Aquat. Living Resour. 21, 227–238 (2008)
© EDP Sciences, IFREMER, IRD 2008
DOI: 10.1051/alr:2008040
www.alr-journal.org

Aquatic
Living
Resources

# Basque inshore skippers' long term behaviour: a logit approach

Ikerne del Valle[a], Kepa Astorkiza and Inmaculada Astorkiza

Department of Applied Economics V, University of The Basque Country, Avda. Lehendakari Agirre No. 83, 48015 Bilbao, Spain

Received 13 September 2007; Accepted 13 March 2008

**Abstract –** Based on the discrete optimal choice theory and a random utility model (RUM) framework, this paper focuses on the firm's long-term choices.A behavioural study on the stay and exit decisions of the fishing firms belonging to the inshore fleet of the Basque Country is undertaken by estimating a logistic model from a set of socio-economical sample panel data for the period 2003-04. Specifically, we aim to determine the set of vessels', skippers' and economic variables that may influence the probability of a fishing vessel to exit from the fishing activity. Special attention will be paid to the roll that incentives generated by decommissioning grants play in the fishermen's long-term behaviour. Our results indicate that the owner's age, years of experience being a skipper, the arrangement of continuity in the familiar business, the degree of dependency upon bank loan and lastly but not least decommissioning grants may significantly determine the decision to abandon the activity.

**Key words:** Random utility model (RUM) / Stay-exit behaviour / Fisheries policy / Decommissioning grants / Basque inshore fleet

## 1 Introduction

Fishing firms face up to different short term and long term dilemmas. In the short term, given the surrounding circumstances of the fisheries such as the sea conditions or economic aspects related to output and input prices, they firstly decide whether they go fishing or not, and additionally, the objective species, fishing gear and area, and the fishing effort to be exercised. The most relevant basic long-term firm's decision is binary, that is, exit from the fishing activity itself in front of carrying on. Usually, the set including all the short and long time feasible alternatives are restricted and influenced by a wide variety of regulation measures (i.e. minimum legal mesh sizes, maximum catch or effort quotas, limited spawning areas, licences, etc.). Specifically fishermen are given incentives such as decommissioning grants aimed at influencing their long-term stay-exit decision in order to favour fleet and capacity adjustments. Understanding how fishermen behave is thus a key question when designing any fisheries management scheme, especially if, like decommissioning grants, it is based on economic incentives.

Inspired by the traditional adjustment mechanism in the long run competitive market, usually entry-exit models take for granted that entry and exit is merely related to profitability and that vessels are free to move in and out of the fishery (Berk and Perloff 1984; Bjørndal and Conrad 1987; Mackinson et al. 1997; del Valle et al. 2001; Pascoe and Revill 2004). Under free entry long-term competitive market equilibrium, the resulting number of firms would be determined by the zero profits condition and total effort in the fishery would be instantaneously adjusted to its total profits. Interesting theoretical amendments to the previous approach are the constraints introduced in effort and fleet size by fisheries management, and the consideration of different conditions for entry-exit decisions due to imperfect malleability (Clark et al. 1979) and irreversible investment (McKelvey 1985; Boyce 1995).

Despite the considerable methodological difficulty involving the approach summarised above, the underlying assumptions may not be good enough to understand real effort and fleet adjustments. In fact, entry and exit in fishing are more pronounced than in other industries due to a higher uncertainty in production, the relative open access nature of ocean fisheries, the significant degree of mobility the production unit involves and also the small family business organisation surrounding some specific fleets. As derived from empirical analysis (Bockstael and Opaluch 1983, 1984; Ward and Sutinen 1994; Ikara and Odink 2000; Pradham and Leung 2004), besides profitability, there may be several reasons for vessel reallocations, such as stock fluctuations and resource abundance levels, regulatory measures, fleet congestion, vessel-specific managerial issues, skipper's characteristics and lastly but not least, the socio-economic framework in which the fishing activity develops (see Table 1 for a empirical survey from the literature). Furthermore, in certain instances, some of the vessels staying in a fishery may not be operating profitably, but

[a] Corresponding author: ikerne.delvalle@ehu.es

**Table 1.** Variables in selected ENTRY(E)-STAY(S)-EXIT(E) fisheries models.

| MODEL | Ward and Sutinen | | Ikiara and Odink | | Pradham and Leung | |
|---|---|---|---|---|---|---|
| VARIABLE | Inclusion | Signif. | Inclusion | Signif. | Inclusion | Signif. |
| Ex-vessel prices (P/£) | √ | √ | - | - | - | - |
| Operating costs (C/£) | √ | √ | - | - | - | - |
| Fleet size (∑GRT) | √ | √ | - | - | √ | √ |
| Vessel length | √ | √ | - | - | - | - |
| Vessel tonnage (GRT) | √ | √ | - | - | - | - |
| Generalist/Specialist vessel | √ | - | - | - | - | - |
| Vessel mobility | √ | - | - | - | - | - |
| Stock abundance | √ | √ | - | - | √ | √ |
| Average daily catch value | - | - | √ | √ | - | - |
| Investments (2 hand market ) | - | - | √ | - | - | - |
| Experience (years) | - | - | √ | √ | - | - |
| Education | - | - | √ | - | - | - |
| Alternative occupation | - | - | √ | - | - | - |
| Family tradition | - | - | √ | - | - | - |
| Ownership (owner = captain) | - | - | √ | √ | √ | √ |
| Income potential (IF/GRT) | - | - | - | - | √ | √ |
| Vessel age | - | - | - | - | √ | - |
| Owner's residency | - | - | - | - | √ | √ |

may be there just to cover the operating costs or just because there is a lack of alternative employment opportunities (Ikiara and Odink 2000). This suggests that not only profitability itself but also the background of each fishery is very important in order to understand fishermen's behaviour when facing long-term decisions, such as to exit from the fishing activity or even short-term decisions related to effort reallocation among species, gears or areas. Thus, fisheries background specific behavioural models, rather than generalist theoretical ones, may offer more clarifying clues when trying to advance the potential consequences of the fisheries management tools.

Following the framework developed by Bockstael and Opaluch (1983, 1984) to model the transfer of vessels from one fishery to another, the behavioural models cited above use a discrete choice optimisation framework to model either short term fishery or location choices and long-term vessel entry-stay-exit decisions. There is a relative lack of papers aiming to model long-term decision-making process. Among not too many more published papers are, for example, Ward and Sutinen (1994) Ikiara and Odink (2000) and Pradham and Leung (2004). We have developed a discrete choice logit model to analyse fishermen long-term behaviour that allows for predicting the probability for a fishing vessel to exit in the inshore fleet of the Basque Country. Unlike earlier papers, the entry option is excluded from the decision set. This exclusion may be easily justified by the continual and progressive decrease of the number of vessels happening since 1986 (Fig. 1). Section 1 presents the theoretical framework of the paper. After a short description of the inshore fleet of the Basque Country and the discussion related to the available data to face the empirical analysis developed in Sect. 2, the main econometric results are presented and interpreted. Section 3 summarises the main concluding remarks, showing the determinants of Basque inshore fishermen long-term behaviour and their answer to the incentives generated by decommissioning grants.

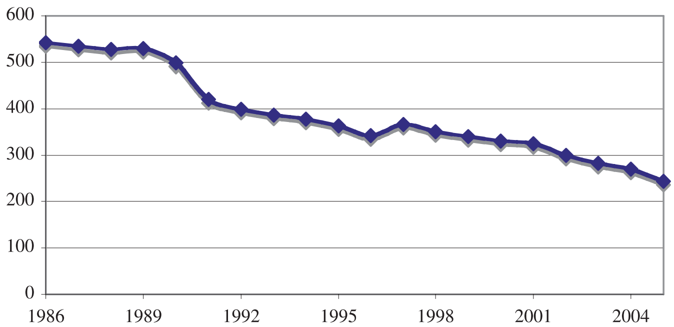


**Fig. 1.** The evolution of the inshore fleet of the Basque Country (1986–2005), source EUSTAT.

## 2 Theoretical framework

The Random Utility Maximisation (RUM) framework provided by McFadden (1973) allows modelling an individual's discrete choice among many possible options using multinomial logit techniques. The aim is to estimate the probability of choosing one of the different options as a function of the characteristics of the individuals. Assuming that individuals pick up the alternative implying the highest utility ($U$), following standard microeconomics, a representative individual $i$ selects alternative $j$ if and only if $U_{ij} > U_{ik} \forall j \neq k$. Since the researcher does not know utilities with certainty, utility is treated as a random variable and additionally, one has to examine variables presumably associated with the utility attached to each choice ($U_{ij}$). Thus, $U_{ij}$ (1) can be interpreted as the *indirect utility function* and can be divided into a systematic (deterministic) term ($V_{ij}$), interpretable as the *expected utility* the individual can obtain (measurable by the researcher), and a random disturbance $\varepsilon_{ij}$ representing unobservable factors, measurement errors, and unobservable variations in preferences and/or random individual behaviour. Generally, it is assumed that $V_{ij}$ (2) is specified as a linear function of the observable variables.

$$U_{ij} = V_{ij} + \varepsilon_{ij} \tag{1}$$

$$V_{ij} = \alpha + \beta X_i \tag{2}$$

where $X_i$ is a vector of characteristics related to individual $i$, and $\alpha$ and $\beta$ are unknown parameters to be estimated. Given data on individuals who have decided among different alternatives belonging to the option set, the logit probabilities can be used in a standard likelihood function to estimate the parameters in the multinomial logit model. Assuming that the random disturbance terms $\varepsilon_i$ are independent and identically distributed type I Weibull random variables the *logit probability* (3) for choosing any given options $j$ in the choice set is:

$$Pr_{ij} = \frac{\exp(X_i\beta)}{\sum_{i=1}^{n} \exp(X_i\beta)} \tag{3}$$

where the numerator is the exponential of the utility related to the choice, and the denominator is the sum of the exponential over all the alternatives in the options set (See Greene 2000 for more details).

The RUM framework briefly described above accommodates well to our needs. In our case a fisherman $i$ selects an option from a set of only two possible choices: STAY (event Y = STAY) or exit from the fishing activity (event Y = EXIT)). Accordingly, instead of the multinomial, the appropriate model is the binomial logit, and the probability of a vessel with a set of characteristics $X_i$ to exit from the fishing activity will be (4):

$$\Pr(Y = EXIT) = \frac{\exp(\alpha + \sum_{i=1}^{N} X_i\beta)}{1 + \exp(\alpha + \sum_{i=1}^{N} X_i\beta)}. \tag{4}$$

Once the dependent variable has been transformed into a logit variable (5) the model will be estimated by maximum likelihood. That is, we are in fact estimating the probability of a vessel with a set of characteristics $X_i$ to exit from the fishing activity.

$$\text{logit}[\Pr(Y = EXIT)] = \ln\left(\frac{\Pr(Y = EXIT)}{1 - \Pr(Y = EXIT)}\right) = \alpha + \sum\nolimits_{i=1}^{N} X_i\beta. \tag{5}$$

## 3 The empirical model

### 3.1 The Basque inshore fleet

Based on data from EUSTAT related to the Basque fishing sector for the reference year 2003, the inshore fleet is the most important Basque fishing sub-sector attending to the number of vessels (76%) and fishermen (56%). However, it only represents 25% of the total gross tonnage (GRT) and 30% of the gross value added (GVA). The total landings of the inshore fleet of the Basque Country added up to 37 627.2 t, with an ex-vessel value of about 70 662.5 thousand € and a GVA of 45 060 thousand €. The most relevant species according to quantity landed were horse mackerel (27%), white tuna (18%), mackerel (13%), anchovy (8%) and hake (9%). The remaining targets include a wide range of species (such as bream, gilthead bream, red mullet, flatfish, angelfish, sole, turbot, sea bass, ray, conger, crabs, octopus, lobster, etc.) that overall hardly reach 25% of the total landings and 18% of the total incomes. The market value of landings changes the picture of the relevance of species, being white tuna (27%), hake (20%) and anchovy (20%), the principal source of incomes of the fleet. 282 vessels and 1995 fishermen distributed by almost all the fishing ports in the Basque Country, but mainly concentrated in Bermeo (30%), Hondarribia (13%) and Getaria (12%), constitute the so called inshore fleet. Broadly speaking these inshore vessels may be catalogued as small family businesses. On the one hand, the owner or any of the co-owners are also the skippers of the vessels and, on the other, the family implication as crewmembers, or as personnel at land involved in accountancy or/and commercialisation etc. is remarkable. In fact only 5% of all the inshore vessels are constituted under the legal condition of limited companies.

The Basque inshore fleet is not homogeneous, quite the contrary, it is rather heterogeneous attending to gears, technical characteristics and also main target species. With 67% of the employment and 70% of GVA purse seines and bait boats are followed in importance by long lines, hand lines and troll lines, the latter representing 23% of the employment and GVA. Finally gillnets account for 10% of the employment and 7% of the GVA. The average vessel of the inshore fleet has 60 GRT, 300 HP, a length (LG) of 16 meters and a crew of 7 fishermen. However there are significant differences among the fishing units. Based on Puente et al. (2000) and del Valle et al. (2008) vessels belonging to the inshore fleet of the Basque Country may be grouped in three different typologies. Artisan vessels (ART) constitute a wide set of heterogeneous small size vessels, with average GRT = 10, HP = 90, LG = 10, CREW = 2, operating in close waters and daily trips, which use alternative fishing gears such as long line, hand line, troll line and gillnet depending on the target species. The so-called *"txikihaundis"* (TXI) are very polyvalent and medium sized vessels with average GRT = 50, HP = 270, LG = 18, CREW = 5, whose main target species are tuna and mackerel, which are normally captured using troll line fishing gear and different hand lines depending on the target species. With about GRT = 110, HP = 470, LG = 24, CREW = 12 on average purse seines and bait boats (CERC) constitute the biggest fishing units. Their principal species are small and medium pelagic, which are captured either by encircling nets (anchovy, mackerel and horse mackerel), troll line or pole (tuna). Both vessels belonging to TXI and CERC operate in the VIII European Division and they carry out larger campaigns, even reaching to spend two week at sea, as it happens during the tuna fishing season.

### 3.2 The data

Cross sectional socio-economic data is available for the years 2003 and 2004 for vessels belonging to the Basque inshore fleet. Data were collected through the Fisheries Economics Group of the University of the Basque Country (UPV-EHU) from a structured socio-economic questionnaire from a sample of 74 vessels, 15 of who abandoned the fishing activity in the year 2003. The respondents of the survey were the skippers, who in all of the cases were also the owners of the vessels, and so, as the main decision makers, are accepted as appropriate sampling units. The survey response rate was rather high (96%).

Table 2 includes descriptive statistics for the final and intermediate variables (i.e. input variables to generate final ones) to be considered in the empirical EXIT/STAY model. These variables may be classified in three different groups. The first one includes a set of variables related to the vessel: gross tones (GRT), length (LENGTH), vessel's age (VESSELAGE) and fishing typology or cluster (CLUSTER). The second group is centred upon characterising the skipper and his background: years until retirement (YRETIREMENT), education (EDUCATION), years of experience as a skipper (EXPERIENCE), family involvement in the fishing activity (FAMILY), the existence of succession after the skipper's retirement (SUCCESSION), a proxy for the skipper's skill (SKILL) and province (PROVINCE). The third group covers economic and/or regulatory issues: length relative current profitability (PROFIT), the degree of dependency on a loan upon the vessel and/or gears (LOAN), and the decommissioning grant that the vessel would perceive in the case of breaking up (DGRANT).

Since we are searching for the variables influencing in the probability to exit, notice that the independent variable in the model is Y = 1 = EXIT. Focusing on the independent variables, taking into account the relative small sample size ($N = 74$), the broad range of variables (Table 2), and the consequent lack of degrees of freedom, efforts have been made to identify a subset of variables a priori excludable. As a general rule, and whilst aiming at avoiding potential collinearity problems, some intermediate variables such as GRT, LENGTH, VESSELAGE or CLUSTER that, as will be shown below, are used to generate a final variable (i.e. DGRANT, SKILL or PROFIT) will not be included as direct variables. Results based on descriptive statistics and also data exploratory analysis via tentative stepwise logistic analysis suggested by Silva and Barroso (2004) are compatible with the decision to exclude them. Additionally, since the variable EDUCATION was not available for 3 of the 74 skippers and the exploratory analysis indicates no significant influence in the exit behaviour, it was omitted. Thus, four independent factor variables (i.e. LOAN, SUCCESSION, FAMILY and PROVINCE) and four numerical variables (YRETIREMENT, EXPERIENCE, GDRANT and PROFIT) will be incorporated to the empirical model (Model 1 from now on).

LOAN captures whether there is a significant loan on the vessel and/or gears. In order to evaluate if the instalments to face are relevant/irrelevant, as well as the skipper's direct (and to some degree subjective) answer, we have taken into account an objective one, which is the ratio net purchase price[1] financed with a bank loan to the number of years since the purchase of the vessel, corrected by the number of partners. The cut off point has been established at 6000 €/year (per partner). Thus, LOAN = 1 implies that the vessel is fully paid or if there is a loan, that it is not significant. The variable SUCCESSION refers to the existence/inexistence of an heir to continue with the activity once the skipper retires. We assign SUCCESSION = 1 when the relief is guaranteed. FAMILY is an indicator for the implication of the skippers' family in the fishing activity. Thus, FAMILY has a value of 1 if none of the crewmembers is a direct relative or in law of the owner or any of the co-owners', while FAMILY = 0 means that al least one of the crewmembers belongs to the owner's family. PROVINCE is a dummy variable for the province the vessel belongs to, PROVINCE = 1 is assigned to vessels of Gipuzkoa, and PROVINCE = 0 to vessels of Bizkaia. YRETIREMENT indicates the remaining years for the skipper's retirement[2], while EXPERIENCE, aiming to measure managerial expertise and sea related knowledge, accounts for the years as a skipper. DGRANT[3] captures the amount of the decommissioning grant that the vessels have or/would have received in the case of breaking up. The derived quantity is based on the order 297/2000 of the Spanish Government and is in fact a lineal and increasing function of GRT and VESSELAGE. Thus, DGRANT not only captures part of the opportunity cost of the capital but it also shows the years passed since the vessel was built and the capacity of the vessel. SKILL intends to stand for the so-called skipper's skill. Instead of using a subjective evaluation of the managerial skills of the boat captains supplied by a person who is thoroughly familiar with the boats and captains implied in the fishery, we undertook a direct measurement approach based on the incomes obtained in the year 2003 adjusted to the average incomes of the cluster the vessel belongs to (see Kirkley et al. (1998), Squires and Kirkley (1999) and del Valle et al. (2003) for a general overview of the different approaches used in empirical studies). The choice of the incomes instead of the profits obeys mainly to the fact that the cost component of the vessels belonging to the same cluster is considerably less variable than the income component of profits. Thus, we are assuming that the skilfulness is more related to incomes rather than to the costs. Finally, PROFIT is the ratio between the profits obtained in the year 2003 divided by the length of the vessel.

[1] Net purchase price = purchase price of the vessel – subvention received.

[2] The retirement age for the fishermen is legally established at 55 years of age.

[3] The chart from below summarises *Spanish 197/2000* order specifying the decommissioning grant to be perceived as a function of GRT and VESSELAGE. To get the DGRANT amount, Maximum DG quantity included in the table is corrected by the year of construction of the vessel (VESELAGE) following these interval rules: a) 10 < VESSELAGE < 15 → Maximum DG; b) 16 < VESSELAGE < 29 → Maximum DG –1.5% year in excess c) VESSELAGE > 30 → Maximum DG –22.5%.

| GT | Maximum DG |
|---|---|
| 0 < 10 | (11 000/GT) + 2000 |
| 10 < 25 | (5000/GT) + 62 000 |
| 25 < 100 | (4200/GT) + 82 000 |
| 100 < 300 | (2700/GT) + 232 000 |

**Table 2.** Descriptive statistics for intermediate and final variables.

| | VARIABLE | TYPE | MEANING | Freq. % | Mean | S.E |
|---|---|---|---|---|---|---|
| | Y = EXIT | Cat. | Dependent variable | | | |
| | | | EXIT (1) | 0.21 | | - |
| | | | STAY (0) | 0.80 | | |
| Group 1 | GRT* | Num* | Gross tonnes of the vessel | | 51.63 | 46.74 |
| | LENGTH | Num* | Length of the vessel | | 16.51 | 6.62 |
| | VESSELAGE | Num* | Vessel's age = [2003 – year built] | | 19.27 | 11.24 |
| | CLUSTER | Cat* | Typology of the vessel | | | |
| | | | ART | 0.39 | | |
| | | | TXI | 0.32 | | |
| | | | CER | 0.28 | | |
| Group 2 | YRETIREMENT | Num | Years until skipper's retirement [age 55 –2003] | - | 10.92 | 1.045 |
| | EDUCATION | Cat | Education of the skipper | | | |
| | | | PRIMARY | 0.35 | | |
| | | | PROFESSIONAL | 0.20 | | |
| | | | SECONDARY | 0.42 | | |
| | | | UNIVERSITY | 0.01 | | |
| | EXPERIENCE | Num | Years being skipper (=owner). | - | 13.97 | 1.08 |
| | SUCCESSION | Cat | Is there a successor to take over from the owner? | | - | - |
| | | | Yes (1) | 0.28 | | |
| | | | No (0) | 0.72 | - | - |
| | FAMILY | Cat | Is there a family in the crew? | | - | - |
| | | | No (1) | 0.68 | | |
| | | | Yes (0) | 0.32 | | |
| | PROVINCE | | Province. Categorical. | | | |
| | | | GI(1) | 0.46 | | |
| | | | BI(0) | 0.54 | | |
| Group 3 | PROFIT | Num | Profits during year 2003/LE | | 3.672 | 3.184 |
| | LOAN | | Is there a significant loan upon the vessel | - | - | |
| | | | No (1) | 0.53 | | |
| | | | Yes (0) | 0.47 | | |
| | DGRANT | Num. | Decommissioning grant obtainable | | 69.000 | 68.592 |
| | SKILL | Num. | Skipper's skill ratio [Current incomes 2003 / mean incomes of the cluster]. | | 0.999 | 0.499 |

Note: $N = 74$.
* Intermediate variables.

### 3.3 Econometric results

The log odds of EXIT choice have been regressed on the four dummies (i.e. SUCCESSION, LOAN, FAMILY, PROVINCE) and four numerical variables (i.e. YRETIREMENT, EXPERIENCE, DGRANT, SKILL, PROFIT) (Model 1). Taking into account that some variables were non-significant, a related restricted nested model including two dummies (i.e. SUCCESSION, LOAN) and four covariates, (i.e. YRETIREMENT, EXPERIENCE, DGRANT, SKILL) (Model 2) will also be estimated; and the differences between the two alternative models compared. The results showing the estimated coefficients ($\beta_i$), the odds ratio ($\text{Exp}(\beta_i)$), alternative tests to analyse the individual significance of the variables (i.e. Likelihood ratio tests (LRT), Wald test, Bayesian Information Criteria (BIC)), and alternative model selection test (LRT) and criteria used to compare nested models (BIC, Akaike Information criteria (AIC)) are shown in Table 3.

As far as the individual significance of the parameters is concerned, notice that in Model 2 each predictor meets the conventional standard for statistical significance attending to the likelihood test. As expected, each of the Wald statistics shows a smaller degree of significance, with the variable SUCCESSION resulting from the rule of thumb $p < 0.05$[4]. According to BIC the link between each $\beta_i$ with the dependent is weak for SUCCESSION, moderate for LOAN, YRETIREMENT,

[4] The *Wald chi-square* has been widely criticized for being too conservative, that is, lacking adequate power. Menard (2001) warns that for large coefficients, standard error is inflated, lowering the *Wald statistic* (chi-square) value. Agresti (1996) states that the *likelihood-ratio test* is more reliable for small sample sizes than the Wald test. BIC should be greater than 0 to support retaining the variable in the model. As a rule of thumb, BIC of 0–2 is weak, 2–6 is moderate, 6–10 is strong, and over 10 is very strong.

**Table 3.** Parameter estimates for alternative binomial EXIT-STAY models.

| | MODEL 1 | | | | | MODEL2 | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| VARIABLE | $\beta_i$ (S.E) | Exp($\beta_i$) | Wald $\chi^2$ ($p$-value) | LRT† ($p$-value) | BIC†† | $\beta_i$ (S.E) | Exp($\beta_i$) | Wald $\chi^2$ (p−*value*) | LRT†) (p−*value*) | BIC†† |
| SUCCESSION | −3.331 | 0.036 | 4.377* | 6.846** | 2.542 | −2.046 | 0.129 | 3.407 | 4.375* | 0.075 |
| | (1.592) | | (0.036) | (0.009) | | (1.108) | 0.129 | (0.065) | (0.036) | |
| LOAN | 3.224 | 25.133 | 7.040** | 10.703** | 6.398 | 2.577 | 13.153 | 6.361* | 8.745** | 4.441 |
| | (1.215) | | (0.008) | (0.001) | | (1.022) | 13.153 | (0.012) | (0.003) | |
| YRETIREMENT | 0.239 | 1.214 | 6.110* | 10.730** | 6.427 | 0.193 | 1.213 | 5.684* | 8.467** | 4.164 |
| | (0.097) | | (0.013) | (0.001) | 6.427 | (0.081) | 1.213 | (0.017) | (0.003) | |
| EXPERIENCE | 0.194 | 1.214 | 6.553** | 10.513** | 6.208 | 0.166 | 1.181 | 5.941* | 8.492** | 3.941 |
| | 0.194 | 1.214 | (0.010) | (0.001) | | (0.068) | | (0.015) | (0.003) | |
| SKILL | −2.997 | 0.05 | (0.020) | 9.010** | 4.706 | −2.442 | 0.087 | 5.156* | 7.395** | 3.092 |
| | (1.287) | | (0.020) | (0.003) | | (1.075) | | (0.023) | (0.006) | |
| DGRANT | 0.000024 | 1.000 | 6.952** | 10.168** | 5.863 | 0.000023 | 1.000 | 9.257** | 13.828** | 9.925 |
| | (0.00000094) | | (0.008) | (0.001) | | (0.00000076) | | (0.002) | (0.0000) | |
| FAMILY | −2.104 | 0.122 | 2.379 | 2.728 | −1.576 | - | - | - | - | - |
| | (1.364) | | (0.123) | (0.099) | | | | | | |
| PROFIT | 0.00017 | 1.000 | 1.521 | 1.580 | −2.724 | - | - | - | - | - |
| | (0.00014) | | (0.217) | (0.209) | | | | | | |
| PROVINCE | 1.049 | 2.856 | 0.862 | 0.922 | −3.383 | - | - | - | - | - |
| | (1.131) | | (0.353) | (0.337) | | | | | | |
| CONSTANT | −7.355 | 0.001 | 7.449 | - | - | −7.134 | 0.001 | 7.792 | - | - |
| | (2.695) | | (0.006) | | | (2.556) | | | | |
| | LRT†††(Model1) | 33.952**(0,000) | | | | LRT†††(Model2) | 30.110**(0.000) | | | |
| | BIC(Model1) | 83.700 | | | | BIC(Model2) | 74.629 | | | |
| | AIC(Model1) | 76.611 | | | | AIC(Model2) | 58.501 | | | |
| | LRT†††† (Model 1 - Model 2) = 33.952 - 30.110 = 3.842 (0.278) | | | | | | | | | |

* Significant at 5% * and 1%**.
† LRT = $L_0 - L_1$ where $L_0$ and $L_1$ are, respectively, the deviance of EM and the reduced model (RM) after eliminating $\beta_i$ from AM.
†† BIC = $BIC_1$- $BIC_0$, where $BIC_1$ and $BIC_0$ are, respectively, the BIC of the reduced model after eliminating $\beta_i$ from the AM and $BIC_0$ is the BIC for the EM.
††† LRT (Model 2) = $L_0 - L_1$ = 74.611–44.501 = 30.110, where $L_0$ and $L_1$ are, respectively, the deviance of EM and AM.
LRT(Model 1) = $L_0 - L_1$ = 74.611–40.659 = 33.952, where $L_0$ and $L_1$ are, respectively, the deviance of EM and AM.
†††† LRT between the two nested models.

EXPERIENCE, SKILL and strong for DGRANT[5]. The fact that $BIC_i > 0$ for all coefficients gives support to retaining all of the independent variables in Model 2 (Raftery 1995). In the case of Model 1, although the common variables in both models are significant, neither the LRT nor the Wald test for the individual parameters dropped from Model 2 (i.e. FAMILY, PROVINCE and PROFIT) are significant. This may indicate no difference between the full (Model 1) and the reduced (Model 2) models, hence justifying eliminating the mentioned variables. Besides, the BIC for FAMILY, PRO and PROFIT is negative, which gives additional support for not retaining them (Raftery 1995).

Regarding the overall significance of each of the two models, their respective LRT states that either of them fits significantly better than the empty or only constant model (EM) and, accordingly that at least one $\beta$ in each of the models is nonzero. Returning to the train of model refinement, since the difference in likelihood ratios for the two models [$\chi^2(3) = 3.842$, $p = 0.278$] is not significant, then one may again conclude that the variables removed from Model 1 (i.e. FAMILY, PROVINCE and PROFIT) do not matter significantly in predicting the dependent. Moreover, according to overall AIC and BIC (it must be borne in mind that the lower the AIC and BIC the better) Model 2 would be the one preferred. In summary, the evidence shown by the LRT and Wald tests for individual significance and BIC for individual parameter performance, the LRT to compare the two nested models, and their related overall AIC and BIC criteria are coincident: dropping the variables FAMILY, PROVINCE and PROFIT makes no difference in prediction. Accordingly, for reasons of parsimony, Model 2 will be the one potentially chosen. From the three omitted variables, the most surprising and unexpected one at first sight is the lack of significance of the variable showing short time economic performance related to the length of the vessel (i.e. PROFIT). This result requires further attention. One might have expected that those skippers with higher profitability should have been more reluctant to abandon the activity, while those on the verge of breaking point were a priori the candidates for exit. However, obviously, bad economic results, even losses, in just one period are not enough to close down. Unfortunately we lack the primary data in order to get a good indicator for each vessel's economic performance over the last 3–5 years, which following standard microeconomics would a priori have been expected to negatively influence the odds to exit.

[5] As a rule of thumb, BIC of 0–2 is weak, 2–6 is moderate, 6–10 is strong, and over 10 is very strong.

**Table 4.** Goodness of fit tests and pseudo $R^2$ (Model 2).

| | | |
|---|---|---|
| Goodness of fit | Deviance $L_1$ | [$\chi^2(67) = 44.5$, $p = 0.985$] |
| | Pearson's test | [$\chi^2(67) = 48.1$, $p = 0.280$] |
| | Hosmer and Levenshow test | [$\chi^2(8) = 6.24$, $p = 0.575$] |
| pseudo $R^2$ | Cox & Snell | 0.33 |
| | Nagelkerke | 0.52 |
| | M.Fadden | 0.40 |

*p*-value in brackets.

Henceforth focusing on Model 2, none of the alternative tests aiming to analyse the model's goodness of fit (i.e. the deviance, the *Pearson's* test, *Hosmer-and Lemeshow's* goodness of fit test) is significant (Table 4), which gives support to accept that there is no significant discrepancy among expected and predicted frequencies, implying that the model's estimates fit the data at an acceptable level. It must be also remarked that, the Cox & Snell $R^2 = 0.3$, Nagelkerke $R^2 = 0.5$ and last but not least MacFadden el $R^2 = 0.4$ are quite high for a cross section logit analysis.

The predictions related to the adjusted model (Model 2) were correct 65 out of 74 times, a considerably higher percentage (90.5%) than the one derived blindly estimating the most frequent (STAY) category (78.9%) (Table 5). The *sensitivity* and *specificity* of prediction of the AM are respectively 60% and 98.3%. The *false positive rate* is 1.69% while the *false negative rate* is 40%. Thus, although classification tables just offer a preliminary and coarse idea of the predictive power of a model, at first sight the accuracy of the group membership prediction of model 2 seems to be fairly good[6]. This conclusion is strongly reinforced by the predictive efficiency tests based on two alternative measures of associations, $\lambda_p$ and $\tau_p$, which offer a more reliable quantitative estimate of how well the cases are classified by the model (Menard 2001). On the one hand, $\lambda_p = 0.53$, which in reality means that using the logistic regression model reduces our errors in classifying the dependent by 53% compared to classifying the dependent by always guessing a case as the most frequent category (i.e. STAY). And on the other, $\tau_p = 0.76$ indicates that the model reduces the error of classification of cases as EXIT/STAY vessels by 1/3. Furthermore, the *binomial d statistic* tests for each of these measures of association [$d(\lambda_p) = 2.32$ ($p = 0.010$) and $d(\tau_p) = 5.55$ ($p = 0.000$)] reveal that the respective reductions in the classification error are statistically significant (Table 6).

The *Box-Tidwell transformation test* supports the required assumption of a linear relationship among the independent variables and the logit of the independent one. The *multicollinearity diagnostic statistics* carried out endorse that the presence of collinearity is not a serious problem (see Appendix 1 for more details). Last but not least, and before concluding the empirical validation of the adjusted model, the logit regression diagnostic was performed. On the one hand, none of the observations are dangerously influential as far as leverage (ht) is concerned, although one (cod 1041) is higher than the rule of thumb for Cook's distance (CD). On the other hand, about 4.5% of the observations may be considered outliers regarding the standardized residuals. However, based on DFBETA and DFFITS statistics, only observation 1041 seems to have a high significance either on the estimated parameters or the predictions of the model. However, deleting observation 1041 from the sample does not undertake a relevant change in the estimated parameters. Even the estimated parameter for SUCCESSION, which has a moderately high DFBETA, doesn't show a significant alteration. Thus, the regression diagnostic analysis gives support to accept that the logistic regression estimates are robust (see Appendix 2 for further details).

[6] Remark that classification tables should be used with certain caution and by no means as goodness-of-fit measures. The reason is that they ignore actual predicted probabilities and instead use dichotomized predictions based on a cut-off (i.e., 0.5). In other words, predicting a 0 (STAY) -or-1 (EXIT) dependent, the classification table does not reveal how close to 1.0 the correct predictions are nor how close to 0.0 the errors were. Thus, a model in which the predictions, correct or not, were mostly close to the .50 cut-off does not have as good a fit as a model where the predicted scores cluster either near 1.0 or 0.0.

**Table 5.** Classification tables for the empty (EM) and adjusted (AM) models.

| | | EM* | | | AM** (Model 2) | | |
|---|---|---|---|---|---|---|---|
| | | predicted | | | predicted | | |
| | | STAY | EXIT | % correct | STAY | EXIT | % correct |
| observed | STAY | 59 | 0 | 100 | 58 | 1 | 98.3 |
| | EXIT | 15 | 0 | 0 | 6 | 9 | 60.0 |

EM* 59 are observed STAY and predicted STAY, 15 are observed EXIT and are predicted STAY, 0 are observed STAY and are predicted EXIT and, 0 are observed EXIT and predicted EXIT.
AM**58 are observed STAY and predicted STAY, 6 are observed EXIT and predicted STAY, 1 is observed STAY and is predicted EXIT and 9 are observed EXIT and predicted EXIT.

**Table 6.** Index and test for accuracy of prediction.

| INDIXES OF PREDICTIVE EFFICIENCY | *d* binomial TESTS |
|---|---|
| $\lambda_p = 0.53$ | $d(\lambda_p) = 2.32$ (0.010) |
| $\tau_p = 0.76$ | $d(\tau_p) = 5.55$ (0.000) |

$\lambda_p$ = [number of cases in the smaller observed category $(c + d)$ – number of cases incorrectly predicted $(c + b)$]/number of cases in the smaller observed category $(c + d)$, where $a = 58$, $b = 1$, $c = 6$, $d = 9$.$\tau_p$ = [expected number of errors $(2*(a + b)*(c + d)/N)$ – actual number of errors $(c + b)$)]/ expected number of errors $(2*(a + b)*(c + d)/N)$, where $a = 58$, $b = 1$, $c = 6$, $d = 9$.
$\tau_p = (ad - bc)/0.5[(a + b)(b + d) + (c + d)(a + c)]$ where $a = 58$, $b = 1$, $c = 6$, $d = 9$
$\lambda_p) = [(c + d)/N\text{-}(c + b)/N)]/\text{sqrt}[((c + d)/N)*(1\text{-}(c + d)/N)/N)$
$\tau_p) = [z/N- (c + b)/N)]/\text{sqrt}[(z/N*(1- z/N))/N)$, where $z= (2*(a + b)*(c + d)/N)$
*NOTE*: $d\lambda_p)$ and $\tau_p)$ are approximately normally distributed.

## 3.4 Interpreting the results

From the results of the logistic regression analysis summarised in Table 3, we obtain the *odds* in favour of the EXIT choice, that is, the number involving how probable EXIT is to

$$Odds(EXIT) = e^{(-7.134-2.046\cdot SUCCESSION+2.577\cdot LOAN+0.193\cdot YRETIREMENT+0.166\cdot EXPERIENCE-2.442\cdot SKILL+0.000076\cdot DGRANT)}$$

occur or not, which is no more than the rate between the probability to exit and stay *(i.e. pr(Y = EXIT)/(1-pr(Y = EXIT)).*

*see equation above*

Applying the odds definition to the logistic model and taking logarithms, the equation (*i.e. log odds ratio*) for the relationship between exit choice of the fishing vessels and the predictors becomes the next linear function of the independent variables:

$$\begin{aligned} Logit(EXIT) = &-7.134 - 2.046 \cdot SUCCESSION + 2.577 \cdot LOAN \\ &+ 0.193 \cdot YRETIREMENT + 0.166 \cdot EXPERIENCE \\ &- 2.442 \cdot SKILL + 0.000076 \cdot DGRANT \end{aligned}$$

where *logit* (*Y* = *EXIT*) = *Ln* (*Odds* (*EXIT*)).

Turning to the individual $\beta_i$ coefficients, each $\beta_i$ measures the change in the logit as a result of a unitary change in $X_i$. These coefficient values may be more intuitively interpretable following the *odds ratio* approach or, even better, by calculating their related *marginal effects* ($\mathrm{MgE}_i$) and *elasticities* ($\varepsilon_i$). On the one hand, it turns out that for numerical variables $\exp(\beta_i)$ is the estimated odds ratio for those that are a unit apart on $X_k$ net of other predictions in the model, while for dummy coefficients a unit different in $X_k$ is in fact the difference between membership in category $X_k$ and membership in the omitted category. On the other hand, each $\mathrm{MgE}_i$[7] has the usual meaning of a standard slope in economics and accordingly, in order to avoid problems related to scaling, each $\varepsilon_i$[8] gives the percentage change in the probability of EXIT in response to a one percentage change in the explanatory variable.

Both $\mathrm{MgE}_i$ and $\varepsilon_i$ are nonlinear functions of the parameter estimates and the levels of the explanatory variables ($X_i$). Accordingly they vary with the observed values of $X_i$, so they cannot generally be inferred directly from the parameter estimates. It is thus necessary to consider adequate summary measures. One possibility may be to evaluate $\mathrm{MgE}_i$ and $\varepsilon_i$ at the sample means of the exploratory variables ($\bar{X}_i$). An extended criticism of this measure is that non-linearity implies that there is no guarantee that the logit function will pass through the point defined by the sample averages. Alternative measures proposed by Greene (2000) and Hensher and Johnson (1981), which are based on evaluating the expressions in the footnotes 11 and 12 at every observation and then taking the average, are included in Table 7.

[7] The marginal effect is the change in predicted probability associated with changes in the explanatory variables. The marginal effect of the $k$th explanatory variable on the response probability is obtained from: $\frac{\partial \Pr(Y_t=EXIT/X_t)}{\partial X_{kt}} = \left[\frac{e^{(\alpha+\sum_{i=1}^{N} X_i\beta)}}{1+e^{(\alpha+\sum_{i=1}^{N} X_i\beta)}}\right] \cdot \left[1-\frac{e^{(\alpha+\sum_{i=1}^{N} X_i\beta)}}{1+e^{(\alpha+\sum_{i=1}^{N} X_i\beta)}}\right] \cdot \beta_{kt} = factor \cdot \beta_{kt}$.

[8] For the $k$th explanatory variable elasticity may be is obtained using partial derivatives as: $\varepsilon_{\Pr, x_{kt}} = \left\{\left[\frac{e^{(\alpha+\sum_{i=1}^{N} X_i\beta)}}{1+e^{(\alpha+\sum_{i=1}^{N} X_i\beta)}}\right] \cdot \left[1-\frac{e^{(\alpha+\sum_{i=1}^{N} X_i\beta)}}{1+e^{(\alpha+\sum_{i=1}^{N} X_i\beta)}}\right] \cdot \beta_{kt}\right\} \cdot \frac{X_{kt}}{\Pr(Y_t=EXIT/X_t)} = factor \cdot \beta_{kt} \cdot \frac{X_{kt}}{\Pr(Y_t=EXIT/X_t)}$

**Table 7.** $\beta_i - s$, odds, Marginal Effects and Elasticities.

| VARIABLE | $\beta_i$ | $\mathrm{Exp}(\beta_i)$ | $MgE_i$ | $\bar{\varepsilon}_i$ | $\bar{\varepsilon}_i^w$ |
|---|---|---|---|---|---|
| SUC (1) | −2.046 | 0.129 | −0.1040 | - | - |
| MORDEP (1) | 2.577 | 13.153 | 0.2130 | - | - |
| YRETI | 0.193 | 1.213 | 0.0182 | 1.69 | 1.00 |
| EXSKI | 0.166 | 1.181 | 0.0156 | 1.72 | 1.24 |
| IP03RA | −2.442 | 0.087 | −0.2306 | −2.03 | −0.90 |
| DGRANT | 0.000023 | 1.000 | 0.0217 | 1.08 | 0.89 |
| CONSTANT | −2.046 | 0.001 | - | - | - |

Following Greene (2000), once the $MgE_{ij}$ for each numerical coefficient ($i$) and individual vessel ($j$) have been calculated, the average values are reported. In the case of dummies, notice that the change in the probability of EXIT that results from changing $X_k$ from zero to one, holding all other variables at some fixed values$\bar{X}$, is given by the difference: *Pr(Y=1* | $X_k = 1, \bar{X}$*) - Pr(Y=1* | $X_k = 0, \bar{X}$), where the values set for $\bar{X}$ are the mean values for each 0 or 1 group independents. Regarding $\varepsilon_i$, two alternative measures have been considered. On the one hand, the average value of individual elasticities ($\bar{\varepsilon}_j$)[9] proposed by Greene ((2000), and on the other, the weighted average elasticities ($\bar{\varepsilon}_i^w$)[10] recommend by Hensher and Johnson (1981). As well as ($\bar{\varepsilon}_i$), ($\bar{\varepsilon}_i^w$) consists on evaluating the elasticities at every observation, but differs from the former because it includes weighted average terms, being the weights the predicted probabilities. Table 7 includes $\beta_i$, the odds to EXIT, $MgE_i$, $\bar{\varepsilon}_i$ and ($\bar{\varepsilon}_i^w$).

The fact of having the continuity arranged decreases the logit(EXIT) in $\beta_{\mathrm{SUCCESSION}} = -2.025$, in other words, skippers with a potential heir to continue with the family business once they retire are $\exp(\beta_{\mathrm{SUCCESSION}}) = 0.129$ times less reluctant to EXIT. From $\mathrm{MgE}_{\mathrm{SUCCESSION}}$ we can conclude that the existence of continuity leads to a 0.1040 decrease in the probability to EXIT. Notice also that 100% of the skippers who stated that their continuity was guaranteed; it was with a family member (generally a son). Thus, it seems that family tradition still has a considerable influence in Basque inshore fishing. This suggests that even in adverse economic circumstances, some of the vessels staying in the fishery may be there just to be transferred from parents to descendants, not only the fishing unit itself, but also the so-called social capital, which includes the accumulated sea and managerial knowledge.

The duty to face a significant loan does also exercise its influence on the behaviour of vessel owners' when deciding whether to EXIT or to STAY. When the debt is not relevant (LOAN = 1), the average of the estimated logit increases in 2.577. Since $\exp(\beta_{\mathrm{DEUPEN}}) = 13.153$, owners who have paid off the vessels or are in the verge of it, are 13 times more prone to EXIT. From $\mathrm{MgE}_{\mathrm{LOAN}}$ we know that on average, whilst maintaining everything else constant, the existence of a significant debt upon the vessel leads to a 0.2130 decrease in the

[9] $\bar{\varepsilon}_i = \left(\sum_{i=1}^{74} \varepsilon_i\right)\big/74.$

[10] The procedure to calculate each is to evaluate the elasticity at every observation and then construct a weighted average with predicted probabilities such as the weights.

probability to EXIT. Summarising, significant indebtedness prevents from abandoning the activity and scrapping the vessel, which, taking into account the evolution of the fleet represented in Figure 1 may be revealing a thin second hand market of vessels. The argument behind this hypothesis is that in second hand market of vessels in which unusually few transactions occur, the monetisation of the sunk costs becomes more complicated for the vessel owners. The real option set may be de facto restricted to the dilemma to choose between breaking up the vessel assuming a considerable amount of loses not totally covered by the decommissioning grant or staying. In this framework the decision to stay might turn on to be a *second best* option. Apart from this, the negative relation between the probability to exit and the variable LOAN might also be an indication of optimism among fishermen or even their despair for satisfactory income elsewhere to pay off their debt.

Surprisingly each one-unit increase in the number of years until the retirement (YRETIREMENT) is associated with an increase of 0.193 in *logit*(*EXIT*). Or in other words, $\exp(\beta_{\mathrm{YRETIREMENT}}) = 1.213$ means that a one year younger skipper is 1.213 more likely to EXIT from the activity. By inspecting $\mathrm{MgE}_{\mathrm{YRETIREMENT}}$ it is found that, on average, and keeping everything else constant, a year increase in YRETIREMENT, leads to a 0.0182 increase in the probability to EXIT. The mean elasticity $\bar{\varepsilon}_{\mathrm{YRETI}} = 1.69$ indicates that 1% increase in YRETIREMENT would imply an increase in 1.69% in the probability to exit. Since this probability is positively related to the number of years until retirement, there are the younger skippers who are in fact more reluctant to stay. This sign, compatible with basic postulates of job market for unqualified work force (i.e. the alternative employment opportunities in the job market for blue collar workers decrease as the age does) and also with unemployment rates close to the natural rate in the Basque economy may be serious evidence of the negative evolution and pessimistic future for the inshore fishing sector of the Basque Country.

$\beta_{\mathrm{EXPERIENCE}} = 0.166$ implies that each one-unit increase in the years of experience as a captain is associated with an increase of 0.166 in *logit(EXIT)*. A skipper with one more year of experience as the manager of the vessel is then $\exp(\beta_{\mathrm{EXPERIENCE}}) = 1.183$ more probable to EXIT from the activity. Or in terms of $\mathrm{MgE}_{\mathrm{EXPERIENCE}}$, one more year of experience as a skipper leads to a 0.0156 increase in the probability to EXIT, while $\bar{\varepsilon}_{\mathrm{EXSKI}} = 1.72$ means that 1% increase in EXPERIENCE would lead to a 1.72% increase in the probability to exit. To a certain extent, this seems to contradict the previous result related to YRETIREMENT, since in general one might expect that more experienced skippers were older. However this is not always the case, since there are relatively frequent sample points where young skippers are even more experienced (as skippers) than older ones[11]. Referring back to the sign of the estimated parameter, however old or young, skippers (100% of the skippers are also the owners or co-owners of the vessels) with more years of experience are the ones with more knowledge of the real economic evolution of the fishing sector, and compared to those being owners for only few years, may have generated not only a major amount of added capital to be reinvested in another business, but also a deeply rooted pessimistic expectation than less experienced ones. Additionally, individual career top aspirations for those working as fishermen in someone's vessel may also play a significant roll. In fact, since being a vessel owner is one of the main professional dreams of crewmembers, it is not surprising that when one reaches this coveted position at a relatively old age (i.e. with not many years to retirement), the obstacle to exit was more pronounced than when one reaches the maximum peak of his career while being relatively young.

$\beta_{\mathrm{SKILL}} = -2.442$ suggests that each one-unit increase in the measure for the skipper's skill (SKILL) is associated with a decrease of –2.442 in logit(EXIT). That is, a one unit more skilful skipper is $\exp(\beta_{\mathrm{SKILL}}) = 0.087$ less probable to EXIT from the activity. From $\mathrm{MgE}_{\mathrm{SKILL}}$, we can derive that being everything else constant, a unit increase in the profits above the average profits of the cluster leads to a –0.2306 decrease in the probability of EXIT. Or in terms of elasticity ($\bar{\varepsilon}_{\mathrm{IP03RA}}$), a 1% increase in SKILL would imply a –2.03% decrease in the probability to exit. Summarising, the probability to EXIT decreases insofar as the measure for the skill raises. This is good news both for the regulator and for the inshore fishing sector as a whole, because the skippers with the best scores seem to be more reluctant to EXIT.

$\beta_{\mathrm{DGRANT}} = 0.000023$ means that each one-unit increase DGRANT that the skipper received or would have received in the case of exiting from the activity is associated with an increase of 0.000023 in logit(EXIT), being the decision to EXIT 0.9998 more probable. By looking over $\mathrm{MgE}_{\mathrm{DGRANT}}$ it is found that, on average, and being everything else constant; for example a 10 000 € increase in DGRANT leads to a 0.0217 increase in the probability to EXIT, while $\bar{\varepsilon}_{\mathrm{DGRANT}} = 1.08$ points that if the regulator increased the amount of the DGRANT in 1%, this would lead approximately to the same increase in the probability to exit. Therefore, the decision to EXIT is more attractive insofar as vessel owners have the chance to perceive more money if they break up their vessel. Recall that since DGRANT is a linear and increasing function of VESSELAGE and GRT, accordingly older and bigger vessels are also the ones with higher probabilities to abandon the activity. Hence, the decommissioning grants seem to generate the correct incentives for fleet and capacity adjustment.

## 4 Conclusion

An empirical long term behavioural model on the stay and exit decisions of the fishermen belonging to the inshore fleet of the Basque Country has been developed in a random utility

[11] A priori one may expect that those counting with more years of experience as a skipper will be in fact the ones closer to retirement age. Nevertheless, after an exhaustive statistical exploration of both variables, this is not exactly the case, and there are different and really interesting correlation patterns between both variables. For instance, the overall correlation between YRETIREMENT and EXPERIENCE is positive as expected and moderately high ($\gamma = 0.6$). The correlation between YRETIREMENT and EXPERIENCE is also positive in the tales of the distribution ($\gamma = 0.4$), that is for skippers younger than 35 and older than 50. However in the central segment (35–50 years) the correlation between the mentioned variables becomes negative ($\gamma = -0.5$).

**Table 8.** The Box-Tidwell transformation test for nonlinearitie.

| VARIABLE | $\beta_i^{\dagger}$ | Exp($\beta_i$) | Wald $\chi^{2\dagger\dagger}$ | LRT$^{\dagger\dagger}$ |
|---|---|---|---|---|
| SUCCESSION | –1.993 (1.340) | 0.136 | 2.212 (0.137) | 4.888 (0.089) |
| LOAN | 2.912 (1.156) | 18.400 | 6.343 (0.012) | 9.286 (0.002) |
| YRETIREMENT | –0.170 (0.196) | 0.844 | 0.755 (0.385) | 0.763 (0.382) |
| EXPERIENCE | 0.203 (0.627) | 1.225 | 0.090 (0.764) | 0.091 (0.763) |
| SKILL | –4.119 (0.00025) | 0.016 | 2.429 (0.119) | 2.704 (0.100) |
| DGRANT | 0.00036 (0.00025) | 1.0003 | 1.929 (0.165) | 2.336 (0.124) |
| YRETIREMENT*LN(YRETIREMENT) | 0.130 (0.069) | 1.139 | 3.556 (0.059) | 3.672 (0.055) |
| EXPERIENCE*LN(EXPERIENCE) | –0.010 (0.0170) | 0.990 | .004 (0.952) | 0.004 (0.952) |
| SKILL*LN(SKILL) | 1.585 (2.862) | 4.878 | .307 (0.590) | .301(0.583) |
| DGRANT*LN(DGRANT) | .0000020 | 0.9999 | 1.695 (0.193) | 2.018 (0.155) |
| CONSTANT | –8.362 (4.185) | 0.0002 | 3.992 (0.046) | - |

$^{\dagger}$SE in brackets, $^{\dagger\dagger}$ *p*-value bracket.

framework. The probability for a fishing vessel to exit from the fishing activity has been calculated by estimating a binomial logistic function with standard maximum likelihood techniques. The empirical results confirm that exit and stay decisions are significantly associated with some characteristics of the skippers (i.e. time to retirement, experience (being a skipper) and skipper's skill) as well as other factors such as the fact of having to face a significant loan for the vessel and the arrangement of the continuity or succession by a son. Incentives, in the form of decommissioning grants also play a role. However, contrary to expected, profitability seems not to influence significantly. The results suggest that younger but more experienced skippers were more likely to exit, while a vessel was more likely to stay if a family member (often the son) intended to continue with the family business and a significant loan on the vessel was still pending. Last but not least, skippers receiving higher grants were more likely to exit, which means that the decommissioning grant designed by the Spanish Government in the form of a lineal and increasing function of the vessel's age and gross tonnage, seems to steer incentives in the correct direction to favour the fleet and capacity adjustment.

*Acknowledgements.* This study has received financial from the EFIMAS project (No SSP8-CT-2003 502516) and ETORTEK2003/IMPRES (Basque Government). The authors are grateful to conference participants at *IV Conference Developments in Economic Theory and Policy* (5–6 July 2007) in Bilbao and XVIII EAFE conference (9–11July) in Reykjavik and the comments of two anonymous refrees. All errors and opinions are the author's responsibility.

## APPENDIX 1: Testing for linearity and multicollinearity (Tables 8 and 9)

Although logistic regression does not require linear relationships between the independent factor or covariates and the dependent, as does OLS regression; however it does assume a linear relationship between the independent variables and the log odds (logit) of the dependent variable. As proposed by Hosmer and Lemeshow (1989) and Menard (2001) the *Box-Tidwell transformation test* has been used to test the nonlinearity in the logit, once the four nonlinear terms {YRETIREMENT*LN(YRETIREMENT), EXPERIENCE*LN(EXPERIENCE), SKILL*LN(SKILL), DGRANT*LN(DGRANT)} have been added. Table 8 presents the results. Taken together, the effects of the four non-linear interaction terms are not statistically significant (change in likelihood ratio $\chi^2$ = 35 207–30 110 = 15 066 with 4 degrees of freedom; $p$ = 0.2774). Furthermore, based on the individual likelihood statistics and also Wald chi-square statistics, none of the added nonlinear terms are significant. Thus, the *Box-Tidwell transformation test* supports the assumption of a linear relationship among the independents and the logit of the independent.

**Table 9.** Testing for multicollinearity.

| VARIABLE | $T_i^{\dagger}$ | $VIF_i^{\dagger\dagger}$ |
|---|---|---|
| SUCCESSION | 0.969 | 1.032 |
| LOAN | 0.876 | 1.149 |
| YRETIREMENT | 0.521 | 1.919 |
| EXPERIENCE | 0.567 | 1.764 |
| SKILL | 0.917 | 1.090 |
| DGRANT | 0.864 | 1.158 |

$^{\dagger}T_i = 1 - R_i^2$ where $R_i^2$ is the coefficient of determination for the regression of that variable on all remaining independent variables.
$^{\dagger\dagger}VIF_i = 1/T_i$, $VIF_i \geqslant 1$.

Joint with the fulfilment of linearity assumption, multicollinearity should also be checked in logistic regression models. Table 9 includes the results of *multicollinearity diagnostic statistics* produced by linear regression analysis, *tolerance* ($T_i$) and *variance inflation factor* ($VIF_i$) for each independent variable. Although there is no formal cut-off value to use with $VIF_i$ for determining risky presence of multicollinearity, as a general setting in logistic regression, values of $VIF_i > 2.5$ may be a cause for concern. All of the tolerances exceed 0.50 and the maximum $VIF_i$ hardly reaches 2.0, indicating that the presence of collinearity is not a serious problem.

## APPENDIX 2: Logistic regression diagnostic (Tables 10 and 11)

As in the lineal regression model, the logit regression diagnostic is strongly recommended in order to see if there are atypical or/and influential observations in the data set

**Table 10.** Proportion of data points exceeding the general and sample adjusted rule of thumbs.

| MEASURE | GENERAL | % | N. obs | SIZE ADJUSTED | % | N. obs |
|---|---|---|---|---|---|---|
| *ht* | $h \in$[0.2-0.5] | 9.45 | 7 | $h > 2p/N$= 0.1891 | 13.5 | 10 |
| *e** | $e > \|2\|$ | 2.7 | 2 | - | - | - |
| CD | CD > 1 | 1.35 | 1 | CD > $4/N$ = 0.0540 | 29.7 | 21 |
| $\text{DFBETA}_{\text{CONSTANT}}$ | DFBeta > \|1\| | 2.70 | 2 | DFBeta > 2/sqrt($N$) = 0.2325 | 20.27 | 15 |
| $\text{DFBETA}_{\text{SUCCESSION}}$ | DFBeta > \|1\| | 0 | 0 | DFBeta > 2/sqrt($N$) = 0.2325 | 5.4 | 4 |
| $\text{DFBETA}_{\text{LOAN}}$ | DFBeta > \|1\| | 0 | 0 | DFBeta > 2/sqrt($N$) = 0.2325 | 9.45 | 7 |
| $\text{DFBETA}_{\text{YRETIREMENT}}$ | DFBeta > \|1\| | 0 | 0 | DFBeta > 2/sqrt($N$) = 0.2325 | 0 | 0 |
| $\text{DFBETA}_{\text{EXPERIENCE}}$ | DFBeta > \|1\| | 0 | 0 | DFBeta > 2/sqrt($N$) = 0.2325 | 0 | 0 |
| $\text{DFBETA}_{\text{SKILL}}$ | DFBeta > \|1\| | 0 | 0 | DFBeta > 2/sqrt($N$) = 0.2325 | 6.75 | 5 |
| $\text{DFBETA}_{\text{DGRANT}}$ | DFBeta > \|1\| | 0 | 0 | DFBeta > 2/sqrt($N$) = 0.2325 | 0 | 0 |
| DFFITS | DFFIT > \|1\| | 20 | 27% | DFBeta > 2*sqrt($p/N$) = 0.6151 | 60 | 44 |

**Table 11.** Logistic regresion diagnostic.

| OBS COD | 1041 | 1066 | 1002 | 1024 | 1006 | 1068 | 1012 |
|---|---|---|---|---|---|---|---|
| PROBABILITY | 0.03 | 0.06 | 0.26 | 0.25 | 0.20 | 0.65 | 0.47 |
| PREDICTED | STAY | STAY | STAY | STAY | STAY | EXIT | STAY |
| OBSERVED | EXIT | EXIT | EXIT | EXIT | EXIT | STAY | EXIT |
| CD | 2.1225 | 0.9362 | 0.4397 | 0.4057 | 0.7985 | 0.7302 | 0.5401 |
| HT | 0.0588 | 0.0606 | 0.1380 | 0.1193 | 0.1638 | 0.2829 | 0.3200 |
| *e** | 2.7483 | 2.4159 | 0.7331 | 1.7735 | 1.9712 | −1.7093 | 1.4994 |
| $\text{DFBETA}_{\text{CONSTANT}}$ | 2.7999 | 0.6406 | 3.7469 | −0.1035 | 0.4474 | 1.0660 | −0.5927 |
| $\text{DFBETA}_{\text{SUCCESSION}}$ | 0.9835 | 0.2173 | 1.7506 | −0.1495 | −0.0130 | −0.5207 | 0.5350 |
| $\text{DFBETA}_{\text{LOAN}}$ | −0.4274 | −0.6813 | 1.6574 | 0.1187 | −0.4532 | −0.3225 | 0.2374 |
| $\text{DFBETA}_{\text{YRETIREMENT}}$ | −0.0884 | 0.0013 | 1.6254 | −0.0085 | 0.0203 | −0.0353 | 0.0288 |
| $\text{DFBETA}_{\text{EXPERIENCE}}$ | −0.0739 | −0.0162 | 0.0088 | 0.0081 | −0.0007 | −0.0360 | 0.0189 |
| $\text{DFBETA}_{\text{SKILL}}$ | −0.1432 | 0.5176 | −0.2090 | 0.3784 | −0.1430 | 0.3073 | −0.2626 |
| $\text{DFBETA}_{\text{DGRANT}}$ | 0.0000 | 0.0000 | 0.1322 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| DFFITS | 0.0909 | 0.1051 | −0.0111 | 0.2075 | 0.2245 | −0.3675 | 0.4574 |

with a powerful influence on the estimated parameters and/or predictions of the model. Usual measures in regression diagnostic (i.e. the leverage (*ht*), Cook's distance (*CD*), the standardised residual (*e**), DFBETAs and DFFITS are summarised in Tables 10 and 11.

While not necessarily undesirable, influential observations are those observations that make a relatively large contribution to the values of the estimates, that is, observations whose inclusion or exclusion may result in substantial changes in the fitted model. The most common measures for the degree of influence are the *leverage* (*ht*) and to some degree *Cook's distance* (CD). As a general rule, data points satisfying [0.2 > $ht$ > 0.5] are considered moderately influent, while those in which $ht > 0.5$ should be especially kept watch. The sample size corrected rule of thumb suggested by Belsey et al. (1980) is $h > 2p/N$, where p is the number of estimated parameters and $N$ the sample size. Similarly, the general criterion stands to watch out for observations where $CD > 1$, although in large samples some authors suggest a sample corrected rule of $CD > 4/N$. Applying these rules to our case study, 7.5% of the observations are moderately influent attending to ht, while hardly 2.5% does go beyond the median value of $F$ (=1.15) relative to *CD*. Thus, it may be concluded that none of the observations are riskily influent according to leverage, although observation 1041 is higher than the rule of thumb for *CD*.

Together with influential observations, it is also convenient to include measures designed to detect large errors. In a model which fits in every cell formed by the independent variables, no absolute standardized residual will be $e* > 2$ (0.05 level) (or $e* > 1.96$(0.01 level)). Cells not meeting this criterion indicate combinations of independent variables for which the model is not working well. In our model 94.5% of the observations fit the specified rule of thumb, and consequently regarded as acceptable in term of the model specification. Thus, about 5.5% of the observations may be considered outliers.

Outliers and high leverage points can be an indication of exceptional data points that are worthy of further study. What is likely to be of more importance however is whether these points significantly contribute to the values of the coefficient estimates and the model predictions. Diagnostics respectively designed for these two purposes are DFBETAS and DFFITS (Belsey et al. 1980). The general cut-off criterion for cases to be considered forceful to the values of the coefficients is $|\text{DFBETAS}_{\text{kt}}| > 1.0$ (Menar 1995), while Belsey et al. recommend further investigation of observations where $|\text{DFBETAS}_{kt}| > 2/N^{(1/2)}$, specially in big samples. Regarding the predictions, the general rule stands that an observation is considered forceful to the predictions when $|\text{DFFITS}_{kt}| > 1$, while the sample corrected rule is $\text{DFFITS}_{kt}| > 2/(p/N)^{(1/2)}$.

Table 10 summarizes the proportion of observations in the sample exceeding both the general and sample adjusted rules of thumb for the regression diagnostic indicators. Taking into account our moderate sample size the general rule may be considered valid. Additionally, Table 11 includes data points with a moderate ($ht > 0.2$) or high ($ht > 0.5$) leverage and/or outliers ($e* > 2$) with a significant contribution on the values of the estimated parameters and/or the model's predictions and all the observations incorrectly predicted. From the observations in Table 11 only 1041 and 1066 excess the cut off for $e*$ or $CD$. It's not surprising that these are the data points with the worst fit to our model, since with a very small estimated probability to EXIT they are wrongly predicted to STAY. However, only DFBETAs for observations coded 1041 are substantially higher than the general rule $CD > 1$ and none of the DFITS excess it, even if we accepted the more conservative sample adjusted rule. Accordingly, only observation 1041 seems to have great significance either on the estimated parameters or the predictions of the model. However since deleting it does not represent a relevant change in the parameters, the regression diagnostic analysis gives support to accept that the logistic regression estimates are robust.

## References

Agresti A., 1996, An Introduction to Categorical Data Analysis. John Wiley and Sons, Inc.

Belsey D., Kuh E., Welsch R., 1980, Regression Diagnostics, John Wiley and Sons, New York.

Berk P., Perloff J.M., 1984, An open-access fishery with rational expectations. Econometrica. 52, 489–506.

Bjorndal T., Conrad J.M., 1987, The dynamics of an open access fishery. Can. J. Econ. 20, 74–85.

Bockstael N.E., Opaluch, J.J., 1983, Discrete modelling of supply response under uncertainty: The case of the fishery. J. Environ. Econ. Manage. 10, 125–137.

Bockstael N.E., Opaluch, J.J., 1984, Behavioural modelling and fisheries management. Ma. Resour. Econ. 1, 105–115.

Boyce J.R., 1995, Optimal Capital accumulation in a fishery: a nonlinear irreversible investment model. J. Environ. Econ. Manage. 28, 324–339.

Clark C.W., Clark F.H., Munro G.R., 1979, The optimal exploitation of renewable resource stocks: problems of irreversible investment. Econometrica 47, 25–47.

del Valle I., Astorkiza, I., Astorkiza K., 2001, Is the current regulation of the VIII division European anchovy optimal? Environ. Resour. Econ. 19, 53–72.

del Valle I., Astorkiza I., Astorkiza K., 2003, Fishing effort validation and substitution possibilities among components: The case study of the VIII division European anchovy fishery. Appl. Econ. 35, 63–77.

del Valle I, Astorkiza I., Astorkiza K., 2008, Prestige's oil spill and its economic effects in the Basque coastal fleet. Communication presented at the XXII ASEPELT Conference, Barcelona.

Hensher D.A., Johnson L.W., 1981, Applied Discrete Choice Modelling. John Wiley.

Hosmer D.W., Lemeshow S., 1989, Applied Logistic Regression. John Wiley & Sons.

Ikiara M.M., Odink J.G., 2000, Fishermen resistance to exit fisheries. Mar. Resour. Econ. 14, 199–213.

Greene W., 2000, Econometric Analysis. 4th ed. Prentice-Hall. New Jersey.

Kirkley J., Squires D., Strand I.E., 1998, Characterizing managerial skill and technical efficiency in a fishery. J. Product. Anal. 9, 145–60.

McFadden D., 1973, Conditional logit analysis of qualitative choice behaviour. Frontiers in Econometrics.Zarembka (Ed.), New York, Academic Press.

Mackinson S., Sumaila U.R., Pitcher T.J., 1997, Bioeconomics and catchability: fish and fishers behaviour during stock collapse. Fish. Res. 31, 11–17.

McKelvey, R., 1985, Decentralized regulation of a common property renewable resource industry with irreversible investment. J. Environ. Econ. Manage. 12, 287–307.

Menard S., 2001, Applied Logistic Regression Analysis. Sage Publications. Ser. Quantitative Applications in the Social Sciences, No. 106.

Pascoe S., Revill A., 2004, Costs and benefits of bycatch reduction devices in European brown shrimp trawl fisheries. Environ. Resour. Econ. 27, 43–64.

Pradhan N.C. Leung P., 2004, Modeling entry, stay, and exit decisions of the longline ?shers in Hawaii. Mar. Policy. 28, 311–324.

Raftery A.E., 1995, Bayesian model selection in social research. In: Marsden P.V. (Ed.), Sociological Methodology. London: Tavistock, pp. 111–163.

Silva L.C., Barroso I.M., 2004, Regresión logística. Cuadernos de Estadística. Editorial La Muralla, Hesperides.

Squires D., Kirkley J., 1999, Skipper skill and panel data in fishing industries. Can. J. Fish. Aquat. Sci. 56, 2011–2018.

Ward J.M., Sutinen J.G., 1994, Vessel entry-exit behaviour in the Gulf of Mexico shrimp fishery. Am. J. Econ. 76, 916–923.