BASQUE INSHORE SKIPPERS' LONG TERM BEHAVIOUR: A LOGIT APPROACH[1]

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Paper presented at XVIII EAFE Conference. 9-11 July 2007 – Reykiavik (Iceland)

Abstract

Based on the discrete optimal choice theory and a RUM framework, this paper focus on 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 on the probability of a fishing vessel to exit from the fishing activity. Special attention will be plaid to the roll that incentives generated by decommissioning grants exercise in the fishermen's long-term behaviour. Our results indicate that owner's age, years of experience being a skipper, the arrangement of continuity in the familiar business, the degree of dependency upon bank mortgage and last but not least decommissioning grants may significantly determine the decision to abandon the activity.

Keywords: 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 pretending to influence their long-term stay-exit decision in order to favour fleet and capacity adjustments. Understanding how fishermen behave is thus a key question when aiming to design any fisheries management scheme, especially if, like decommissioning grants, it is based on economic incentives.

[1] This study has received financial from the EFIMAS project (No SSP8-CT-2003 502516) and ETORTEK2003/IMPRES (Basque Government).
[2] 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. All errors and opinions are the author's responsibility.

Primarily concerned with capital theoretic bio-economics and inspired by the traditional adjustment mechanism in the basic economic theory of 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, P. 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, the consideration of different condition for entry and 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 the 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 by 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 last but not least the socio-economical framework in which the fishing activity develops (See Table 0 for a empirical survey from the literature). Furthermore, in some instances, some of the vessels staying in a fishery may not be operating profitably, but may be there just to cover the operating costs or just because lack of alternative employment opportunities (Ikiara and Odink, 2000). This suggest that not only profitability itself but also the background of each fishery is very important to understand fishermen 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 give 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 no too much more published papers are for example Ward and Sutinen (1994) Ikiara and Odink (2000) and Pradham and Leung (2004). We develop a discrete choice logit model to analyse fishermen long-term behaviour that allows 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, as illustrated in figure 1. Section 1 gives a short understanding of the theoretical framework of the paper. After a short discussion related to the available data to face the empirical analysis developed in section 2, the main econometric results as well as their interpretation is presented. 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.

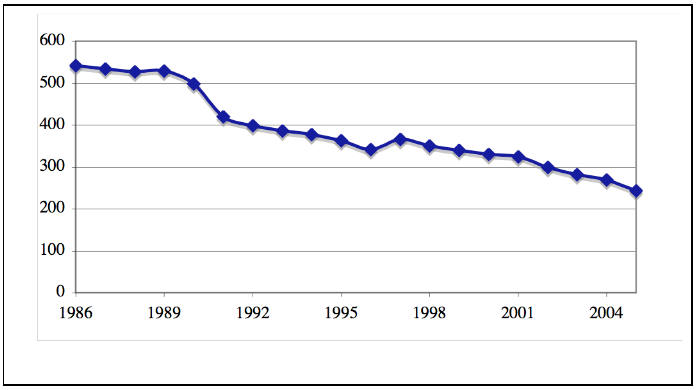
-TABLE 0-

Variables in selected ENTRY(E)-STAY(S)-EXIT(E) fisheries models

MODEL	Ward &Sutinen		Ikiara & Odink		Pradham & Leung	
VARIABLE	Inclusion	Signif.	Inclusion	Signif.	Inclusion	Signif.
Ex-vessel prices (P/£)	√	√	-	-	-	-
Operating costs (C/£)	√	√	-	-	-	-
Fleet size (∑GRT)	√	√	-	-	√	√
Vessel length	√	√	-	-	-	-
Vessel tonnage	√	√	-	-	-	-
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 (I/TRB)	-	-	-	-	√	√
Vessel age	-	-	-	-	√	-
Owner's residency	-	-	-	-	√	√

-FIGURE 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 ε_{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 α and β 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 ε_i are independent and identically distributed type 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 Green, 2000 for more details).

The RUM framework briefly described above accommodates rightly to our needs. In our case a fisherman *i* is selecting an option from a set of only two possible: 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 in 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 to exit from the fishing activity.

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

3. THE EMPIRICAL MODEL

3.1. 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) of 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 100% of the cases were also the owner's, and accordingly as the main decision maker's, are accepted to be the appropriate sampling unit. The survey response rate was rather high (96%).

-TABLE 1-

Descriptive statistics for intermediate and final variables

	VARIABLE	TYPE	MEANING	Freq. %	Mean	S.E
	Y(1)= EXIT	Cat.	Dependent variable EXIT (1) STAY (0)	 0,2027 0,7973		-
Group 1	GT*	Num*	Gross tonnes of the vessel		51,63	46,74
Group 1	LE	Num*	Length of the vessel		16,51	6,62
Group 1	VEAGE	Num*	Vessel's age= [2003 – year built]		19,27	11,24
Group 1	CLU[3]	Cat*	Typology of the vessel. ART TXI CER	 0,3918 0,3242 0,2837		
Group 2	YRETI	Num	Years until skipper's retirement [55 – age 2003].	-	10,92	1,045
Group 2	EDU	Cat	Education of the skipper PRIMARY PROFESSIONAL SECONDARY UNIVERSITY	 0,3513 0,2027 0,4189 0,0135		
Group 2	EXSKIP	Num	Years being skipper (=owner).	-	13,97	1,08
Group 2	SUC	Cat	Is there a successor to take over from the owner? YES(1) NO (0)	 0,2837 0,7163	-	-
Group 2	FAFISH	Cat	Family in the crew. No (1). YES (0).	 0,6756 0,3243	-	-
Group 2	PRO		Province. Categorical. GI(1) BI (0)	 0,4594 0,5405		
Group 3	PROF03	Num	Profits during years 2003/ LE.		3672	3184
Group 3	MORDEP		Significant mortgage upon the vessel NO (1) YES (0)	 0,5270 0,4729	-	-
Group 3	DGRANT	Num.	Decommissioning grant obtainable		69.000	68.592
Group 3	IF03RA	Num.	Skipper's skill ratio [Current incomes 2003 / mean incomes of the cluster].		0,9990	0,49926

Note: N=74

* Intermediate variables

Table 1 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 (GT), length (LE), vessel's age (VEAGE) and fishing typology or cluster (CLU). The second group is centred upon characterising the skipper and his background: years until retirement (YRETI), education (EDU), years of experience being a skipper

[3] Based on del Valle et al. (2004) three different typologies of vessels are considered. Artisan vessels (ART) are a set of heterogenous small size vessels operating in close waters. The so-called "txikihaundis" (TXI) are medium size and polyvalent vessels, and (CER) are the biggest in size mainly catching anchovy and white tuna.

(EXSKIP), family involvement in the fishing activity (FAFISH), the existence of succession after the skipper's retirement (SUC), a proxy for the skipper's skill (IF03RA) and province (PRO). The third group covers economic and/or regulatory issues: length relative current profitability (PROF03), the degree of dependency on a mortgage upon the vessel and/or gears (MORDEP), 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 in the independents, taking into account the relative small sample size (N=74), the broad range of variables in Table 1, and the consequent lack of degrees of freedom, efforts have been made to identify a subset of variables a priori excludable. For one side, as a general rule, and following also to avoid potential collinearity problems, some intermediate variables such as GT, LE, VEAGE or CLU that, as we will show below, are used to generate a final one (i.e. DGRANT, IF03RA or PROF03) 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 EDU was not available for 3 of the 74 skippers and the exploratory analysis indicates no significant influence in the exit behaviour we decided to omit it. Thus, four independent factor variables (i.e. MORDEP, SUC, FAFISH and PRO) and four numerical variables (RETI, EXSKIP, GDRANT and IF03RA) will be incorporated to the empirical model (Model 1 from now on).

MORDEP captures whether there is a significant mortgage 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 and objective one, which is the ratio net purchase price[4] financed with a bank loan to the number of years since the vessel's purchase, corrected by the number of partners. The cut off point has been established in 6000 €/year (per partner). Thus, MORDEN = 1 implies that the vessel is fully paid or if there is a mortgage, that it is not significant, while if it takes value zero the amount of the mortgage is considered to be significant. The variable SUC refers to the existence/inexistence of an heir to continue with the activity once the skipper had been retired. We assign SUC =1 when the relief is guaranteed. FAFISH is an indicator for the skippers' family implication in the fishing activity. Thus, FAFISH takes value 1 if none of the crew-members is a directed or in law relative or the owner's or any of the co-owners', while FAFISH =0 means that al least on of the crew members belongs to the owner's family. PRO is a dummy variable for the province the vessel belongs to, PRO=1 is assigned to vessels of Gipuzkoa, and PRO = 0 to vessels of Bizkaia. YRETI indicates the remaining years for the skipper's retirement[5], while EXSKI, aiming to measure managerial expertise and sea related knowledge, accounts for the years as a skipper (EXSKI)[6]. DGRANT[7]

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

[5] The retirement age for the fishermen is legally established in 55 years.

[6] A priori one may expect that those counting with more years of experience being a skipper will be in fact the ones closer to the 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 one side, the overall correlation between YRETI and EXSKI is positive as expected and moderately high ($\gamma = 0{,}6$). The correlation between YRETI and EXSKI 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 ($\gamma = -0{,}5$).

[7] The chart from below summarises *Spanish 197/2000* order specifying the decommissioning grant to be perceived as a function of GT and VEAGE. To get the DGRANT amount, Maximum DG quantity included in the table is corrected by the vessel's bulding year (VEAGE) following the next interval rules: a) 10<VEAGE<15 → Maximum DG; b) 16<VEAGE<29 → Maximum DG -1,5% year in excess c) VEAGE>30 → Maximum DG -22,5%.

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 between gross tons (GT) and vessel's age (VEAGE). Thus, DGRANT not only captures part of the opportunity cost of the capital, it also reflects the years passed since the vessel was built and the vessel's capacity. IP03RA intends to capture 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 for example Kirkley et al. (1998) del and Valle et al. (2003) for a general overview of the different approaches having 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 incomes component of profits. Thus, we are assuming that the skilfulness is more related to incomes rather than to the costs. Finally, PROF03 is the ratio between the profits obtained in the year 2003 divided by the length of the vessel.

3.2. Econometric results

The log odds of EXIT choice have been regressed on the four dummies (i.e. SUC, MORDEP, FAFISH, PRO) and four numerical variables (i.e. YRETI, EXSKI, DGRANT, IF03RA, PROF03) (Model 1). Taking into account that some variables resulted to be non-significant, a related restricted nested model including two dummies (i.e. SUC, MORDEP) and four covariates (i.e. YRETI, EXSKI, DGRANT, IF03RA) (Model 2) will be also estimated; and the differences between the two alternative models compared. The results showing the estimated coefficients (β_i), the odds ratio ($Exp(\beta_i)$), 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 to compare nested models (BIC, Akaike Information criteria (AIC)) are shown in Table 2.

The same as *t-test* in lineal regression, *the likelihood ratio test* tests (LRT), the *Wald chi-Square* and Bayes Information Criterion (BIC) permit testing the statistical significance of each (β_i) individual coefficients[8]. 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* gives a smaller degree of significance, with the variable SUC becoming out of the rule of thumb $p<0,05$. According to BIC the link between each β_i with the dependent is weak for SUC, moderate for MORDEP, YRETI, EXSKI, IF03RA and strong for DGRANT. The fact

GT	Maximum DG
0<10	(11.000/GT)+2.000
10<25	(5.000/GT)+62.000
25<100	(4.200/GT)+82.000
100<300	(2.700/GT)+232.000

[8] The *Wald chi-square* has been widely criticized for being too conservative, that is, lacking adequate power. Menard (1995) 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.

that $BIC_i>0$ for all coefficients gives support to retaining all of the independent variables in the model. However, although in Model 1 all the variables included both in Model 1 and Model 2 are significant, neither the LRT nor the Wald test for the individual parameters dropped from Model 2 (i.e. FAFISH, PRO and PROF03) is significant, which indicates no difference between the full (Model 1) and the reduced (Model 2) models, hence justifying eliminating the given variables so as to have a more parsimonious model that works just as well. For another, the BIC for each of the variables dropped from Model 1 is negative which, following Raftery (1995), gives support not to retaining them in the model.

-TABLE 2-
Parameter estimates for alternative binomial EXIT-STAY models

	MODEL 1					MODEL2				
VARIABLE	β_i (S.E)	Exp(β_i)	Wald χ^2 (p-value)	LRT† (p-value)	BIC††	β_i (S.E)	Exp(β_i)	Wald χ^2 (p-value)	LRT† (p-value)	BIC††
SUC (1)	-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)		(0,065)	(0,036)	
MORDEP(1)	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)		(0,012)	(0,003)	
YRETI	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)		(0,081)		(0,017)	(0,003)	
EXSKI	0,194	1,214	6,553**	10,513**	6,208	0,166	1,181	5,941*	8,492**	3,941
	(0,076)		(0,010)	(0,001)		(0,068)		(0.015)	(0,003)	
IP03RA	-2,997	0,05	5,422*	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)	
FAFISH	-2,104	0,122	2,379	2,728	-1,576	-	-	-	-	-
	(1,364)		(0,123)	(0,99)						
PROF03	0,00017	1,000	1,521	1,580	-2,724	-	-	-	-	-
	(0,00014)		(0,217)	(0,209)						
PRO	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 β_i from AM.

†† BIC= BIC_1- BIC_0, where BIC_1 and BIC_0 are respectively the BIC of the reduced model after eliminating β_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 two nested models

The same as the *F test* in linear regression, specifically the *likelihood ratio test* (LRT) is useful to test the overall significance of the whole model, the null hypothesis that all the set of parameters related to the variables included in the adjusted model (AM) are equal to zero. The LRT for Model 1 [$\chi^2(9)$= 33,952, p=0,000] and LRT for Model 2 [$\chi^2(6)$= 33,952, p=0,000] stand respectively that the inclusion of variables reduces the -2logLikelihood statistic by 33,952 and 30,110, a statistically high significant decrease, which implies that both adjusted models, Model 1 and Model 2, as a whole fits significantly better than the empty or only constant model (EM) and accordingly that at least one β in each of the models is non zero. The likelihood ratio test (LRT) can be also used as a test for model refinement to test the difference between Model 1 and any nested model such as Model 2. Since the difference in likelihood ratios for the two models [$\chi^2(3)$=3,842, p=0,278] is not significant, then one may conclude that the variables removed from Model 2 (i.e. FAFISH, PRO and PROF03) do not matter significantly in predicting the dependent. Additionally both AIC and BIC may be used to compare two nested models, where the lower the AIC and BIC, the better. According to these criteria Model 2 will the one preferred.

Based on the evidence given by the LRT to compare the two nested models, their related AIC and BIC criteria as well as the LRT and Wald tests for individual significance and BIC for individual parameters performance, dropping the variables (i.e. FAFISH, PRO and PROF03) makes no difference in prediction. For reasons of parsimony the variables are dropped from the Model 1, and accordingly Model 2 will be the one potentially chosen. From the omitted variables (i.e. FAFISH, PRO and PROF03), at first glance the most surprising and unexpected one is the lack of significance of the variable showing short time economic performance related to the length of the vessel (i.e. PROF03). 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 at the verge of the break point were a priori the candidates to exit. However, it is straightforward to understand that, 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 during the last 3-5 years, which following standard microeconomics would a priori have been expected to negatively influence in the odds to exit.

Focusing on Model 2, Table 3 shows the results of the alternative tests to analyse the model's goodness of fit as well as alternative measures of effect size. Neither the deviance [$\chi^2(67)$=44,5, p=0,985] nor the Pearson's test [$\chi^2(67)$=48,059, p=0,280] are significant, which let us conclude that the model has an adequate fit. In the same way, since *Hosmer-and Lemeshow's* goodness of fit test is not significant [$\chi^2(8)$=6,24, p=0,575], support is given 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. Although the adapted R^2 measures of effect size are not in practice comparable to the adjusted R^2 in lineal regression, notice however 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.

-TABLE 3-

Goodness of fit tests and pseudo R^2

Goodness of fit	*Deviance* L_1	44,501 (0,985)
	Pearson's test	48,059 (0,280)
	Hosmer & Levenstone test	8,335 (0,401)
pseudo R^2	*Cox & Snell*	0,33
	Nagelkerke	0,52
	M.Fadden	0,40

p-value in brackets

Although the principal concern before validating the results is to test the overall and individual significance and goodness of fit of the adjusted model, that is, how well the model fits the data and thereby predicts probabilities; However, some attention should be also plaid to the accurate prediction of group membership and so to the *predictive efficiency* of the model (Menard, 2001). For this purposes classification tables indicating the predicted and observed values of the dependent variable (Table 4) and also predictive efficiency measurement indices are reported (Table 5). At the first glance, the classification table of correct and incorrect estimates related to EM and AM appears to indicate a fairly good accuracy of prediction. The predictions related to AM were correct 65 out of 74 times. The overall percent correctly predicted seems good at 90,5%, a higher percent correct than blindly estimating the most frequent category (STAY) (78'9%). 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* 40%. However, classification tables offer no more than a preliminary and testimonial idea of the predictive power of a model[9] and should be considered with certain caution and complemented with predictive efficiency tests (Menard, 2001). In this sense, as alternative measures of associations, λ_p and τ_p offer a quantitative estimate of how well the cases are classified by the model. For one side, λ_p=0.53 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 of the dichotomous dependent, which is a considerable strong reduction in the error of prediction. For another, τ_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 4-

Classification tables for the empty (EM) and adjusted (AM) models

		EM*			AM**		
		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 EXIT and are predicted STAY, 0 are observed STAY and are predicted EXIT and, o 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 5-

Index and test for accuracy of prediction

INDIXES OF PREDICTIVE EFFICIENCY	*d* binomial TESTS
λ_p=0,53	$d(\lambda_p)$=2,32 (0,010)
τ_p=0,76	$d(\tau_p)$ =5,55 (0,000)

λ_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.τ_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.

τ_p= (ad-bc)/0,5[(a+b)(b+d)+(c+d)(a+c)] where a=58, b=1, c=6, d=9

$d(\lambda_p)$=[(c+d)/N-(c+b)/N)]/sqrt[((c+d)/N)*(1-(c+d)/N)/N)

$d(\tau_p)$=[z/N-(c+b)/N)]/sqrt[(z/N*(1-z/N))/N), where z=(2*(a+b)*(c+d)/N)

NOTE: $d(\lambda_p)$ and $d(\tau_p)$ are approximately normally distributed.

[9] Remark that classification tables should not be used as goodness-of-fit measures because 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 were nor how close to 0.0 the errors were. 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.

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 independents and the log odds (logit) of the dependent. 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 {YRETI*LN(YRETI), EXSKI*LN(EXSKI), IF03RA*LN(IF03RA), DGRANT*LN(DGRANT)} have been added. Table 6 presents the results. Taken together, the effects of the four non-linear interaction terms are not statistically significant (change in likelihood ratio χ^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 is significant {YRETI*LN(YRETI) Wald=3556(p=0,06) LRT=3,672 (p=0,055); EXSKI*LN(EXSKI) Wald=0,004(p=0,952) LRT=0,004 (p=0,952); IF03RA*LN(IF03RA) Wald=1,307 (p=0,590) LRT=0,301 (p=583); DGRANT*LN(DGRANT) Wald=1,695 (p=0,193) LRT=2,018 (p=0,155)}. Thus, the *Box-Tidwell transformation test* supports the assumption of a linear relationship among the independents and the logit of the independent.

-TABLE 6-

The Box-Tidwell transformation test for nonlinearities

VARIABLE	β_i†	Exp(β_i)	Wald chi-square††	LRT††
SUC (1)	-1,993 (1,340)	0,136	2,212 (0,137)	4,888 (0,089)
MORDEP(1)	2,912 (1,156)	18,400	6,343 (0,012)	9,286 (0,002)
YRETI	-0,170 (0,196)	0,844	0,755 (0,385)	0,763 (0,382)
EXSKI	0,203 (0,627)	1,225	0,090 (0,764)	0,091 (0,763)
IP03RA	-4,119 (2,643)	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)
YRETI*LN(YRETI)	0,130 (0,069)	1,139	3,556 (0,059)	3,672 (0,055)
EXSKI*LN(EXSKI)	-0,010 (0,170)	0,990	,004 (0,952)	0,004 (0,952)
IF03RA*LN(IF03RA)	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)	-

†SE in brackets, †† p-value brackets

-TABLE 7-

Testing for multicollinearity

INDEPENDENT VARIABLE	T_i†	VIF_i††
SUCESIÓN	0,969	1,032
DEUPEN	0,876	1,149
EDADJUB	0,521	1,919
EXPAT	0,567	1,764
IP03RA	0,917	1,090
DGRANT	0,864	1,158

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

Joint with the fulfilment of linearity assumption, multicollinearity should also be watched in logistic regression models. Table 7 includes the results of *multicollinearity diagnostic statistics* produced by linear regression analysis, *tolerance* (T_i) and *variance inflation factor* (VIF_i) for each dependent variable.

Although there is no formal cut-off value to use with VIF_i for determining risky presence of multicollinearity, as a general setting values of $VIF_i>10$ are often regarded as indicating multicollinearity. In logistic regression, $VIF_i>2.5$ 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.

Even if logistic regression enables to overcome many of the restrictive assumptions of OLS regression (such as normality and homoscedasticity), nevertheless, as well as the linearity assumption and multicollinearity checked above, it is also convenient to analyse the model's behaviour in order to see if there are atypical or/and influential observations in the data set. The same as in the lineal regression model, the regression diagnostic is thus strongly recommended. Usual measures in regression diagnostic (i.e. the leverage (ht), Cook's distance (CD), the standardised residual (e*), DFBETAs and DFFITS are summarised in Table 8 and Table 9.

While not necessarily undesirable, influential observations in an estimated regression equation 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 [(14/74=0,1891)], where p is the number of estimated parameters and N the sample size. Similarly, the general criterion stands to check observations whose D>1, although in big samples some authors suggest a size corrected rule of D>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 is riskily influent attending to the leverage, although observation number 49 is higher than the rule of thumb for CD.

Joint 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 independents, no absolute standardized residual will be e*>2 (0,05 level) (or e*> 1.96(0,01 level)). Cells not meeting this criterion signal 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. About 4'5% 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 contribute significantly to the values of the coefficient estimates and the model predictions. Diagnostics respectively designed for these two purposes, are DFBETAS, DFFITS (Belsey, Kuh, and Welsch,1980). $DFBETAS_{it}$ gathers the contribution of the each observation to each of the β_i estimators, that is, measures the change in the logit coefficients for a given variable when a case is dropped. The general cut-off criterion for cases to be considered outliers is $|DFBETAS_{kt}| > 1.0$ (Menar, 1995), while Belsey, Kuh, and Welsch recommend further investigation of observations where $|DFBETAS_{kt}| > 2/N^{(1/2)}$), specially in big samples. $DFITS_i$ is the scaled difference between the predicted responses from the model constructed from all of the data and the predicted responses from the model setting the i-th observation aside[10]. Regarding to the predictions, the general rule stands that an observation is considered influential to the predictions to the model when $|DFFITS_{kt}| > 1$, while the sample corrected rule is $DFFITS_{kt}| > 2/(p/N)^{(1/2)}$).

-TABLE 8-

Proportion of data points exceeding the general and sample adjusted rule of thumbs

MEASURE	GENERAL	%	N. obs	SIZE ADJUSTED	%	N. obs
ht	h∈[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
$DFBETA_{C}$	DFBeta>|1|	2,70	2	DFBeta>2/sqrt(N)=0,2325	20,27	15
$DFBETA_{SUC}$	DFBeta>|1|	0	0	DFBeta>2/sqrt(N)=0,2325	5,4	4
$DFBETA_{MORDEP}$	DFBeta>|1|	0	0	DFBeta>2/sqrt(N)=0,2325	9,45	7
$DFBETA_{YRETI}$	DFBeta>|1|	0	0	DFBeta>2/sqrt(N)=0,2325	0	0
$DFBETA_{EXSKIP}$	DFBeta>|1|	0	0	DFBeta>2/sqrt(N)=0,2325	0	0
$DFBETA_{IP03RA}$	DFBeta>|1|	0	0	DFBeta>2/sqrt(N)=0,2325	6,75	5
$DFBETA_{DGRANT}$	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 9-

Logistic regresión 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
$DFBETA_{C}$	2,7999	0,6406	3,7469	-0,1035	0,4474	1,0660	-0,5927
$DFBETA_{SUC}$	0,9835	0,2173	1,7506	-0,1495	-0,0130	-0,5207	0,5350
$DFBETA_{MORDEP}$	-0,4274	-0,6813	1,6574	0,1187	-0,4532	-0,3225	0,2374
$DFBETA_{YRETI}$	-0,0884	0,0013	1,6254	-0,0085	0,0203	-0,0353	0,0288
$DFBETA_{EXSKIP}$	-0,0739	-0,0162	0,0088	0,0081	-0,0007	-0,0360	0,0189
$DFBETA_{IP03RA}$	-0,1432	0,5176	-0,2090	0,3784	-0,1430	0,3073	-0,2626
$DFBETA_{DGRANT}$	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

Table 8 summarizes the proportion of observations in the sample exceeding both the general and sample adjusted rule of thumbs for the regression diagnostic indicators. Taking into account our moderate sample size the general rule may be considered valid. Additionally Table 9 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 and also all the observations incorrectly predicted. From the seven observation in Table 9 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

[10] Unlike the Cook's distance, it does not look at all of the predicted values (i-th observation aside), it only looks at the predicted values for the i-th observation.

(pr<0,06) 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 for the more conservative size adjusted rule. Accordingly, only observation 1041 seems to have a high significance either on the estimated parameters or the predictions of the model. Deleting observation 1041 from the sample does not undertake a relevant change in the estimated parameters. Even the estimated parameter for SUC, which has a moderately high DFBETA, doesn't stand a remarkable change. Thus, the regression diagnostic analysis gives support to accept that the logistic regression estimates are robust.

3.3. Interpreting the results

From the results of the logistic regression analysis summarised in Table 2 we obtain the *odds* in favour of the EXIT choice, that is, the number involving how much probable is to happen EXIT than not to happen, which is no more than the rate between the probability to exit and stay *(i.e. pr(Y=EXIT)/(1−pr(Y=EXIT)).*

$$Odds(Y = EXIT) = e^{(-7{,}134-2{,}046\cdot SUCESION(1)+2{,}577\cdot DEUPEN(1)+0{,}193\cdot AÑOSJUB+0{,}166\cdot EXPPAT-2{,}442\cdot IP03RA+0.000076\cdot DGRANT)}$$

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 independents:

$$\begin{aligned}Logit(Y = EXIT) = -7{,}134 - 2{,}046\cdot SUCESION + 2{,}577\cdot DEUPEN + 0{,}193\cdot AÑOSJUB + \\ + 0{,}166\cdot EXPPAT - 2{,}442\cdot IP03RA + 0.000076\cdot DGRANT\end{aligned}$$

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

Turning to the individual β_i coefficients, each β_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* (MgE_i) and *elasticities* (ε_i). For one side, 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 the difference between membership in category X_k and membership in the omitted category. For another, each MgE_i [11] has the usual meaning of a standard slope in economics and accordingly, in order to avoid problems related to scaling, each ε_i [12] gives the percentage change in the probability of EXIT in response to a one percentage change in the explanatory variable.

Since both MgE_i and ε_i vary with the observed values of X_i, following Greene (2000), once each of the MgE_{ij} for each coefficient (i) and individual vessel (j) has been calculated the average values will be reported. In the case of dummies the change in the probability of a success (Y=1=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

[11] The marginal effect of the kth explanatory variable on the response probability is obtained from:

$$\frac{\partial \Pr(Y_t = EXIT/X_t)}{\partial X_{kt}} = \left[\frac{e^{(\alpha+\sum_{i=1}^{N} X_i\beta)}}{1+e^{(\alpha+\sum_{i=1}^{N} X_i\beta)}}\right]\cdot\left[1-\frac{e^{(\alpha+\sum_{i=1}^{N} X_i\beta)}}{1+e^{(\alpha+\sum_{i=1}^{N} X_i\beta)}}\right]\cdot\beta_{kt} = factor\cdot\beta_{kt}$$

[12] For the kth explanatory variable elasticity may be is obtained using partial derivatives as:

$$\varepsilon_{\Pr,x_{kt}} = \left\{\left[\frac{e^{(\alpha+\sum_{i=1}^{N} X_i\beta)}}{1+e^{(\alpha+\sum_{i=1}^{N} X_i\beta)}}\right]\cdot\left[1-\frac{e^{(\alpha+\sum_{i=1}^{N} X_i\beta)}}{1+e^{(\alpha+\sum_{i=1}^{N} X_i\beta)}}\right]\cdot\beta_{kt}\right\}\cdot\frac{X_{kt}}{\Pr(Y_t = EXIT/X_t)} = factor\cdot\beta_{kt}\cdot\frac{X_{kt}}{\Pr(Y_t = EXIT/X_t)}$$

difference: $Pr(Y=1 \mid X_k=1, \overline{X}) - Pr(Y=1 \mid X_k=0, \overline{X})$, where the values set for $\overline{X}$ are the mean values for each 0 or 1 group independents. Regarding ε_i, as well as average elasticities ($\overline{\varepsilon}_i$), the weighted average ones ($\overline{\varepsilon}_i^w$)[13] proposed by Hensher and Johnson (1981) have been also calculated. Table 10 includes β_i, the odds to EXIT, MgE_i, $\overline{\varepsilon}_i$ and ($\overline{\varepsilon}_i^w$).

-TABLE 10-

β_i-s, odds, Marginal Effects and Elasticities

VARIABLE	β_i	$Exp(\beta_i)$	MgE_i	$\overline{\varepsilon}_i$	$\overline{\varepsilon}_i^w$
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	-	-	-

The fact of having the continuity arranged decreases the logit(EXIT) in β_{SUC}=-2,025, or to put in another words, skippers with a potential heir to carry on once they had retired are exp(β_{SUC})=0,129 times less reluctant to EXIT. From MgE_{DGRANT} we can conclude that the existence of continuity leads to a 0,1040 decrease in the probability to EXIT. Taking into account that 100% of the skippers who stated that they had the continuity guarantied, it was with a family member (generally a son), it seems that family tradition still has a considerable influence in the Basque inshore fishing. This suggest that even in adverse economic circumstances, some of the vessels staying in the fishery may be there just to transfer from parents to descendants not only the fishing unit itself but also the so-called social capital including the accumulated sea and managerial knowledge.

The duty to face a significant mortgage 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 (DEUPEN=1), the average of the estimated logit increases in 2,577. Since exp(β_{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 MgE_{DEUPEN} we know that on average, and holding all else constant, the existence of a significant debt upon the vessel leads to a 0,2130 decrease in the probability to EXIT. Summarising, significant indebtedness acts as a brake to abandon the activity, which may reveal a narrow second hand market of vessels.

Surprisingly each one-unit increase in the number of years until the retirement (YRETI) is associated with an increase of 0,193 in *logit(EXIT)*. Or to put in another terms, exp(β_{YRETI})=1,213 means that a one year younger skipper is 1,213 more probable to EXIT from the activity. By inspecting MgE_{YRETI} it is found that, on average, and holding all else constant, a year increase in YRETI, leads to a 0.0182 increase in the probability to EXIT. The mean elasticity $\overline{\varepsilon}_{YRETI}$=1,69 indicates that %1 increase in YRETI would imply an increase in 1,69% in the probability to exit. Since the probability to EXIT rises with the years until the retirement, there are the younger

[13] The procedure to calculate each $\overline{\varepsilon}_i^w$ is to evaluate the elasticity at every observation and then construct a weighted average with predicted probabilities as the weights.

skippers who are less reluctant to abandon the activity. This sign, compatible with basic theory of job market (i.e. the alternative employment opportunities in the job market decrease as the age does) may be a serious evidence of the negative evolution of the inshore fishing sector of the Basque Country.

B_{EXSKI}=0,166 implies that each one-unit increase in the years of experience being a captain (EXSKI) is associated with an increase of 0,166 in *logit(EXIT)*. A skipper with one more year of experience being the manager of the vessel is then exp(B_{EXSKI})=1,183 more probable to EXIT from the activity. Or in terms of MgE_{EXSKI}, a one more year of experience being a skipper leads to a 0.0156 increase in the probability to EXIT, while $\overline{\varepsilon}_{EXSKI}$=1,72 means that 1% increase in EXSKI would lead to a 1,72% increase in the probability to exit. To some extent, this result seems to contradict the previous related to YRETI, since in general one might expect that more experienced skippers were older. However there are relatively frequent sample points where young skippers are highly more experienced than older ones. Turning back to the sign of the estimated parameter, old or young, skippers (100% of the skippers are also the owner's or co-owners of the vessels) with more years of experience are the ones with major knowledge about 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 roll. In fact, since being a vessel owner is one of the maximum targets of crewmembers, it is not strange that when one reaches this coveted position relatively old (i.e. with no much years until the retirement), the brake to exit was more pronounced than when one reaches the maximum peak of the career being relatively young.

β_{IF03RA}=-2,442 involves that each one-unit increase in the measure for the skipper's skill (IF03RA) is associated with a decrease of -2,442 in logit(EXIT). That is, a one unit more skilful skipper is exp(β_{IP03RA})=0,087 less probable to EXIT from the activity. From MgE_{DGRANT}, we can derive that, holding all 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 ($\overline{\varepsilon}_{IP03RA}$), a 1% increase in IP03RA would imply a -2,03 % decrease in the probability to exit. Summarising, the probability to EXIT decreases insofar as the measure for the skill goes up. These are good news both for the regulator and the inshore fishing sector as a whole, because the skippers with the best scores seem to be more reluctant to EXIT.

β_{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 MgE_{DGRANT} it is found that, on average, and holding all else constant, for example a 10.000€ increase in DGRANT leads to a 0.0217 increase in the probability to EXIT, while $\overline{\varepsilon}_{DGRANT}$=1,08 points that if the regulator went up the amount of the DGRANT in 1%, this would lead approximately in 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 VEAGE and GT, 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. CONCLUDING REMARKS

An empirical long term behavioural model on the stay and exit decisions of the fishers belonging to the inshore fleet of the Basque Country has been developed in a random utility 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. the years until the retirement, the experience (being a skipper) and skipper's skill) as well as other factors such as the fact of having to face a significant mortgage for the vessel and the arrangement of the continuity or succession by a son. Incentives, in the form of decommissioning grants also play a roll. However, contrary as 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 mortgage 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 Govern in the form of a lineal and increasing function of vessel's age and gross tonnage seems to steer incentives in the correct direction to favour the fleet and capacity adjustment.

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