.294	0.551	0.178	0.461	0.236	0.442	0.222
ε_{Scod}	0.561	0.179	0.326	0.220	0.543	0.205	0.551	0.241
$\varepsilon_{\mathrm{Snephrops}}$	0.522	0.352	0.180	0.406	0.495	0.364	0.480	0.368
$\varepsilon_{Sshrimp}$	0.252	0.322	0.289	0.356	0.212	0.301	0.257	0.286
ε_{Sother}	0.060	0.284	0.146	0.233	0.087	0.257	0.072	0.239
ε_{T}	0.286	0.139	0.437	0.373	0.258	0.129	0.281	0.121
ε_{H}	0.719	0.119	0.622	0.233	0.588	0.106	0.579	0.101
ε_{ntrips}			2.020	0.196	0.791	0.037	0.777	0.029
$\varepsilon_{Herfindahl}$							-0.006	0.172
R^2	0.99		0.89		0.99		0.99	
Vessel effects	Fixed		No		Fixed		Fixed	
Vessel-specific effect:								
Mean	2.641		N.A		2.166		-0.770	
St.dev.	0.515		N.A		0.433		0.508	
Min	1.458		N.A		1.129		-1.963	
Max	3.833		N.A		3.353		0.398	

With the exception of the fishing time elasticity (ε_H), the elasticities from the trip data models are generally lower than elasticities from the annual data models. This should reflect the short-term nature of trip level decisions. The ability to respond to changes in prices and stocks increases with time, and that is probably what we see when we go from trip data to annual data. However, if vessels' short-term responsiveness to changes in exogenous variables is sufficiently high, then one should not expect large differences between trip data and annual vessel data.

The models estimated on trip level data provide information on the revenue efficiency associated with different gear choices. However, we would also like to learn about the returns to target species specialization and diversification. Specialized fishing vessels should be the most efficient in their particular fishery. On the other hand, they are not able to respond to revenue opportunities in other fisheries, and may lie idle in periods when the stock of their target species is low. Specialized fishing vessels will operate until marginal revenue drop to the level of the marginal operating costs. The diversified vessels enter a particular fishery, if at all, as to balance their net return against that obtainable in other fisheries (McKelvey, 1983). If the diversifiers are as efficient as the specializers, they should have higher net returns, since they have the option of targeting other species as well. But as suggested earlier, this may not be the case. Diversification may be costly both in terms of reduced operating efficiency in the fishery, and additional investments in vessel and gear. Here, we can only compare the revenue efficiency of diversifiers and specializers. In the estimated model, the coefficients associated with the Herfindahl specialization index are significant at conventional confidence levels. However, the estimated revenue elasticity w.r.t. the Herfindahl index, ε_{HERF}, is very low, with a sample mean value of –0.006, indicating small returns to diversification. This finding suggests that the revenue opportunities due to target species flexibility is outweighed by reduced efficiency in the fisheries compared to specializers. Moreover, choice of a diversification strategy may also reflect risk aversion. Here, it seems like the cost of risk reduction through species diversification, is reduced fishing efficiency.

4.2. PROBIT EXIT MODEL RESULTS

Next, we empirically examine the relationship between vessel productivity and exit in a Probit model framework. The fixed effects estimates from revenue functions are included together with other vessel characteristics. Of the 101 vessels in the sample 14 left the fishery during the data period.

Table 3. Probit Exit Model Estimates (101 obs)

Model	A		B		C		D		E	
Variable	Coeff.	T-ratio	Coeff.	T-ratio	Coeff.	T-ratio	Coeff.	T-ratio	Coeff.	T-ratio
Vessel F.E.	-1.291	-2.120	-1.070	-1.480	-0.859	-1.400	-0.850	-1.390	-0.701	-1.250
Constr. year	-0.013	-1.340	-0.011	-1.120	0.013	0.980	0.018	1.090	0.010	0.830
Vessel size (GRT)	0.006	1.620	0.004	1.140	0.005	1.100	0.004	1.050	0.004	0.930
Constant	30.809	1.470	31.058	1.280	-25.519	-0.990	-36.467	-1.130	-1.169	-1.620
									-20.25	-0.86
F.E. model predictions	II		III		VI		VII		VI	

Table 3 provides Probit model estimates, where the predicted vessel-specific fixed effect are from four different revenue functions, two estimated on trip data and two estimated on annual vessel data. In general, the results show that the probability of exit decreases with increasing productivity, as measured by the vessel-specific fixed effect. However, only in model A, where the fixed effects are based on revenue model II, is the coefficient associated with the vessel-specific effect statistically significant (at the 5% level). The effect of construction year is not consistent across models, and is statistically insignificant. The probability of exit is increasing in vessel size in all four models, but only in model A is the coefficient significant (at the 10% level). We also estimated one model (E) where the Herfindahl index of gear diversification is included, to examine whether it is specializers or diversifiers that are most likely to exit. The coefficient associated with the Herfindahl index is negative and significant at the 10% level. This implies that the probability of exit declines with higher degree of specialization. Such a result may be contrary to what one could expect, since diversifiers should be more robust to changes in relative stocks and prices. On the other hand, we have found earlier in this paper that diversifiers did not benefit from their strategy in terms of revenue increases.

5. SUMMARY AND CONCLUSIONS

This paper analyzed the behavior and productive performance of a panel of Swedish fishing vessels observed from 1995 to 2000. The panel includes a wide variety of vessels, ranging from 12 to 40 meters in size. The vessels are probably heterogeneous in terms of the technological restrictions they face. This heterogeneity, if not embodied in observables included in the model, should be captured by vessel-specific effects. However, vessel-specific effects should also capture differences in skipper skill.

We were primarily concerned about how the information in the trip level data set could be exploited in the econometric modeling, and how empirical results from trip data on behavior and productivity would diverge from annual vessel data. With the exception of revenue w.r.t. fishing time, elasticities from the trip data were generally lower than elasticities from annual data. This suggests that fishers' responsiveness to fish prices and fish stocks increase over time.

Vessels are found to be heterogeneous in terms of productivity. However, there is weak correlation between the trip data and the annual vessel data models in terms of the ranking of vessels. One potential caveat with productivity analyses based on trip data, is that vessels may behave differently with respect to the length and number of trips during a year. Some vessels may be highly efficient on each trip but make few trips. With heterogeneous technological constraints across vessels, different trip length-number behavior may be due to pure profit-maximizing decisions. But it is also possible that, at least for small vessels, factors outside the fishery play a role (e.g. onshore employment opportunities).

As expected, the probability of vessel exit, either through scrapping or through sales, is found to be negatively related to vessel productivity. Other factors such as vessel age and size could not explain exit behavior.

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