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DOES SPECIALIZATION AFFECT THE EFFICIENCY OF SMALL-SCALE FISHING BOATS?

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Abstract

We use a stochastic frontier approach to estimate the technology and the technical efficiency of a sample of small-scale fishing boats in the Spanish island of Gran Canaria. Using a model that allows for the determinants of inefficiency, we find that boat efficiency increases with boat size while it is inversely related to the age of the vessel. We pay special attention to the specialization of the fishing boats. For this purpose, we include two variables: one that measures the specialization in few species and another one that reflects technological specialization, which is measured as number of gears used. We find that both variables reduce the efficiency of fishing boats.

JEL Classification: C23, D24, Q22

Keywords: Small-scale fisheries, boat efficiency, specialization, stochastic frontier, panel data.

DOES SPECIALIZATION AFFECT THE EFFICIENCY OF SMALL-SCALE FISHING BOATS?

Introduction

While the main problem of the fishing sector is the exhaustion of the stocks, the decreasing profitability of fishing activity has been receiving increasing attention (Commission of the European Communities, 2006). Low profits lead to a decrease in the number of fishers and to a reduction in the income of fishing villages. These are well known problems and have been a source of concern to the public authorities for several decades.

While many solutions have been proposed to alleviate the problem of declining stocks (quotas, input controls…), the problem of fishers' income is more complex. On the one hand, gross revenue is the product of catches times the price of fish. Since catches are regulated in order to prevent the exhaustion of the stocks, an increase in income appears to depend solely on prices. According to the FAO (FAO, 2018), there is a positive trend in world fish prices, although probably not large enough to compensate the decrease in catches. Therefore, revenues seem to be difficult to increase.[1]

On the other hand, most of the costs in fishing are fixed. However, an important variable that affects fishermen' income is the efficiency with which they operate the technology. Identifying inefficient boats and understanding the causes of inefficiency can allow policymakers to establish programs oriented towards reducing inefficiency.

[1] This is true for the sector as a whole. One way to increase revenue per boat is to allow for a further reduction in the number of fishers.

For these reasons, in recent years there has been an increasing interest in the measurement of technical efficiency in the fishing sector (e.g., Tingley *et al*., 2005; Pascoe *et al*., 2011; Solis et al., 2014). The study of technical efficiency has relied on the estimation of production frontiers, defined as the maximum amount of output achievable from a given set of productive inputs. The difference between this theoretical maximum and actual data is interpreted as technical inefficiency. In this study, we use a stochastic production frontier model to estimate not only the technical efficiency of the boats but also the characteristics of the technology.

This paper uses a panel data set of fishing boats of the artisanal fleet on the Spanish island of Gran Canaria. Since we are interested in identifying variables that explain the differences in technical efficiency across boats, we estimate a model that allows technical inefficiency to be a function of some explanatory variables (see Kumbhakar and Lovell, pp. 261-279). While some papers have recently applied this approach to fisheries (especially the well-known model by Battese and Coelli, 1995), we use a model developed by Hadri (1999) that allows the variances of both the random noise and the inefficiency term to be a function of exogenous variables. To the best of our knowledge, this is the first attempt to apply this model to fisheries data.

We are interested in studying the role of specialization in fishing efficiency. Since Adam Smith, specialization has been considered a driver of productivity and several papers have therefore included different measures of productive specialization when trying to study the determinants of technical efficiency (e.g., Latruffe et al., 2005). Specialization is usually associated with the division of labor, i.e., productivity gains come from the fact that workers specialize in a narrow set of tasks. However, our hypothesis is that in multi-species fisheries this need not be the case. In multi-species fisheries, some species are more abundant than others at some points in time, so that concentration in a few species may result in lower total catch. On the other hand, technological specialization in the form of, for example, using just one gear may result in missing opportunities to catch more abundant species that require the use of a different gear. For these reasons, we believe that specialization in fisheries may result in lower technical efficiency.

We consider two measures of specialization. The first one is the concentration of catches in a few species, which tries to reflect specialization in the output side. The second one is the specialization in gear use, which proxies technological specialization from the input side. Pascoe and Coglan, (2002) also used a variable to measure the degree of specialization in a particular gear type.

The paper is organized as follows. The next section reviews the modeling of technical efficiency using stochastic frontiers. Then we describe the data and present the empirical model, followed by the econometric estimation and the discussion of the results. Finally, an analysis of fishing efficiency is presented.

Modeling technical efficiency

The key to obtaining an estimate of technical efficiency is the estimation of the production frontier. This can be done using parametric or non-parametric techniques. Non-parametric methods, the most popular being Data Envelopment Analysis (DEA), use linear programming to estimate the frontier, while parametric methods employ econometric techniques. In this study, we follow the parametric approach not only because of the inherent stochasticity involved in fisheries (Kirkley *et al.*, 1995) but also because we are interested in estimating the characteristics of the technology, such as the output-elasticities.

Aigner *et al*. (1977) and Meeusen and Van den Broeck (1977), independently proposed the estimation of stochastic frontiers. These models consider that deviations from the production frontier can be decomposed, allowing for the separation of uncontrollable random effects, such as climatic events or luck, from the effect of technical efficiency[2].

A general stochastic production frontier model can be given by:

$$y_{it} = \beta' x_{it} + v_{it} - u_{it} \tag{1}$$

where subscript i indexes boats and subscript t denotes time, y_{it} represents output from boat i at time t, x_{it} is a vector of inputs, β is a vector of unknown parameters to be estimated, v_{it} is a symmetric random disturbance which captures the effect of statistical noise, whereas u_{it} is a non-negative stochastic term that is assumed to be independent from *v* and which captures the distance from the stochastic frontier, i.e. technical inefficiency. When $u=0$, the observation lies on the technological frontier and is therefore efficient. When $u>0$, the observation is below the frontier, indicating that it is technically inefficient.

Since we are interested in finding which variables explain differences in the efficiency of the boats, we use an augmented version of equation (1) by allowing the inefficiency term *u* to be a function of some exogenous variables *z*. The general form of this type of models is:

$$y_{it} = \beta' x_{it} + v_{it} - u_{it}(z_{it}) \tag{2}$$

There are two possible alternative specifications of $u_{it}(z_{it})$, depending on the way that the variables *z* affect the distribution of *u.* In particular, they can affect the mean or the variance of *u*.

[2] See Alvarez and Arias (2014) for a recent survey on stochastic frontier modelling or Kumbhakar and Lovell (2000) for a book-level treatment.

Battese and Coelli (1995) is the most popular model among practitioners when allowing technical inefficiency to be a function of some exogenous variables. The inefficiency term can be expressed in the following way:

$$u_{it} = z_{it}\delta + w_{it} \tag{3}$$

where *z* are the explanatory variables associated with technical inefficiency and W_{it} is defined by the truncation of the normal distribution with zero mean and variance σ^2, such that the point of truncation is $-z_{it}\delta$.

This model has been widely employed in the field of fisheries to study the technical efficiency of the fleets (Campbell and Hand, 1998; Kirkley *et al*., 1998; Sharma and Leung, 1999; Eggert, 2001; Pascoe et al., 2001; Pascoe and Coglan, 2002; Fousekis and Klonaris, 2003; Kompas *et al*., 2004).

The other alternative is to model the variance of the pretruncated distribution of u. Reifschneider and Stevenson (1991) was the first paper to incorporate heteroskedasticity in the stochastic frontier model. Caudill *et al*. (1995) assumed that *u* exhibits multiplicative heteroscedasticity, a choice that we will use in this paper. In particular, they suggest an exponential function:

$$u_{it} \sim N^{+}\left(0, \sigma_{it}^2\right), \quad \sigma_{it} = g(z_{it}, \delta) = \sigma_u \cdot \exp(\delta z_{it}) \tag{4}$$

where the + sign indicates truncation of the distribution at zero.

Modeling the variance of the one-sided error term is very important since the presence of heteroscedasticity in *u* will yield biased estimates of both the frontier parameters and the efficiency scores. This result differs markedly from the typical effect of heteroscedasticity in the two-sided error term *v*, which causes the variances of the parameter estimates to be biased. For this reason, the heteroscedastic model will be our preferred model.[3]

The empirical model estimated in this paper is a double-heteroscedastic model developed by Hadri (1999). This model is an extension of the Caudill *et al*. (1995) model, where both the variance of the pre-truncated distribution of *u* and the variance of the random term *v* are assumed to be a function of several variables.

Data

Gran Canaria is an island of the Canarian Archipelago, located off the northwest coast of the African continent. The artisanal fishery is managed by the Canary Islands Government and each vessel is associated with one of the six main fishing ports existing in the island: Agaete, San Cristóbal, Melenara, Castillo del Romeral, Arguineguín and Mogán. The fleet consists mainly of small and old vessels made of wood or fiber, and fishing trips are daily. Most vessels use several gears.

Across the archipelago, there are no limitations on the maximum catches that can be harvested by professional fishermen except for tunas, whose catches are regulated by the International Commission for the Conservation of Atlantic Tunas (ICCAT). Furthermore, there are no restrictions on the number of fishing trips and the management policies only include some limitations on the use of fishing gears and minimum landing sizes.

[3] Additionally, Caudill et al. (1995) state that "…the ranking of firms as to their relative inefficiency changes dramatically when the correction for heteroscedasticity is incorporated into the estimation. This is considerable evidence that inefficiency measures are sensitive to errors like heteroscedasticity and must be viewed with caution unless the heteroscedasticity is incorporated into the estimation.

The catches of the artisanal fishing fleet on the island are conditioned by the characteristics of the coast, in particular, its narrow island shelf and the seabed. The main target species can be grouped into three categories: benthic-demersals, coastal pelagics and tunas. In recent years, there has been an increase in total catches, although the landings of benthic-demersal species as well as some pelagic coastal communities, such as mackerels or sardines have shown a decrease (Couce-Montero *et al.*, 2015).

The data employed in this paper were obtained from different sources. The Canary Islands Government provided official landings by boat at the monthly level, as well as the characteristics of the vessels. To collect information about the crew and other aspects of the artisanal fleet, face-to-face interviews with owners, captains or fishermen were conducted. The data are aggregated on a monthly basis, forming an unbalanced panel dataset with 7279 observations from 195 vessels during the period 2005-2010.

Landings of the artisanal fleet feature more than 150 species, so a single aggregate output was created. This is standard practice in the empirical papers that deal with multi-species fisheries (e.g. Sharma and Lueng, 1999)[4]. While most papers use the value of catches, we will aggregate catches both in terms of weight (kg) and value (euros), as in Herrero and Pascoe (2001). Since we do not have individual prices we aggregate the catch in value terms using average prices for the whole region, so that the weights are both boat- and time-invariant. The use of fixed weights still allows us to distinguish boats that catch highly-priced species from other boats which are more specialized in less profitable species.

[4] Very few studies use primal models that allow for multiple outputs, such as input-distance functions. Some exceptions are Orea *et al*. (2006) and Solís *et al*. (2015).

As it is common in the fishing sector, the variability of the crew is rather limited, especially over time. Boats only increase the number of crew members at specific points in time and only if the gear employed allows for this increase, such as in pole-line fishing. The main boat characteristics, such as length, gross tonnage and engine power, are fixed over time and therefore can be considered as fixed inputs. Since these variables are highly collinear[5], in the empirical model we have just included engine power as a fixed input.

An original contribution of this paper is to control for the quality of the fishing grounds by means of a variable that measures the concentration of chlorophyll in the water. Chlorophyll-a, which is its technical name, is an indicator of plankton biomass and indirectly, of the biological activity of a given area. The organisms that contain chlorophyll-a are at the base of the food chain, and in oceanic waters the concentration of these organisms is related to fish abundance. This variable was obtained from the satellite SEAWIFS, belonging to the Global Marine Information System (GMIS, http://gmis.jrc.ec.europa.eu/).

We also include several control variables to account for the observed heterogeneity in the sample. First, we include the number of fishing days for each boat in each month, since this variable varies substantially across boats and over time. Finally, the unobserved characteristics of the fishing ports are accounted for through a set of fixed effects

With respect to the inefficiency term, we include several explanatory variables. The age of the boat (*Boat Age*) is probably the most common variable included as explanatory of inefficiency since it is assumed that older boats will tend to be more

[5] Corr(GT,Length)=0.92, Corr(GT,HP)=0.71, Corr(HP,Length)=0.74.

inefficient (e.g., Fousekis and Klonaris, 2003). Our variable *Boat Age* is constructed as the difference between the final year of the sample (2012) and the year when the boat was put into service. Therefore, the variable is time invariant since it is intended to capture differences across older and newer boats. The vessel length (*Length*) accounts for boat size since it is customary in these models to study if there is a relationship between inefficiency and size. As stated before, we also consider two variables that intend to reflect the specialization of the fishing boats. The first one is a concentration index that measures the degree of concentration of the total catch on several species (*Concentration*). The second one (*Flexibility)* tries to reflect the degree of 'technological specialization' of the fishing boat and is measured as the inverse of the number of different gears used during each year. This variable is assumed to detect the flexibility of the skipper in switching gear when convenient due to weather conditions or, mainly, due to a change in the target species.[6] Therefore, the higher the value of *Concentration* or *Flexibility*, the higher the specialization of the boat.

The variable Concentration can be measured in several ways. For example, in the Industrial Organization literature it is customary to measure the degree of competition in a market using concentration variables. The most employed ones are Concentration Ratios, denoted by CR_N, where N indicates the number of firms being considered. CR_N measures the market share of the N largest firms. We will use this approach and compute several CR variables that will measure the share of the total catch by the N main species caught by the boat in a given month. In particular, we computed CR1-CR3.

The concentration ratios have the problem that they do not distinguish between the values of the catches of the boats taken into account. For example, for a given total

[6] Pascoe and Coglan (2002) include a specialization variable which is measured as the proportion of total time fished using the main gear.

catch, the value of the CR2 is the same if the catches of the two main species are 80 and 40 or if they are 70 and 50 (or any two values that sum to 120). Another concentration measure, the Hirschman-Herfindahl index (HHI) avoids this problem. The HHI is computed as the sum of the squares of the shares of the species. In this way, it gives more weight to the species with larger catches.

The main variables included in the empirical model are described in Table 1. [7]

TABLE 1 HERE

The summary statistics of output and input variables, as well as the variables included in the inefficiency model, are presented in Table 2.

TABLE 2 HERE

The figures in Table 2 reflect the characteristics of a typical artisanal fleet composed by small, and rather old boats.[8] They also reveal that there exists a high degree of heterogeneity in the fishing boats of this sample, especially in some variables, such as boat age, engine power, or days at sea.

Empirical model

[7] Unfortunately, we do not have information on the characteristics of the skippers that would allow us to control for skipper skill, which is considered an important determinant of fishing efficiency (e.g. Kirkley et al., 1998; Squires and Kirkley, 1999).

[8] Some minimum values indicate the presence of very small boats as well as some non-productive fishing trips. We deleted some atypical observations, but the estimates did not change with respect to using the whole sample. For this reason, we decided to leave all the observations in the sample.

The empirical model to be estimated is the following Cobb-Douglas stochastic production frontier:

$$\begin{aligned}\mathrm{LnCatch}_{it} = \beta_0 + \beta_1\mathrm{LnCrew}_{it} + \beta_2\mathrm{LnEngine}_i + \gamma\mathrm{Gear}_{it} + \beta_3\mathrm{LnDays}_{it} + \beta_4\mathrm{LnCH}_t \\ + \theta\mathrm{Port}_i + \eta\mathrm{Quarter}_t + \varphi\mathrm{Year}_t + v_{it} - u_{it}\end{aligned} \quad (5)$$

where subscript *i* indicates vessel and subscript *t* represents time. The dependent variable is aggregate output. We will estimate two models, one using aggregate catch by weight and the other using aggregate catch in terms of value. The only variable input is the crew, while the engine power is included as a fixed input.

On-board technology is an important factor in detecting the presence of fish and therefore it is expected to explain part of the variation in catches. We do not have data on technological gadgets (radar, sonar…), but we expect the availability of those onboard to be highly correlated with boat size, which is accounted for by engine power. Other differences in technology across boats are accounted for using gear-type dummy variables (*Gear*) that take the value 1 if a gear was used during the month. The three included dummies reflect whether the boat used purse seine, hand line or traps. Drums is the excluded category.

Some control variables are also included to account for the heterogeneity in the data: *Days* is the number of days at sea in each month. The variable *CH*, that reflects the nutrients in the sea and is measured as the concentration of chlorophyll in the water, is an average for the whole island and therefore it only has temporal variation. We expect that higher CH will lead to larger catches. The *Port* dummies try to account for possible unobserved differences among the six fishing areas considered. Finally, *Quarter*, and *Year* are fixed time-effects.

The empirical specification of the inefficiency model estimated implies making both the variance of the pre-truncated distribution of *u* and the variance of the random term *v* a function of several variables. Our specification is the following:

$$\sigma_u^2 = \delta_0 + \delta_1 \mathrm{LnBoatAge_i} + \delta_2 \mathrm{LnLength_i} + \delta_3 \mathrm{LnConcentration_{it}} + \delta_4 \mathrm{LnFlexibility_{it}} + \delta_5 \mathrm{t} \quad (6)$$

$$\sigma_v^2 = \phi_0 + \phi_1 \mathrm{LnLength_i}$$

We make σ_u a function of several characteristics of the vessels: the age of the boat (*Boat Age*), the boat length (*Length*), the degree of concentration of the total catch on the two species with the largest catches (*Concentration*), and a variable that reflects the degree of 'technological specialization' of the fishing boat (*Flexibility*). Additionally, we also include a time trend (t) in order to capture whether some unobserved variables are causing inefficiency to vary over time. The variance of v is assumed to depend on vessel size, which is proxied by the length of the vessel (*Length*).

Results and discussion

The stochastic frontier was estimated by maximum likelihood, using the program Limdep V10. The parameter estimates of the stochastic production frontier model and the technical inefficiency model are presented in Table 3.

TABLE 3 HERE

The results using catch (by weight) as the dependent variable show that all the continuous explanatory variables (Crew, Engine power, Days at sea, and Chlorophyll) are significant and carry a positive sign, meaning that, as expected, larger values of these variables have a positive effect on fish landings. The gear dummies are all positive and significant, reflecting that the use of these gears allows fishermen to catch more fish than the gear in the excluded category (drums).

The coefficients on the home port dummies are all positive and significant. We can interpret these fixed effects as estimates of time-invariant technical efficiency, since, for given inputs, a positive fixed effect means that boats in that port catch more fish than boats in the excluded port. The larger the fixed effect, the more efficient the boats in that port. Given that the Port of Agaete is the excluded category, the rest of the ports have some port-specific unobserved characteristics, which do not vary over time, and which make them more efficient than the boats in Agaete. This time-invariant unobserved characteristic could be, for example, the richness of the fish stock in the port area or some features that make fishing easier, such as the presence of favorable winds. In particular, wind is a relevant factor in fishing activity since the presence of northern winds is common. When this northern wind is strong, the northern ports, mainly Agaete, are more affected than the rest of the ports since the island produces a shelter effect that causes the southern ports to be less affected by these winds. This is important because sometimes boats go out fishing, but the sudden presence of strong winds makes them return to port with few catches.

The quarterly dummies indicate that trips in spring and summer have significantly higher landings per trip, relative to winter (January through March). Spring and summer coincide with the months in which the tuna harvest season occurs, with a resulting increase in the volume of total landings.

The coefficients on the year dummies between 2006 and 2010 are significant and positive, reflecting that, due to other factors different from those included in the model and common to all boats, total catch was higher in those years than in 2005. A common way to interpret these year effects is as proxies for the fish stock (e.g., Fousekis and

Klonaris, 2003). Obviously, the higher the stock, ceteris paribus other inputs, the higher the catch. The year effects increase over time (except for the last year of the sample), which could be interpreted as a sign that the state of the stock has improved during the sample period.

We now proceed to comment the results of the estimation of the inefficiency part of the model. As expected, the coefficient of *Boat Age* was found to be positive and significant, indicating that older boats tend to be more inefficient. This result is consistent with those obtained in similar studies (Pascoe and Coglan, 2002; Fousekis and Klonaris, 2003; Tingley *et al*., 2005). The artisanal fleet of Gran Canaria is characterized by its old and obsolete vessels in most cases; approximately 52% of vessels were built before 1970 and only 18% of the boats were constructed from 1990 onwards. The coefficient of *Length* is negative and significant, indicating that the larger the boat the lower the inefficiency.

Now we turn to our two specialization variables. The positive sign of *Concentration,* which was measured as the percent of catches from the two species with the largest catch on each month,[9] indicates that the more concentrated the catch on fewer species the higher the inefficiency. The concentration of catch on a few species can be due to the use of more selective gears or simply that the skipper lacks enough ability or interest to target other species. The *Flexibility* variable, which is measured as the inverse of the number of gears employed by the boat, is in fact picking up the capacity of the boat to adjust to different seasons in terms both of weather and fish species. Therefore, if a boat is unable to switch from, say, purse seine to hand line in the tuna

[9] It could be more appropriate to have a concentration variable more stable over time. For this reason, we built other concentration variables as the percent of the largest species catch in a month over total yearly catch. Therefore, this variable takes on the same value for all trips in a given year. However, the value of the likelihood function was larger using variables with monthly variability.

season, it will not be able to exploit the availability of the additional stock due to the presence of tuna. The positive sign of this variable therefore indicates that boats that use less gears (probably because of higher managerial ability) are more inefficient.

Finally, the time trend in the inefficiency term is positive and significant, indicating that some factor(s), common to all boats and different from those included in the model, are increasing the inefficiency of the fleet. The explanation for this finding is not easy since the only unobserved factor (common to all boats) that comes to mind is the fish stock. If the stock was deteriorating over time, it would be harder to obtain catches for given inputs, implying that technical inefficiency should increase over time. However, since we have interpreted the fact that the time-effects in the frontier were positive and increasing over time as a possible indicator that the stock was improving, another explanation for the sign of this variable is needed. One possibility is that the boats that exit the sector are the most efficient ones. This goes contrary to basic economic analysis unless those boats that leave are not only the most efficient ones but also the ones run by the oldest captains who accumulate many years of experience but quit the activity due to reaching retirement age.

The results when the dependent variable is revenue are very similar to those obtained with catch by weight. Now, the dummy for quarter 3 (summer) is not significant since most of the tuna fishing takes place during these months, and most of the tuna species carry a low price. The main difference is found in the estimation of the coefficient of crew which is now much lower. This is probably due to the fact that, given other inputs that represent boat size, crew usually increases in the tuna season since tuna is mainly caught using pole lines and therefore, boats try to optimize deck size in terms of crewmen.

Technical Efficiency Analysis

Even though the estimation of the production frontier by maximum likelihood only gives an estimate of the composed error term, it is possible to obtain an estimate of *u*, using a formula developed by Jondrow *et al*. (1982). With the estimated *u*, if the dependent variable is measured in logs, the technical efficiency of the i-th boat in the t-th period can be calculated as:

$$\mathrm{TE_{it}} = \mathrm{e}^{-\mathrm{u_{it}}} \tag{7}$$

The estimation of the stochastic frontier yields estimates of σ_u and σ_v. It is customary to present this information in relative terms. For example, the parameter λ ($\lambda=\sigma_u / \sigma_v$) is equal to 6.61 (1.05) when the dependent variable is catch (revenue). A value of λ larger than 1 means that inefficiency is more important than random noise in explaining differences in output across boats. Alvarez and Schmidt (2006) argue that in fishing activity it should not be surprising that the noise component *v* (that accommodates, among other factors, differences in luck) could dominate the inefficiency component *u*. In fact, they show that the estimated values of λ vary with the temporal level of data aggregation. That is, the higher this level, i.e., data at the monthly level vs. daily, the higher the value of λ. This is logical since when data are aggregated over time, the time-invariant part of the inefficiency component is added while the noise component tends to vanish since it has a zero mean.

The technical efficiency index for each boat can be computed using the formula in equation (7). Figure 1 shows the kernel distribution of the estimated boat-specific indices. The distribution of the technical efficiency index using revenue as the dependent variable is more skewed to the right than the distribution using catch. This was somehow expected since technical inefficiency reflects the inability to achieve a maximum due to some type of poor practice in the activities carried out by the boats. The fact that boats are on average further away from the frontier when the output is in value terms, simply reflects that obtaining catches with high value has an additional component of difficulty (aiming for the highest combination of quantity and price) as compared to just trying to catch as much fish as possible for given inputs.

FIGURE 1 HERE

Conclusions

This paper provides an assessment of technical efficiency for the Gran Canaria´s artisanal fleet. A production frontier is estimated using a double-heteroscedastic model that seems to provide a good representation of the technology. The mean technical efficiency is estimated to be 78% in the model using catch (weight) as the dependent variable and 64% when the dependent variable is revenue. The results indicate that there is room for efficiency improvement. In fact, eliminating revenue inefficiency would result in revenue per vessel increasing 36% on average. This is an important result that points towards efficiency improvement as a possible source of more income to the sector.

The variables included in the inefficiency model indicate that the age of the boat increases inefficiency, while boat size, as measured by the length of the boat, increases efficiency. Our two specialization variables, the concentration of catches in few species and the use of few gears, carry a positive sign, indicating that both tend to increase inefficiency. This result points towards the need for diversification, which in turn implies that improving fishing skills should be an objective. Finally, the positive sign of a time trend suggests that some unobserved factors are causing inefficiency to increase over time. This is also an important result that needs further investigation since the model is not able to point at the explanation for this increasing trend. As pointed out in the document, it could happen that some of the most efficient fishermen are leaving the sector, due for example to reaching retirement age

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Table 1
Description of variables used in the empirical analysis

Variables	Description
Catch	Total monthly landings per vessel, expressed in Kg
Revenue	Total monthly revenue per vessel, expressed in €
Crew	Number of crew members on the vessel per month, including the skipper
Engine	Engine power expressed in horsepower
Days-at-sea	Total days at sea per vessel and month
CH	Chlorophyll concentration of each fishing area (mg/m^3 per month)
Boat Age	Age of the vessels (years)
Length	Length of the vessel's hull (m)
Concentration (CR_N)	Percent of total catch from the N species with the largest catches
Flexibility	Inverse of the number of gears employed in a month by each boat

Table 2

Summary statistics for the variables included in the models

Variables	Mean	S.D.	Minimum	Maximum
Catch (Kg)	1329	3355.63	1	47807
Revenue (€)	3322	4432.31	1.10	66471
Crew	2.40	0.64	2	4
Engine (hp)	43.31	38.66	4	200
Days-at-sea	8.74	5.94	1	27
CH (mg/m^3 per month)	0.17	0.07	0.05	0.47
Boat Age (years)	41.83	21.72	3	108
Length (m)	9.10	2.65	3.57	17.63
Concentration – CR1 (%)	56.80	24.84	10.71	100
Concentration – CR2 (%)	75.24	19.91	20.75	100
Concentration – CR3 (%)	84.54	15.26	28.91	100
Concentration – HHI	45.42	27.59	6.57	100
Flexibility (1/number of gears)	0.37	0.09	0.2	0.5

Table 3

Production stochastic frontier estimation

	Catch (weight)		Revenue	
	Estimate	t-ratio	Estimate	t-ratio
Constant	2.303	24.58	4.846	55.18
Ln Crew	1.209	14.63	0.487	5.90
Ln Engine	0.129	6.26	0.196	9.60
Dummy Purse Seine	0.764	29.02	0.157	6.01
Dummy Hand Line	0.656	18.37	0.076	2.04
Dummy Traps	0.246	2.41	0.527	6.48
Ln Days	1.019	94.40	1.004	94.57
Ln Chlorophyll	0.077	2.37	0.052	1.70
Dummy Port 2	0.550	17.11	0.563	17.16
Dummy Port 3	0.249	5.89	0.252	5.81
Dummy Port 4	0.241	5.15	0.277	6.42
Dummy Port 5	0.366	11.05	0.306	9.22
Dummy Port 6	0.238	5.26	0.374	8.27
Dummy Spring Quarter	0.153	4.80	0.105	3.38
Dummy Summer Quarter	0.102	2.83	-0.006	-0.19
Dummy Autumn Quarter	-0.015	-0.50	-0.054	-1.86
Dummy Year 2006	0.082	2.13	0.081	2.27
Dummy Year 2007	0.105	2.74	0.159	4.46
Dummy Year 2008	0.116	2.91	0.179	4.87
Dummy Year 2009	0.245	5.50	0.353	8.53
Dummy Year 2010	0.124	2.51	0.234	5.03
Inefficiency model				
Parameters in variance of v				
Constant	-2.369	-17.89	-1.599	-10.54
Ln Length	0.857	14.68	0.367	5.23
Parameters in variance of u				
Constant	-18.565	-5.73	-20.621	-12.09
Ln Boat Age	1.807	5.68	0.339	5.82
Ln Length	-0.580	3.32	-0.227	3.26
Ln Concentration	2.662	4.82	4.274	11.97
Ln Flexibility	-4.105	-6.03	-1.209	-6.40
Time Trend	0.195	2.58	0.206	6.68
$\sigma^2=\sigma_v^2+\sigma_u^2$	0.78		0.92	
$\lambda=\sigma_u/\sigma_v$	0.50		0.98	
Mean lnL	-8776		-8544	
Observations	7279		7279	

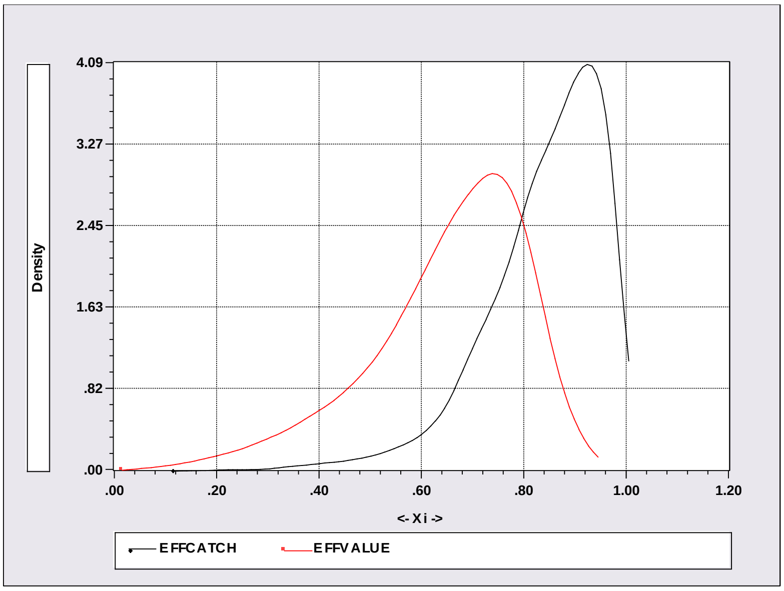

Figure 1. Kernel density of the technical efficiency indexes

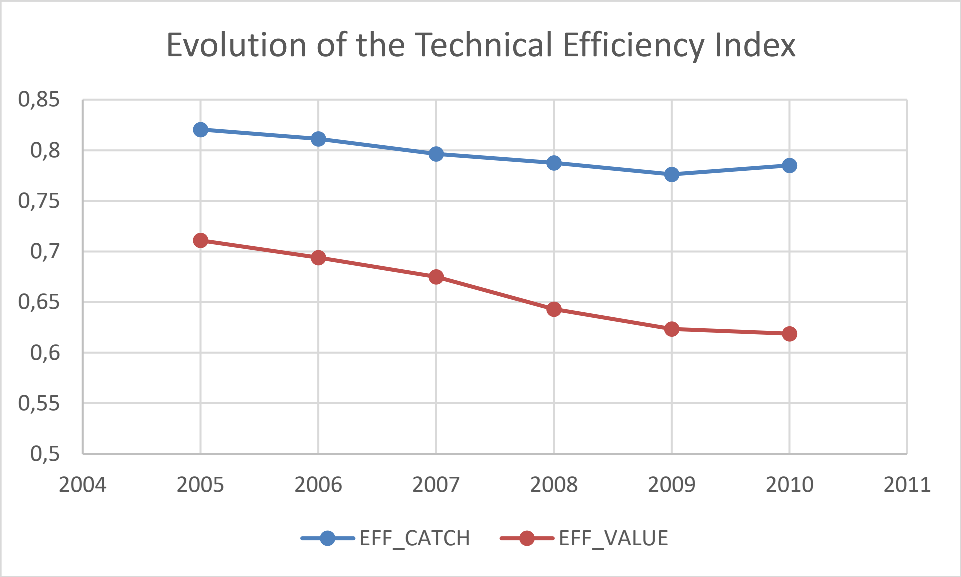

Figure 2. Evolution of the efficiency indexes