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CATCH EFFICIENCY IN THE CHILEAN PELAGIC FISHERY: DOES SIZE MATTER? *

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Abstract

This paper examines the determinants of technical efficiency for a sample of 204 industrial vessels operating in the Southern-Central pelagic fishery of Chile during the 1985-95 period. Data on vessel's annual landings and fishing effort, vessel's size, age, fishing experience and vessel's controlling firm are analysed considering a Translog stochastic frontier model à-la Battese-Coelli (1995), which includes a vessel-specific inefficiency model. Yearly averages for vessel efficiency vary from 50% to 86%. Close to 90% of the residuals' total variance is accounted by the inefficiency term, suggesting a significant disparity in vessels' catch performance. Vessel age and scale of operation are found to be significant in explaining efficiency. Larger vessels tend to be the most efficient and the ones showing least variance in their efficiency. Smaller vessels, which on average are also the oldest in the fleet, show greater dispersion and lower efficiency scores. We confirm prior results suggesting vessel-level economies of scale at this fishery, related to fishing effort intensity. Explanatory variables aggregated at the ship-owner level, which aim at controlling the firm's operating scale, are also significant as a whole when explaining vessel-level efficiency. We find positive search externalities associated to the number of vessels under control of a given firm, as well as external diseconomies related to each firm's fleet use. Overall, we report significant productive heterogeneity in the fleet under study where control variables associated to 'size effects' do indeed play a significant role.

Key words: Stochastic frontiers, technical efficiency, panel estimations, Chilean pelagic fishing.
JEL Classification: Q22, C33, L7

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1. Introduction

This paper carries out technical (catch) efficiency estimations for industrial vessels that operated during the 1985-95 period in the Southern-Central pelagic fishery in Chile. In terms of landed volumes, currently this is by far the most important fishery in Chile and it is certainly one of the largest of its kind in the world. In its peak of production (1994-95), this fishery landed 4.5 million tons/year. Today annual landings range around 2 million tons/year, of which a dominant proportion (about 75%) corresponds to jack mackerel. This trend of declining catches has motivated different initiatives aimed at achieving more binding access regulations and more effective enforcement of catch quotas. As part of this process, since early 2001 this fishery operates under a temporary (2-year) system of individual catch quotas, subject to transferability limits (Peña-Torres, 2002). The issue of how this develops towards more permanent regulations, involving decisions regarding continuity or reforms of current regulations, is a subject of current controversy.

This policy background motivates this paper. Adjustment towards lower production levels can involve regulatory as well as industry changes implying non-trivial distributive effects. In industries that exploit a common-pool resource the significance of these distributive consequences usually transform them into binding constraints with respect to politically feasible policy reforms. As a source of differentiated distributive effects, productive heterogeneity in a common-pool fishery facing downward production adjustments usually is an important influence upon negotiations aiming at achieving a consensus on policy reforms. In this setting, the main focus of this paper is to estimate and analyse sources of productive heterogeneity in this fishery.

This paper analyses 'productive heterogeneity' by estimating relative catch efficiencies achieved by each industrial vessel that operated in this fishery along the decade under study. Our estimation model calculates vessel-specific technical efficiency scores, relative to the ship having the highest catch performance. This concept of catch efficiency is defined with respect to the set of regressors used as control variables in the estimation model.[1] We use a stochastic production frontier methodology, in particular the model proposed in Battese and Coelli (1995) which includes a vessel-specific inefficiency equation as well. The efficient production frontier is defined as the maximum quantity of output (annual tons of catch) attainable by a given set of inputs. In this sense 'technical inefficiency' corresponds to differences that arise between that theoretical maximum, and what each vessel actually harvests with these factors. Consequently, estimations in this paper exclusively refer to technological efficiency and hence exclude allocative efficiency arguments.

[1] This is a different concept than that of 'catch per unit effort' (*e.g.* tons/hour of fishing), frequently used among fishing analysts. Our concept of 'technical efficiency' is also a measure of harvest yield, but considers a set of relevant inputs which are proxied by control variables when explaining the levels of landed catch. The set of relevant inputs includes

Given our focus on productive heterogeneity, we are particularly interested in analysing the resulting ranking among vessel-specific efficiency scores, their dispersion and how they correlate with variables that characterise vessel type and vessel-level fishing effort. Arguments more directly focused on the estimated *levels* of catch efficiency, or about the pattern and magnitude of technical change (i.e. productivity growth), are not priorities in this paper.

On the other hand, we are interested in studying possible correlation between vessel-specific efficiencies and variables aimed at controlling for different fishing operation scales. In addition to vessel-scale variables, we also test for the possible relevance of scale or size effects that are defined at greater levels of aggregation; i.e. at the level of the vessel's controlling firm as well as for the fishery as a whole. These firm- or fishery-aggregated control variables aim at testing the possibility of technological externalities having effect on vessel-level catch efficiencies. Externalities of this type may affect individual incentives when downward adjustments in fishing efforts are needed.

Generally speaking, the economic literature referring to fishing industries from an empirical viewpoint is rather scant. This is related to difficulties in accessing relevant information. Regarding efficiency estimations for fishing industries, there are but a few exceptions. Earlier studies focused on deterministic frontiers analysis (e.g. Comitini and Huang, 1967; Hannesson, 1983), where all unexplained variations in the endogenous variable (production or cost levels) are associated with inefficiency. More recent studies however, have given increasing attention to efficiency as well as productivity estimates based on stochastic production frontiers. In this vein, recent examples of fishery studies are Sharma (1999), Squires, Grafton *et al*. (1998), and Kirkley, Squires & Strand (1995), all focusing on estimations of efficiency concepts. Squires (1992) and Jin *et al.* (2001) also consider stochastic frontier analysis, but aiming more directly on total factor productivity measures and the corresponding estimates of productivity growth.

In stochastic frontier analysis only a portion of the estimated residuals is associated with inefficiency terms, the remainder being associated with random sources of errors, be they either pure random shocks or random measurement and/or specification errors. How the estimated residuals are separated into these two residual types is something that hinges on the particular estimation algorithm. In this paper the estimation model resembles a random-effects panel algorithm, in which the separation between the two types of residuals is achieved by imposing *ad-hoc* distributional assumptions.

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variables that proxy 'fishing effort' (including fixed and variable inputs), as well as state variables that control for fish stock abundance and for relevant regulatory changes.

Regarding Latin-American and Chilean fisheries, as of yet we do not know of any prior estimates of technical efficiency at the harvesting or processing stages. In the Chilean case, the appeal for this type of applied analysis goes beyond the fishery studied in this paper. Since the mid-eighties, several fisheries in Chile (both industrial and small-scale[2]) have begun to show signs of growing scarcity of their main fish stocks. This has called for regulatory reforms aiming at achieving less wasteful allocations of aggregate fishing efforts, leading in turn to a more efficient use of scarcer fish stocks. This brings forth diverse policy challenges, from consolidating more effective entry rules up to allowing for more equitable and economically efficient opportunities for the various participants operating in the sector. In the search for politically feasible solutions, productive heterogeneity in fishing fleets has had non-trivial economic impacts in the past. Analysing the sources of differences in catch efficiencies achieved by different sized vessels, can help assess from a better vantage point the allocative as well as distributive trade-offs that underlie the general goal of improving allocative efficiency in extractive fishing industries.

This paper is organised as follows. Section 2 describes relevant features of the fishery. Section 3 presents the theory and its implications while Section 4 describes our econometric model. Section 5 analyses the estimation results, while Section 6 shows an evaluation of the predictive power of our estimations. Section 7 presents final considerations.

2. The Southern-Central Fishery

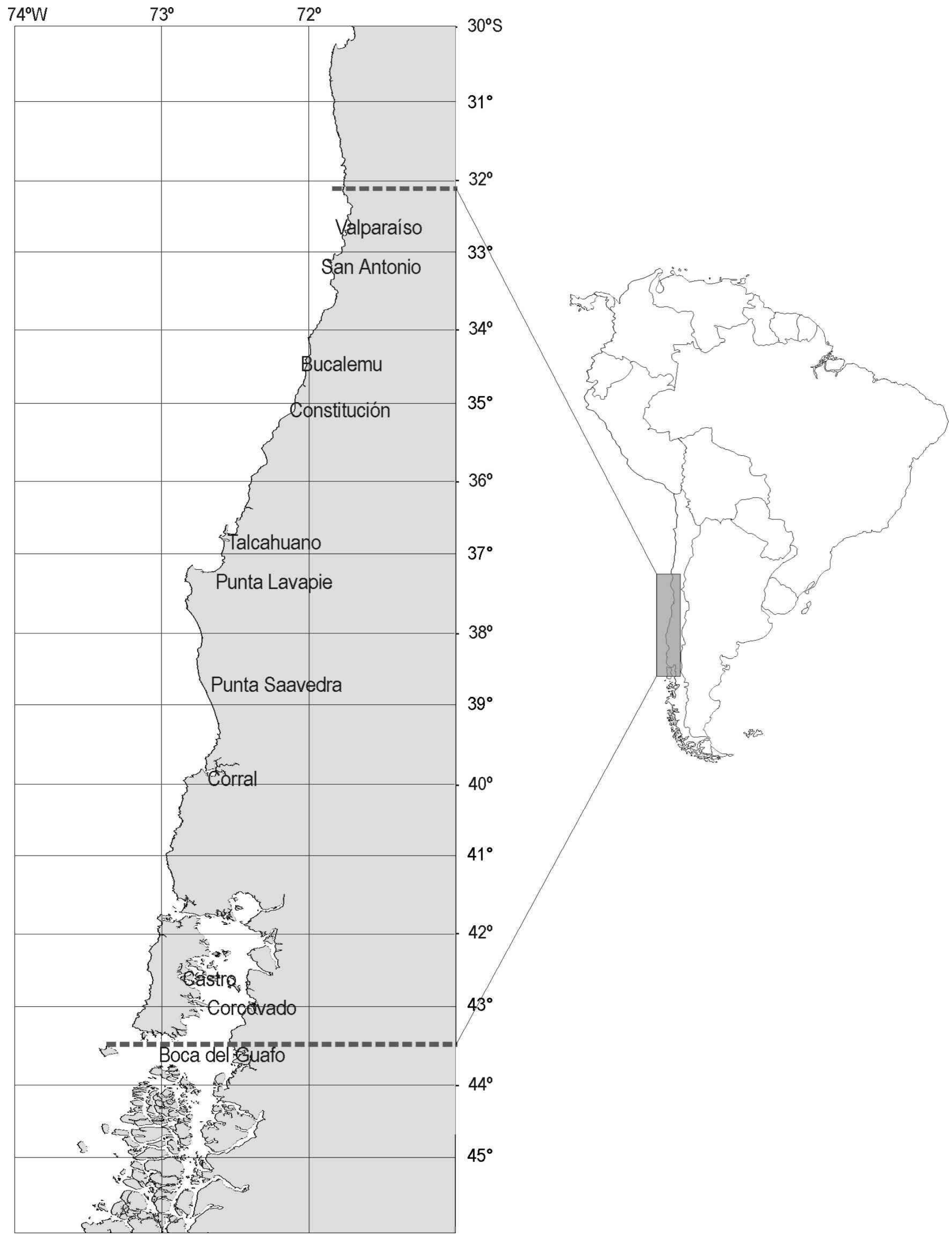
This fishery has currently the greatest volume of landings in Chile. Toward the end of the decade studied in this paper, this fishery reached its peak annual catch (4.5 million tons), with the Jack Mackerel as the predominant species. At the peak Jack Mackerel catch reached 4.1 million tons/year. Since then the fishery has relapsed significantly. Currently the Jack Mackerel catch is about 1.5 million tons/year.[3]

This fishery runs along the central-southern coastline of Chile, starting at the port of San Antonio in central Chile up to the Valdivia region in the South[4] (Figure 1). Along its history, Chilean owned purse seiners have mostly exploited this fishery. The exception happened during the years 1980s, when a fleet composed of vessels from Poland, Cuba and Russia fished jack mackerel in high seas areas in front of Central Chile (as well as in other high seas areas of the South East

[2] By small-scale fleet we mean vessels which on average rely on less sophisticated technology, relative to industrial vessels, and have a gross tonnage capacity of no more than 80 tons and vessel length of 18 meters at most.

[3] The Southern-Central fishery generates between US$200-250 million/year, in terms of export value and national sales, valued at current prices. This value represents between 20% and 25% of the yearly exported value by the Chilean extractive fishing industry. In terms of regional fishing employment, if we consider total national *direct* employment that the Chilean fishing sector (extractive and aquaculture sectors) generates on an annual basis, *i.e.* close to 85,000 regular job positions, about a quarter of these are based at the Talcahuano region.

Figure 1: Chilean Southern-Central Pelagic Fishery: Northern and Southern Limits



[4] This covers a coastline of about 1000 kms. The historical and still most productive core of this fishery is located in sea areas of the Talcahuano region.

Pacific).[5] Industrial fishing is concentrated on pelagic species, primarily destined for the fishmeal industry**.** Although in its early industrial development the main harvested species in this fishery were anchovy and sardine, since the beginning of the eighties jack mackerel has become the dominant species for industrial vessels. The industrial catch of these three main species fluctuated between 86% and 98% of the total landings in this fishery during the 1985-95 period.[6]

The decade under study coincides with a phase of explosive investment (see Table 1). From 1980 to 1985 the number of industrial vessels doubled, while the fleet's storage capacity quadrupled. In the following decade the aggregate storage capacity again increased four times. This occurred at a moment when larger vessels began to increase their participation in the fleet.[7] In terms of fishing effort, measured by aggregate annual haul of the fleet, [8] there was an increase of 6.5 times during the 1985-95 period.

The growth in annual harvest continued uninterruptedly until 1994-95. From then on annual catch began to fall, following a pattern that was aggravated as a result of the *El Niño* phenomenon that began in 1997 and lasted until late 1999.[9] If we consider the three main species, current catch levels are less than half the 1994-95 peak; in the case of Jack Mackerel catches, the drop is still bigger. Figure 2 illustrates the relationship over time between annual industrial harvest and several population dynamics variables, all for the Jack Mackerel.

With respect to the regulatory context, the investment boom in the fishery began under free access conditions, which prevailed from 1978 to 1986. From that point on, access regulations went into effect that 'froze' the fleet's storage capacity to the limits it had in 1986. However, legal loopholes remained, allowing for further expansions of the fleet's fishing capacity[10] (column #3 of Table 1). No further regulatory measures were implemented, except for a 'minimum catch size' clause that has been in place since the mid-eighties (Peña-Torres, 1997 and 2002).

Regarding temporary shocks, during the 1985-95 period two events of interest occurred. Firstly, the presence of an *El Niño* phenomenon of moderate intensity in 1987.[11] The second event

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[5] Fishing operations did occur 210 to 250 miles off the Chilean coast. During the late 1980s, this fleet was composed of about 70 factory mid-water trawlers. In 1990 they caught about 1.1 million tons of jack mackerel in adjacent high seas waters in the South East Pacific. Retreat from this fishery in 1992 was an economic consequence of the disintegration of the ex Soviet Union (Crone-Bilger, 1990, p. 118).

[6] Pelagic fish normally swim in high-density schools, in which various species often share the same sea area, competing for food.

[7] The first ships with a storage capacity over 800 m^3 began operating in 1989. In 1995 this size category represented 44% of total available storage capacity.

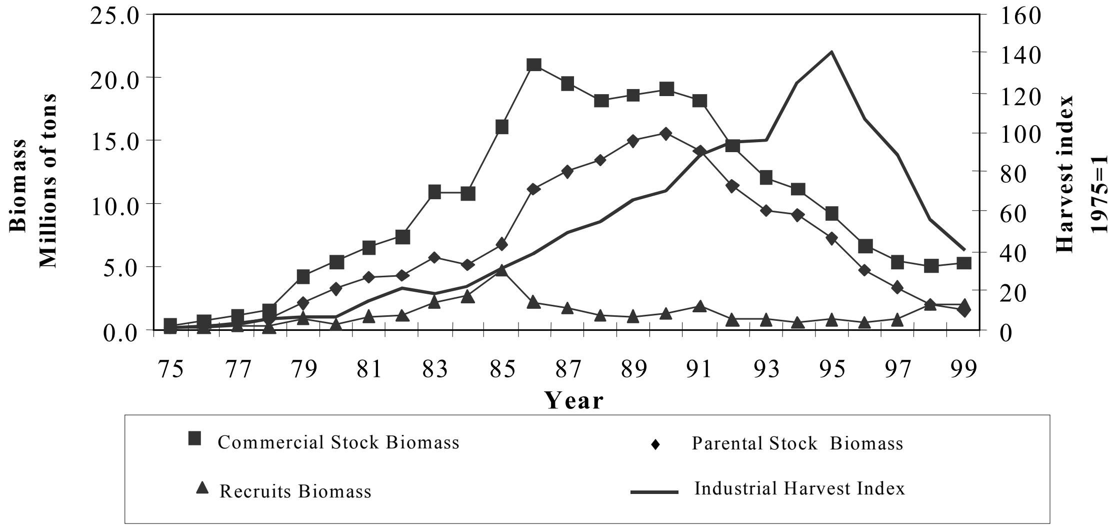
[8] The concept of haul or aggregate effort proxies the level of use given to the available aggregate fishing capacity. It is defined as the sum of the storage capacity for all industrial ships, weighted by each vessel's annual fishing hours.

[9] This was the 'El Niño' phenomenon of greatest intensity occurring during the 20th century.

[10] For example, the substitution of two or more small ships for a larger one was allowed if the resulting storage capacity remained fixed. In practice, this allowed for the entry of vessels with greater fishing capacity.

[11] This refers to a seasonal warm ocean current whose presence significantly alters the location and survival rates of different marine species.

Figure 2
Biomass and Harvest of Jack Mackerel



Source: Authors' elaboration based on IFOP information

refers to discussions regarding the enactment of a new fisheries law, which began towards the end of 1987 and continued until its final approval in September of 1991. During these years the possibility of assigning individual catch quotas, based on 'historic catch' records, was appraised.

Table 1: Southern-Central Pelagic Fishery

Year	Industrial Fleet			Landings: Industrial & Small-Scale fleets (10^6 tons)		Available Biomass (10^6 tons)	
	Fishing Effort (index) (1)	Number of vessels (2)	Total Storage Capacity (10^3 m^3) (3)	3 main species (4)	Jack Mackerel (5)	3 Main Species (6)	Jack Mackerel (7)
1975		37	4.3		0.023		
1980		47	6.3		0.274		
1985	100.0	97	27.8	0.960	0.870	17.25	15.42
1986	142.4	93	29.5	1.158	1.075	21.97	20.47
1987	157.0	93	32.7	1.518	1.391	20.96	18.42
1988	192.7	105	40.0	1.714	1.644	20.33	17.32
1989	231.6	108	48.4	2.296	1.861	21.84	18.51
1990	302.3	140	60.3	2.412	1.983	21.95	17.93
1991	356.0	174	76.3	3.342	2.517	20.89	15.89
1992	412.7	173	78.7	3.445	2.735	15.82	12.54
1993	440.8	172	90.8	3.208	2.759	14.34	11.18
1994	511.8	167	97.2	4.507	3.691	13.02	9.94
1995	640.3	177	110.4	4.472	4.089	12.06	7.50
1999		153	122.8	3.115	1.267		
2000				2.072	1.065		

(1) Total annual haul (A^I_t) of industrial fleet, where $A_t^I = \sum_i H_{it} \cdot E_{it}$, $\forall$i that operated at year t, with H_{it} denoting vessel i's storage capacity (in m^3) and E_{it} : i's annual fishing hours during year t.

(6) - (7): Yearly average stocks estimated by IFOP. Availability measure of the commercially exploitable stocks (recruits + older age cohorts) in Southern-Central zone.

Sources: IFOP and Fishing Annals (Sernapesca).

3.- The Theoretical Model

In this paper we follow the literature that estimates efficient production frontiers using panel data (Schmidt and Sickles, 1984; Fried, Knox-Lovell and Schmidt, 1993, chs. 1-2; Kumbhakar and Knox-Lovell, 2000). In this context, panel models present some advantages with respect to those that rely solely on cross-section data. The former allows for a greater number of observations, usually enabling more efficient estimation. Additionally, panel models can simultaneously estimate the technological process underlying a particular industry as well as determinants of productive efficiency. This increases the options for testing relevant hypotheses.

Following traditional literature on stochastic frontier models (*e.g.* Aigner, Knox-Lovell and Schmidt, 1977; Schmidt and Sickles, 1984), the simplest panel data model is:

$$y_{it} = x_{it}\beta + \nu_{it} - u_{it} \quad ; \quad i = 1,2,...,N \, ; \, t = 1,2,...,T \tag{1}$$

Here y_{it} denotes the logarithm of the product for the i^th^ unit in period t; x_{it} represents a vector corresponding to technological factors and other variables which may be relevant, and β a vector of parameters. The v_{it} terms are i.i.d. errors following a $N(0,\sigma_v^2)$ distribution, which are independent of the u_{it} errors, as well as of the explanatory variables x_{it}.

The u_{it} values take into account the technical inefficiency in the model; they are also i.i.d., but not 'white noise' errors since they are non-negative variables corresponding to the positive truncation of $N(0,\sigma_u^2)$. In general, the u_{it} values can be correlated with the explanatory variables.

In this framework, the Battese and Coelli (1995) model specifies that technical inefficiencies, defined as non-negative random variables, are to be distributed independently, although not identically. For the i^{th} productive unit in period t, the technical inefficiency u_{it} is obtained through the positive truncation of the $N(\mu_{it},\sigma^2_u)$ distribution, where the mean value μ_{it} of this distribution is modelled as:

$$\mu_{it} = z_{it}\,\delta \tag{2}$$

with z_{it} representing observable explanatory variables, and δ a vector of parameters. If we estimate equation (1) using maximum likelihood for example, one estimates the residuals $\xi_{it} = (\nu_{it} - u_{it})$, and then, by following Jondrow *et al* (1982), it is possible to indirectly estimate residue $\hat{u}_{it}$ through the conditional expectation of u_{it} given estimated values of ξ_{it}:

$$E(u_{it}|\xi_{it}) = \psi[\phi(\xi_{it}\lambda/\sigma_s)\,/\,(1-\Phi(\xi_{it}\lambda/\sigma_s))-(\xi_{it}\lambda/\sigma_s)] \tag{3}$$

Here, $\sigma^2_s = (\sigma^2_u+\sigma^2_v)$; $\psi^2 = (\sigma^2_u\sigma^2_v / \sigma^2_s)$; $\lambda = (\sigma_u/\sigma_v)$; ϕ and Φ represent the standard normal density and distribution functions, respectively. With this notation the technical efficiency of the i^{th} unit in period t is given by:

$$TE_{it} = \exp(-\hat{u}_{it}) \tag{4}$$

The technical efficiency score of i has a value equal to one if vessel i obtains an estimated inefficiency equal to zero. In the remaining cases, TE will be positive but less than one.

Battesse and Coelli (1995) rely on maximum likelihood to estimate their "random-effects" model.[12] The likelihood function itself appears in Battese and Coelli (1992), together with the first order conditions. They introduce parameter $\gamma = (\sigma^2_u / \sigma^2_s)$ with $\sigma^2_s = (\sigma^2_v + \sigma^2_u)$; here γ takes a value between 0 and 1. If all parameters corresponding to δ and γ are equal to zero, then the model is equivalent to a traditional "production function" model, which in principle could be estimated efficiently through ordinary least squares.

4.- Functional Form and Variables

The methodology introduced by Battese and Coelli (1995) considers the estimation of a production frontier as a function of input and state variables, simultaneously with the estimation of an associated technical inefficiency function. The latter correlates the resulting inefficiencies, whose proxies are obtained from the residuals obtained when estimating the stochastic production frontier, with respect to a set of explanatory variables. A subset of these may coincide with some of the regressors used in the production function.

In our exercise we model the technology that describes the harvesting process by means of a Translog production function. The model in question is:

$$c_{it} = \beta_0 + \sum_j\beta_j x_{jit} + \sum_j\sum_k\beta_{jk}x_{jit}x_{kit} + \nu_{it} - u_{it} \tag{5}$$

where the indexes i and t indicate observations for vessel i and year t; and indexes j and k indicate explanatory variables. The variables considered are:

[12] Although panel data is used in the Battesse-Coelli (1995) model, using assumptions in the line of a random-effects model, their estimation model does not correspond to the traditional version encountered in the literature on panels. In the latter case estimates are obtained through generalized least squares or by specifying a different log-likelihood function. In Battese-Coelli (1995) model, the computational algorithm (T. Coelli's FRONTIER 4.1 software) pools the panel data allowing the model, defined by equations (5)-(6), to be estimated as a "cross-sectional model" (private communications with T. Coelli and A. Álvarez).

c_{it} = natural log of total annual landings (all species) in tons.[13]

x_1 : h_{it} = natural log of storage capacity (measured in m^3).

x_2 : e_{it} = natural log of annual fishing hours.

x_3 : g_{it} = natural log of vessel age (in years).

x_4 : x_{it} = natural log of 'fishing experience'.

x_5 : b_t = natural log of total aggregate biomass, measured in tons, at year t−1.

x_6: T = trend variable (1985=1, ….., 1995=11)

Age G_{it} is defined as the difference between year t and the vessel's construction year. The variable 'Fishing Experience' is defined as $X_{it}= (M_{it})\cdot(G_{it})$; where M_{it} is a variable that accumulates annual fishing hours from year 1985 up to year t. The variable X_{it} purportedly measures accumulated levels of fishing activity, weighted by the ships' age, aiming to control for possible "learning by doing" efficiency effects.

The data were obtained from the Chilean Institute for Fishing Development (IFOP), covering the 1985-1995 period. It includes annual data on: (i) catch per vessel; (ii) storage capacity of each vessel; (iii) annual fishing hours per vessel; (iv) construction year of each vessel; (v) yearly average biomass for each of the three main fish species; and (vi) the owning firm of each vessel.

Our model controls for two types of effects: first, it controls for possible time effects, and second, for vessel-specific factors. For the first kind of effects, we consider a trend that controls for time changes in the technological frontier. In addition, we use a proxy variable to control for the fish stock in each year t, denoted by B_t, which is calculated by aggregating all fish stock for year t−1 to avoid possible endogeneity effects.

Notwithstanding the Zellner, Kmenta, Drèze (1966) argument regarding the exogeneity of input variables when estimating a production function,[14] *ad hoc* explicit exogeneity tests of the Hausman variety (Hausman, 1978) were carried out for the more relevant variables in our analysis. Specifically, a subset of variables −from a larger set consisting of all variables whose exogenous character is in doubt− was tested for exogeneity using the pooled data panel, namely fishing effort and fish stock (Holly, 1982; Maddala, 1992). For testing purposes, all quadratic and mixed terms involving these variables were also included in this subset. The test in question is a Wald type test

[13] Catch per ship (C_{it}) considers total species caught. During the period under study, the dominant species in this fishery is the Jack Mackerel, followed by Anchovy and Sardine. Other species with minor catch shares are Mackerel, Hoki and Chilean Hake.

[14] Assuming that output is stochastic due to uncontrollable shocks such as weather, Zellner et al. suppose that firms choose their inputs so as to maximise expected profits. However, in stochastic environments entrepreneurs will commit non-systematic errors (Zellner et al. speak of 'managerial inertia' and 'random human errors') in their profit-maximising

which uses for instruments the respective lagged variables of the questionable 'exogenous' regressors *(i.e.* vessel's fishing effort and fish stock). The Wald test results in an F = 2.42 (p-value = 0.037). This value gives ample support to our proxy variables for fishing effort and fish stock, especially considering the large number of vessels involved in the fishery (Cox and Hinkley, 1990).

To estimate yearly average biomasses IFOP uses a methodology known as Virtual Population Analysis (Gulland, 1988). Due to the multi-species nature of this fishery, where significant price differences between the main species caught are not observed, we define annual fish stock availability as the sum of the yearly-average exploitable biomasses[15] estimated by IFOP for the three most important species. We also consider a proxy for the biomass linked to the remaining species caught.[16]

With respect to the vessel-specific variables, we use storage capacity to proxy fixed factors that may affect catch yields. Information for other fixed factors *(e.g.* search technologies; the ship's motor power; fishing gear; or the fishing experience of the captain and crew) was not available. As a further effort to control for the influence of these other fixed factors, we carry out estimations dividing our total estimation sample into three sub-panels of vessels, differentiated according to vessel storage capacity. We are therefore implicitly assuming that the joint effect of other fixed factors is on average positively correlated to vessel size.

The sub-panels defined are: P1: 80-300 m^3; P2: 301-800 m^3; and P3: 801m^3 and more. Table 2 shows the number of vessels comprising our sample, according to how many vessels were in operation at each year and for each sub-panel. Table 3 provides information on the average scales of operation of the ships included in each sub-panel.

The division of the vessels into sub-panels was decided after considering IFOP's studies regarding technological characteristics that different sized vessels have in this fishery. For example, a significant fraction of the fleet has the capacity to fish beyond the 200 miles limit. However, larger vessels (panel P3) are the ones that more frequently carry out longer fishing trips and travel farther from the coastline, whilst smaller ships (panel P1) tend to concentrate their fishing effort closer to the coastline.

The remaining vessel-specific variables are: (i) Annual number of hours (E_{it}) that the vessel was at sea. This variable adds up the time in which the ship actually carries out catch operations, as well as the time it spends searching for fish. It aims at approximating the fishing effort performed

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endeavours. When these 'random' human errors are not correlated with the stochastic shocks from Nature, Zellner et al. prove that standard OLS estimation procedures are consistent when estimating a production function.

[15] *Exploitable* biomass is smaller than the annually available biomass, because of prevailing regulations on minimum catch size.

by each vessel, as a proxy of variable input use; (ii) Age of ship (G_{it}) controls for possible effects related to technological obsolescence. To the extent that technological innovations might have occurred, everything else constant, the expected *a priori* effect would be a negative correlation between G_{it} and catch efficiency. However, age may also be associated with accumulated *"learning by doing"* type effects. In an effort to control for these effects, presumably having a positive impact on technical efficiency, we use (iii) the fishing experience variable (X_{it}) which considers the accumulated level of each vessel's fishing effort over the period studied, weighted by the ship's age.

Table 2: Number of Vessels at the Southern-Central Pelagic Fishery

Year	*P1*	*P2*	P3	*Total*
1985	48	24	.	72
1986	47	39	.	86
1987	40	47	.	87
1988	31	58	.	89
1989	31	62	4	97
1990	42	71	8	121
1991	43	78	13	134
1992	33	77	17	127
1993	30	85	25	140
1994	26	79	39	144
1995	20	84	38	142
Total vessels*	61	100	43	204

*: This total corresponds to the number of vessels that fished for at least one year during the 1985-95 period
Source: Authors elaboration based on IFOP information.

The deviations of the data with respect to the frontier (5), are captured by two error terms. The v_{it} term absorbs measurement and/or specification errors in the model and is assumed to be a white noise; while the non-negative u_{it} term measures the technical inefficiency.

The model used to explain the u_{it} errors, estimated in the first stage, is:

$$\mu_{it} = \delta_0 + z_{it}\delta \tag{6}$$

where μ_{it} corresponds to the conditional expectation of the u_{it} variables, given the residuals $\xi_{it} = (\nu_{it} - u_{it})$, and z_{it} is a vector of variables that help explain the efficiency of the vessels, being δ a vector of parameters.

[16] Due to lack of official biomass estimates pertaining the remaining species, a proxy based on catch information was used. For this we assume that for the remaining species, the (catch/biomass) ratio is equivalent, each year, to the ratio obtained using the landings and the sum of the biomasses estimated by IFOP for the three main species.

Table 3: Industrial Fleet's Scale of Operation
(Yearly averages per vessel, period 1985-95)

Panel	(1) Annual Catch (10^3 tons)	(2) Annual fishing trips (number)	(3) Annual Fishing trips with catch success (Number)	(4) Annual fishing days (Number)	(5) [Annual catch/ Storage Capacity] (# of times)
P1	7.7	145	98	97.2	35.9
P2	22.2	133	98	144.7	42.3
P3	38.9	90.7	76	165.5	39.2

(1): Catch of three main species; (2): Trips with and without catch success; (5): Number of times the vessel storage capacity is annually filled with catch. Source: Authors calculations based on IFOP data.

The variables we consider for (6) are:

z_1 : a^j_t = natural log of annual haul of all vessels belonging to firm j.

z_2 : n^j_t = natural log of the number of operating vessels belonging to firm j.

z_3 : h^j_t = natural log of storage capacity of vessels belonging to firm j

z_4 : a^I_t = natural log of the aggregate annual haul, of the whole industrial fleet.

z_5 : n^I_t = natural log of total number of operating vessels at the industrial fleet.

z_6 : e_{it} = natural log of vessel's annual fishing hours.

z_7 : g_{it} = natural log of vessel's age.

z_8 : x_{it} = natural log of vessel's experience.

z_9 : b_t = natural log of aggregate biomass, at year t-1

D(t) = dummy variable for year t (for t = 1987, 1988, 1989 and 1990).

The Haul variable, defined as $A_{it}= (H_{it})\cdot(E_{it})$, proxies the use intensity given to the vessel's storage capacity H_{it}. For firm j the haul is defined as $A^j_t = \Sigma_i A_{it}$ ($\forall i \in j$). Thus A^j_t considers the storage capacity as well as the annual fishing hours of all operating vessels that belong to firm j. Likewise, aggregate industrial haul of the fishery is defined as $A^I_t=\Sigma_i A_{it}$ ($\forall$i that operated during year t). The latter encompasses the total industrial fleet.

By specifying (6), variables were introduced that relate external factors to the vessel in question. Firstly, there are variables aggregated at the level of the firms which own the operating ship: (a) The haul variable defined at firm-j level (A^j_t) captures possible impacts, of the use intensity given to firm j's total fleet, on each (j-owned) vessel's catch efficiency. This variable may be thought of as a proxy for the complexity level of the fishing activities that firm j performs. On the other hand, A^j_t also accounts for effects associated with the scale of fishing efforts performed at the firm level. (b) As an alternative control for effects associated with the level of complexity of fishing operations at the firm level, we consider the accumulated storage capacity (as a proxy of installed productive capacity) of all operating vessels controlled by firm j (H^j_t). (c) The N^j_t variable aims at controlling effects on efficiency associated with the number of ships belonging to firm j.

Secondly, we also include two variables aggregated at the fishery level. Aggregate haul A^I_t aims at capturing externality effects at the vessel level, related to the aggregate annual fishing effort performed at the fishery. For instance, congestion effects might prevail, causing a negative impact on individual vessels' catch efficiency. On the other hand, positive externalities associated with collective efforts aimed at fish search could be present. The N^I_t variable aims at controlling more directly for the latter possibility.

Thirdly, we include the biomass variable (lagged 1 year) to control for the possibility that fish abundance might also affect vessels' catch efficiency in this fishery, beyond its impact on the technological frontier. In addition, we include four dummy variables that control for time effects such as regulatory changes or natural phenomena such as the year-1987 *El Niño*. We have included additive dummy variables only in those years which have been significant in prior studies of this fishery (Peña-Torres, Basch and Vergara, 2002).

Finally, we have also included three vessel-specific variables that were already considered in the first stage of the model. Annual fishing hours of the vessel control for possible influences on catch efficiency arising from the ship's scale of operation. With a similar motivation we include vessel's age and fishing experience. Everything else being constant, we would expect to find a positive correlation between age and inefficiency and a negative correlation between fishing experience and catch inefficiency.

To simplify notation, in what follows we use lower-case letters to denote the natural logarithm of variables (*e.g.*, x = ln X); in addition we eliminate the time sub-index.

To carry out the different hypothesis tests with respect to the parameters in model (5)-(6), a generalised likelihood ratio (GLR) test is used, defined by:

$$\lambda = -2\ [l(H_0) - l(H_1)] \qquad (7)$$

where $l(H_0)$ corresponds to the log-likelihood function of the restricted model (as specified in the null), and $l(H_1)$ is the log-likelihood function of the unrestricted hypothesis. The statistic distributes asymptotically as a chi-square distribution with degrees of freedom equal to the difference between the number of parameters in each hypothesis.

To test the null hypothesis of no inefficiency effects in the fishing process, for example, the hypothesis $\gamma = \delta_1 = \ldots = \delta_{13} = 0$ is specified (where sub-indexes 1, 2,…,13 denote each one of the explanatory variables included in equation (6); see Annex 1). In this case, λ asymptotically follows a mixed chi-square distribution, where the critical values are obtained from Kodde and Palm (1986). If the null cannot be rejected, then the estimated function is equivalent to a traditional 'production function' model.

5.- Empirical Results

Prior to carrying out the estimations, outliers were eliminated through the use of a robust methodology.[17] Then equations (5) and (6) were estimated simultaneously. Annex 1 shows the final results for the model. The estimated parameters of the three sub-panels appear column-wise, as well as for the entire panel. At the bottom of the chart, we see estimations for σ^2_S, γ, log-likelihood, and the mean technical efficiencies (MTE).

For choosing our final model, we considered all explanatory variables and estimated various alternative models. The reported results show the best fit using the GLR criterion. In the selection process, we chose to keep the same variables for all sub-panels, considering that all vessels use the same fishing technology, all operate in the same fishery, and there hardly exists any heterogeneity with respect to the dominant final product.[18]

Table 4 reports values for the GLR tests with respect to parameter restrictions associated with different hypotheses, the last four of which relate to the inefficiency model.

Table 4: Generalised Likelihood Ratio Results

Null Hypotheses	P1	P2	P3	Total Panel	Critical Value (95%)
Production Frontier Tests:					
1. Cobb-Douglas function	55.4	112.00	39.8	210.6	32.67
2. Trend effects, (T) = 0	164.5	54.50	18.7	160.6	14.07
3. Storage capacity effects, (h_i) = 0	150.2	88.2	118.3	155.9	14.07
4. Age effects, (g_i) = 0	55.4	33.9	95.3	66.8	14.07
5. Experience effects, (x_i) = 0	10.8	104.8	16.8	3.9	14.07
Inefficiency Model Tests:					
6. D88=D89=D90= 0	44.0	215.9	3.6[a]	43.4	7.81
7. $\gamma = \delta_1 = \ldots = \delta_{13} = 0$	100.6	147.1	15.35	257.5	21.74[b]
8. Firm effects, ($n^j=a^j=h^j=0$)	13.5	15.68	16.7	16.8	5.99
9. Industry effects, ($n^I=a^I=0$)	10.2	2.56	2.11	14.4	5.99

[a]/ Test corresponds to Ho: D89=D90=0. Critical value is 5.99.
[b]/ The GLR test for $\gamma = \delta_1 = \ldots = \delta_{13} = 0$ follows a mixed chi-square distribution (Kodde and Palm, 1986). The critical value for panel 3 is 17.67 at a 95% significance, while at 90% it is 16.67.

[17] The methodology combined the Cook, Huber, and Beaton-Tukey methods (Huber, 1981). Specifically, all observations having weights equal to zero, after estimating equation (5), were eliminated. Basically, this eliminated vessels that operated less than 1 month per year from our estimation sample.
[18] As we see from Annex 1, some explanatory variables that appear in (5) also show up in (6). This kind of evidence has shown up before in the literature concerning these models (*e.g.* Lundvall and Battese, 2000). This brings up the possibility

Analysis:

(1) The Cobb-Douglas functional form is rejected in all four cases. This implies that input elasticities are dependent on the production scale. Table 5 shows biomass and fishing effort elasticities, using annual averages (at year t) for the relevant variables in each elasticity function.[19] Estimations for the effort elasticity are consistently greater than one.[20] The estimated values for P1 and P2 are similar in magnitude, showing stability over the period. The values for P3 are larger in magnitude, showing a declining pattern between 1989 and 1995. Values greater than one imply increasing marginal returns from fishing effort. Differences between panels are consistent with the observed substitution of P1-vessels in favour of P3-vessels. Likewise, the falling trend evidenced by the P3-effort elasticity could reflect a gradual exhaustion of scale economies, related to the increasing effort levels evidenced by P3-vessels.

With respect to the biomass elasticity: (a) for most years of the sample period this elasticity is different from zero.[21] (b) Values estimated for P1 tend to consistently exceed those for P2. For the 1993-95 period, a declining trend is observed for the annual averages of this elasticity, for all panels. For vessels in panels P1 and P2, the 1993-95 period coincides with a declining trend in yearly average catch efficiencies (see Figure 3). This period also coincides with declining fish stocks, which in turn is related to sustained increases in total annual landings (Figure 2).

Some of the yearly estimations for the biomass elasticity have negative values: *i.e.*, reductions in biomass would be correlated with greater catch levels. A biological process may help explain this result: in effect, pelagic fish tend to increase their density when their population decreases, as a defence mechanism from predators. This greater population density would then imply more catch per fishing effort.

(2) In all panels the hypothesis of no trend effects is rejected. As we have seen, during the 1985-95 period aggregate catch levels grew steadily, while fish stock availability was declining (Figure 2). Additionally, for all sub-panels we observe significant trend-input interactions that correspondingly affect the respective input elasticities. Figure 3 shows the annual averages of vessel-level technical efficiency for all panels. Beginning in 1989, a falling trend for efficiency

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that some of the estimated coefficients might be inconsistent. As such this issue remains to be solved (personal communication with G. Battese).

[19] For the analytic formula, see Battese and Broca (1997).

[20] The null for effort elasticity equal to 1 is rejected for all panels, testing on its average value for 1985-95, the t statistics being 4.88, 7.57, 8.55, 15.35 for P1, P2, P3, and the total panel, respectively.

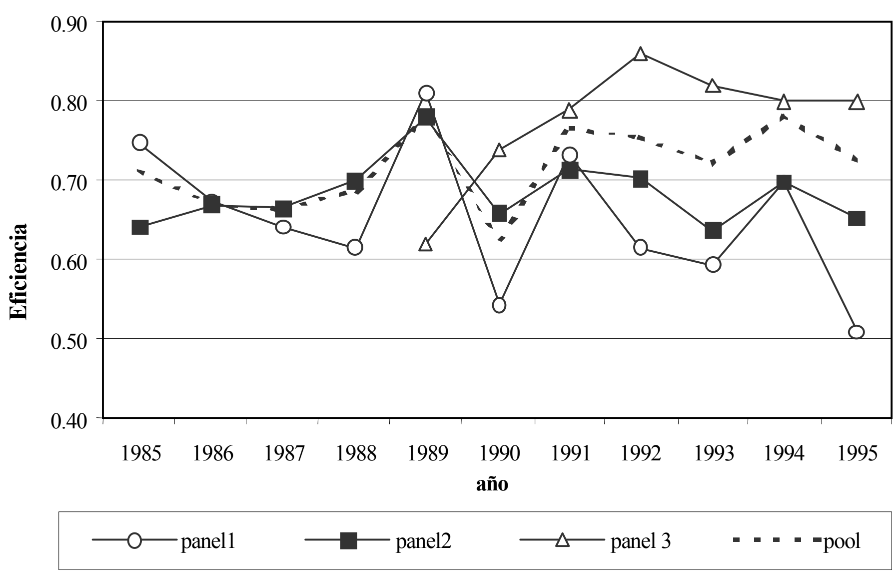
[21] The null that the biomass elasticity equals zero is rejected for all three sub-panels, for the entire period, being the t statistics equal to 4.43, 2.63 and -7.83 for P1, P2, and P3 respectively, while for the total panel the value is 3.77.

scores is observed in panels P1 and P2;[22] while the opposite occurs with P3. This is consistent with a growing substitution in favour of P3-sized vessels, at the expense of smaller ships.

Table 5. Input Elasticities: Biomass and Fishing Effort

	Panel 1		Panel 2		Panel 3		Total Panel	
	Biomass	Effort	Biomass	Effort	Biomass	Effort	Biomass	Effort
1985	-1.14	1.41	-1.23	1.12	-	-	-1.10	1.71
1986	0.56	1.24	0.00	1.19	-	-	0.50	1.48
1987	1.73	1.10	0.91	1.20	-	-	1.64	1.32
1988	1.52	1.09	0.81	1.19	-	-	1.32	1.34
1989	1.27	1.07	0.64	1.17	-2.10	2.11	0.98	1.33
1990	1.49	1.10	0.82	1.15	-0.01	1.71	1.12	1.24
1991	1.65	1.06	0.97	1.15	1.78	1.29	1.21	1.15
1992	1.34	1.00	0.77	1.16	1.93	1.07	0.82	1.13
1993	0.29	1.07	0.02	1.12	-1.36	1.22	-0.28	1.24
1994	-0.26	1.10	-0.35	1.09	-2.64	1.11	-0.97	1.26
1995	-0.78	1.03	-0.64	1.08	-3.71	0.87	-1.55	1.21
Avr.85-95	*0.70*	*1.12*	*0.25*	*1.15*	*-0.87*	*1.34*	*0.34*	*1.31*
(St.Dev.)	*(0.15)*	*(0.02)*	*(0.09)*	*(0.01)*	*(0.11)*	*(0.04)*	*(0.09)*	*(0.02)*

Figure 3
Vessel-level Efficiency Scores (annual averages)



[22] During 1989 there was a peak in public policy discussions that were assessing the possibility of allocating, free of charge, individual transferable quotas based on 'historical presence'. These controversies triggered strong incentives to maximize that year's individual landings.

On the other hand, Figure 4 shows efficiency histograms for all ships in our sample. In the case of P3, practically all observations have efficiency scores over 50%, with a significant proportion being in the 75%-96% range. In the case of P1 and P2, the distributions are less concentrated in the upper ranges of the ranking; both groups include a distinct proportion of vessels with efficiencies between 5%-25%.

(3) Catch effects linked to vessel's storage capacity (in all panels) are overall significant (equation 5). This supports the hypothesis of systematic differences between vessel-size categories, with respect to parameters concerning production frontiers and efficiency levels. In effect, when testing for the validity of sample segmentation, this hypothesis cannot be rejected.[23]

(4) Regarding the production frontier equation, the age variable is clearly significant for all panels considered. With respect to equation (6), a positive correlation is observed between inefficiency and age; only in panel P3 this effect is no significant,[24] though its sign is consistently maintained.

(5) Regarding 'fishing experience', we have less robust results. Concerning the frontier equation, the hypothesis of non-significance is rejected for P2 and P3. As for its effect on inefficiency, we observe significance only for P2, and with the expected sign. We conjecture that the proxy we use for 'fishing experience' probably does not successfully capture the relevant underlying processes to accumulative productive learning.[25]

(6) The dummy variables D88, D89 and D90 are jointly significant for all panels; P3 being again the exception. D89 is the most consistent dummy regarding significance; next is D90. During 1989, the discussion about a possible free assignment of individual fishing rights reached its maximum intensity. Therefore, the negative sign obtained for D89 supports the hypothesis of attempting to consolidate fishing rights by increasing individual landings as much as possible.

(7) In three of the four panels the joint non-significance of inefficiency errors and inefficiency explanatory variables is rejected. The exception is again P3, although only marginally. The γ estimates (the proportion of total residual variance attributed to inefficiency residuals) vary between 0.82 and 0.9 for the various sub-panels.

(8) Considering the above results for sub-panels P1, P2 and the total panel, we observe significant deviations with respect to the estimated efficiency frontier. The latter supports our

[23] The value of the GLR is 451.6, whereas its critical value is 85.3 (this statistic distributes asymptotically as a chi-square distribution with 84 degrees of freedom). Therefore, the null hypothesis that the parameters for the three sub-panels are equal is categorically rejected.

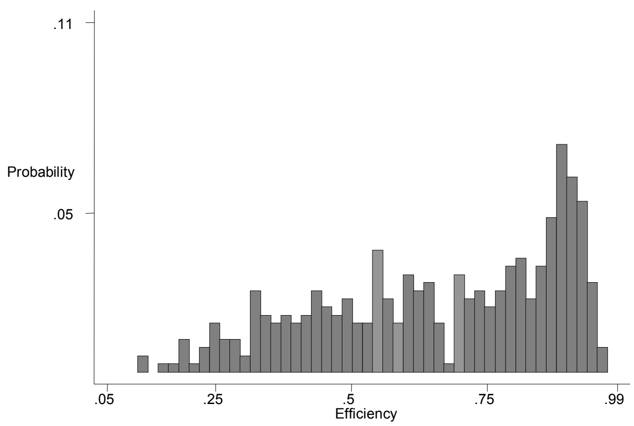
[24] Panel P3 has the fewest observations in our sample. This could help explain this finding, as well as other similar results (implying 'no statistical significance') that we obtain for P3.

[25] Informal descriptions by fishing sector experts deem the fishing experience of the captain and crew to be clearly relevant in understanding the rate of success of harvesting operations.

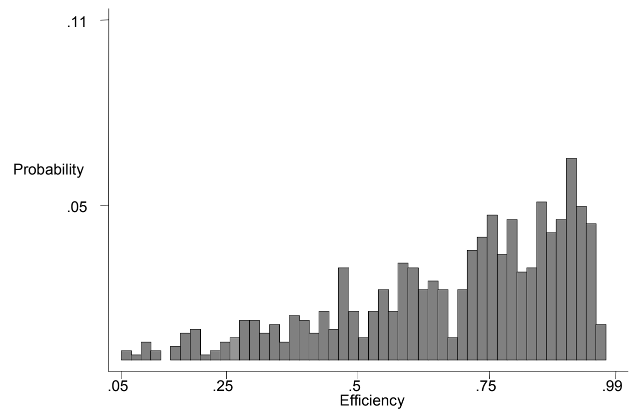
hypothesis regarding ample productive heterogeneity related to vessel-size effects. This is also evidenced at different aggregation (vessel-, firm-, and fishery-) levels.

Figure 4
Vessel-level Catch Efficiency Histograms

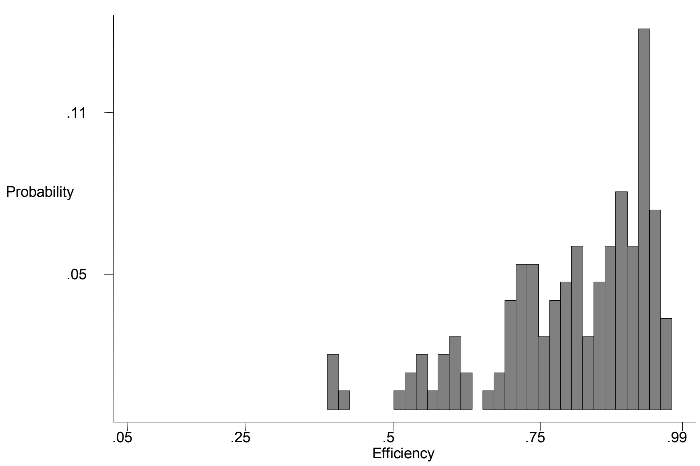
(A) Panel 1



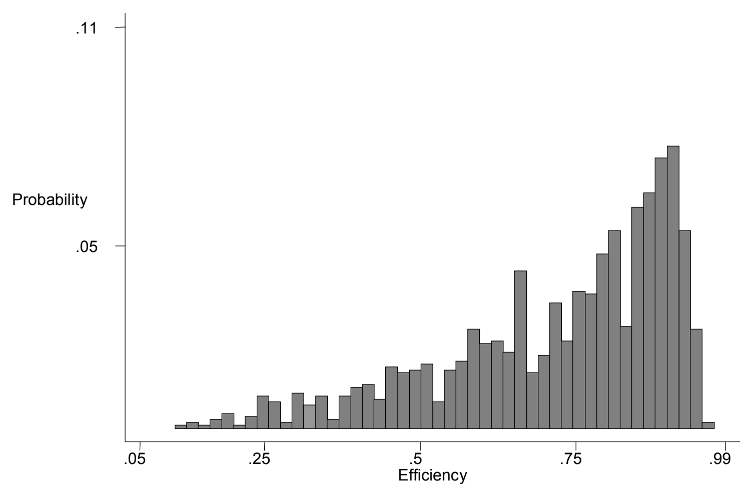
(B) Panel 2



(C) Panel 3



(D) Total Panel



(9) For all panels, the joint set of variables aggregated at the controlling firm level is significant. The strongest result is found for the total number of vessels under firm j's control. Its significance is systematic in all four cases, and with negative sign in three cases. According to this finding, the number of vessels controlled by a firm correlates positively with vessel efficiency. This result might be reflecting external economies at the vessel level, related to search efforts for locating fish patches of productive interest.

Regarding haul at the firm level, a positive and significant sign is obtained in three cases, the exception being P3. A positive sign indicates that as firm's total haul increases, vessel-level efficiency decreases. This may reflect production diseconomies at the firm level; perhaps reflecting increasing complexity in the fishing business as firm's total fishing effort goes up.

The results for the firm-level storage capacity have no clear significance. We obtain significance only for P1 and P3, but with opposite signs. The fact that h^J is not clearly significant but that A^J is, reaffirms our interpretation that the external diseconomies, which appear to be related to the controlling firm's haul, would be associated to the intensity of use of the available fishing capacity.

(10) The results obtained for variables aggregated at the fleet level do not show clear robustness. The joint non-significance of these variables can only be rejected for P1 and the total panel. The total number of vessels in the entire fleet shows a negative sign for all panels except for P3; though the negative sign is significant only for P1 and the total panel. With respect to aggregate haul at the fleet level, its sign is positive for all cases. This might be capturing congestion effects in terms of aggregate fishing effort productivity. However, this effect is significant only for the total panel and for P2.

6. Predictions

Annex 2 describes the vessels that operated in this fishery in 2001.[26] Of the 29 vessels that were chosen by entrepreneurs to operate in this fishery during 2001, 26 are in our estimation base: 6 corresponding to panel P2 and 20 to panel P3. Several characteristics of the vessels chosen by the entrepreneurs are consistent with our results:

- No P1-sized vessel was chosen to operate at year 2001. This is consistent with the efficiency score ranking that we have found for the three estimated sub-panels (Figure 3).

[26] Not all of the existing vessels operated that year. There were in total 180 vessels that had valid fishing licenses to operate in this fishery. Of these, at the beginning of year 2001 only 29 were officially registered by entrepreneurs for performing fishing operations. The chosen vessels represented about half of the total fleet's storage capacity. Entrepreneurs' choices in this respect were conditioned by regulations introduced at the beginning of year 2001, which allowed entrepreneurs to freely decide which vessels to use in order to catch their (individually assigned) fishing quotas.

- In general, the chosen vessels tend to correspond with those of more recent entry to the fishery. This is consistent with the sign of the correlation found between inefficiency and vessel age.
- The chosen vessels tend to obtain higher efficiency scores than the average efficiency of vessels in the same size category.
- The chosen vessels tend to have use intensities that are above the corresponding average use for vessels in the same size category.

However, the matching between the entrepreneurial choice of vessels and our efficiency ranking is far from perfect[27]; Tables 6(A)-(B) illustrate the degree of matching.

The vessels chosen to operate at year 2001 implicitly rank the fleet, differentiating between operating vessels (denote them by *O*) −29 in total− and non-operating ones (denote them by *NO*). Of the 29 vessels in the first group, 26 can be found in our estimation sample. To obtain a matching matrix, we selected the 26 most efficient vessels according to our frontier model; these are denoted by *EF*. Remaining vessels are consequently denoted by *INEF*. Table 6A shows the matching for the entire panel.

Of the 26 vessels that were chosen to operate by the entrepreneurs, and which are also part of our estimation sample, 12 were among the 26 most efficient according to our model (a matching rate of 5.9%). On the other hand, 164 of the remaining 178 vessels (in total, there are 204 vessels in our estimation sample; see Table 2) correspond to non-operating vessels and which at the same time are selected by our frontier model as part of the *INEF* group (a matching rate of 80.3%). Therefore, our model obtains overall an 86.2% matching rate. Table 6B shows the results of a similar exercise but now constraining our database to consider only the 43 vessels that belong to sub-panel P3.

Table 6A: Matching Matrix (for the Total Panel)

	Model Selection:		
Entrepreneurs' choice:	*EF*	*INEF*	Total
O	12 (5.9%)	14 (6.9%)	26
NO	14 (6.9%)	164 (80.3%)	178
Total	26	178	204

[27] See Peña-Torres, Basch and Vergara (2003) for more detailed analysis on the underlying reasons for this outcome.

Table 6B: Matching Matrix (only for Panel 3)

Entrepreneurs' choice:	*Model Selection* *EF*	*INEF*	Total
O	12 (27.9%)	8 (18.6%)	20
NO	8 (18.6%)	15 (34.9%)	23
Total	20	23	43

In the case of Table 6B, our model achieves an overall 63% matching rate; which is lower than that for the entire panel. This occurs because the latter includes a significant number of non-operating vessels which are 'correctly classified' according to our model (all P1 vessels and a majority of those in P2).[28]

7. Final Comments

One of the key issues that we have tried to convey in this paper relates to the very nature of the pelagic fishing industry in Chile, where the predominant destination of the landings goes to the fishmeal industry. With common-pool fish resources, the gist of this type of business is to maximise the volume of landings per unit of time at the vessel level.[29] The latter objective naturally puts a heavy toll on the fish stocks and contributes to aggravate the 'tragedy of the commons'. This type of harvesting frenzy, where the vessels compete against each other for catch, was a major cause for the collapse of Chile's Northern pelagic (especially sardine) stocks in the mid 1980s. It is in such a setting where different size effects appear to be relevant. We have presented ample evidence showing that the latter are indeed a relevant issue in the Chilean Southern-Central pelagic fishery.

We have obtained evidence of significant effects at three different size levels. At the individual vessel level, our results indicate that for constant levels of fishing effort, the larger vessels are more efficient in the harvesting process than the smaller sized boats. Similarly, when we control for vessel size, we observe greater levels of catch efficiency the larger the fishing efforts of the vessel are. In the absence of adequate regulation, these results go in the direction of reinforcing the tragedy of the commons.

When we analyse scale effects at the firm and industry levels, we observe, on the one hand, that as the number of vessels owned by a single firm increases (or when the same happens for the

[28] We also calculated alternative matching matrices, *e.g.* separating between 'chosen' and 'non-chosen' groups of vessels according to the percentage share of chosen vessels' total storage capacity in the whole fleet's storage capacity. Considering this criterion, we get a matching rate of 77% (using the entire panel) and 61% for P3-type vessels.

whole fleet operating in the fishery), vessel catch efficiencies increase likewise, showing evidence of positive search economies that reinforce incentives to increase individual fishing effort. On the other hand, our results show that as fishing haul increases at the firm- and fishery-level, catch efficiency decreases at the vessel level. This result might be interpreted as a negative congestion effect that in turn might help ameliorate the magnitude of the tragedy of the commons. If the former effect proves to be strongest, in a *ceteris paribus* situation, it would help explain the stylised fact of frequent collapses in various pelagic fisheries around he world (Peña-Torres, 1996). If congestion effects were to dominate, the event of a fishery collapse might be diminished. Nonetheless, and albeit the imminence of this danger may be lessened, as long as common-pool fish stocks prevail, individual vessels will most probably continue to strive in their endeavour of maximising catch performance.[30]

Further results are related to the type of production function used. The Translog option is definitely preferred over the Cobb-Douglas form, confirming prior results in that no scale invariance is observed in pelagic fisheries with respect to harvest (Peña, Basch & Vergara, 2002); hence the values of input elasticities differ at different catch levels.

Regarding the influence of some of the proxy variables in our model we obtain mixed evidence. On the one hand, a strong correlation between vessel age and inefficiency is observed. This fact endorses the observed evidence in this fishery pertaining to the entry of newer and larger vessels in the decade under study, where no explicit restraints were enforced in this sense. On the other hand, We find that for small sized vessels the harvest-biomass elasticity is larger.

Finally, the correlation found between a large proportion (close to 90%) of the residuals in our model and the inefficiency term could be interpreted as a signal of significant productive heterogeneity at the vessel level. The larger vessels appear to be the most efficient while showing at the same time a lower efficiency-score dispersion. Smaller boats are associated with lower levels of efficiency and with a greater dispersion; at the same time, the latter tend to be the oldest vessels in the fleet.

Overall, our results hinge upon the type of panel estimation model that we have used, i.e. a random-effects type algorithm. It remains to be tested whether our conclusions are robust and remain so with other estimation algorithms.[31]

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[29] For other fishing industries, e.g. the Chilean hake fishery where catch is mainly destined for human consumption, the main objective is to harvest top-grade quality fish. This implies that fish must be handled with care once harvested, not like their pelagic counterparts which are stored bulkwise in the storage hold of the vessel.

[30] In the meantime, beginning in 2001, individual catch quotas have been introduced in this fishery. This has stopped frenzy harvesting competition and is helping sustain the dwindling fish stocks.

[31] The authors are in the process of finishing a new paper with alternative estimation algorithms within a stochastic frontier setting.

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Annex 1: Stochastic Frontier Model

(I) Technological Model:

Variables	*P1*	*P2*	*P3*	*Total Panel*
Constant	534.57	411.71	2863.1	491.71
	(537.1)*	(3.56)*	(2873.0*	(493.9)*
Biomass (b)	-65.78	-48.59	-324.0	-63.46
	(-91.5)*	(-3.68)*	(-446.8)*	(-98.7)*
Storage Capacity (h_i)	-2.18	1.56	-64.2	3.42
	(-2.25)*	(0.36)	(-67.07)*	(3.58)*
Effort (e_i)	7.66	-3.26	32.07	7.63
	(8.2)*	(-0.77)	(34.28)*	(8.34)*
Age (g_i)	-5.48	-1.62	9.26	-0.75
	(-5.5)*	(-0.56)	(9.30)*	(-0.77)
Experience (x_i)	-0.72	1.18	-5.23	-0.67
	(-0.79)	(0.48)	(-5.90)*	(-1.27)
Trend (T)	-0.07	-0.73	-26.42	0.76
	(-0.11)	(-1.01)	(-26.88)*	(2.18)*
b^2	2.03	1.52	9.35	2.07
	(38.1)*	(3.96)*	(56.86)*	(57.1)*
h_i^2	0.55	0.06	1.53	-0.10
	(3.63)*	(0.28)	(2.20)*	(-2.67)*
e_i^2	-0.17	0.03	-0.24	-0.14
	(-3.65)*	(0.2)	(-2.25)*	(-3.06)*
g_i^2	-0.04	0.00	-0.04	-0.03
	(-0.13)	(-0.02)	(-1.51)	(-2.6)*
x_i^2	0.04	0.02	0.01	0.00
	(1.96)*	(0.69)	(1.12)	(0.15)
T^2	-0.01	0.01	0.04	-0.01
	(-1.46)	(2.06)*	(3.65)*	(-2.21)*
$b \cdot h_i$	-0.10	-0.23	2.51	-0.32
	(-0.42)	(-1.04)	(3.95)*	(-5.44)*
$b \cdot e_i$	-0.33	0.06	-1.43	-0.44
	(-2.84)*	(0.28)	(-4.74)*	(-7.67)*
$b \cdot g_i$	0.55	0.19	-0.45	0.07
	(3.22)*	(1.11)	(-4.73)*	(1.21)
$b \cdot x_i$	0.03	-0.13	0.20	0.03
	(0.53)	(-0.91)	(2.66)*	(1.1)
$b \cdot T$	0.01	0.06	1.52	0.00
	(0.34)	(1.3)	(15.75)*	(0.08)
$h_i \cdot e_i$	0.17	0.26	-0.27	0.51
	(1.3)	(1.62)	(-0.36)	(9.1)*
$h_i \cdot g_i$	-0.69	-0.22	-0.11	-0.07
	(0.83)	(-1.91)$^{++}$	(-0.61)	(-1.92)$^{++}$
$h_i \cdot x_i$	-0.02	0.05	0.21	0.01
	(-0.21)	(0.6)	(1.77)$^{++}$	(0.54)
$h_i \cdot T$	-0.03	0.03	0.45	-0.01
	(-0.6)	(1.27)	(2.52)*	(-1.12)
$e_i \cdot g_i$	0.19	-0.01	-0.09	0.01
	(0.46)	(-0.1)	(-1.90)$^{++}$	(0.19)
$e \cdot x_i$	-0.02	0.07	0.02	0.01
	(-0.35)	(0.86)	(0.41)	(0.75)
$e_i \cdot T$	-0.05	-0.01	-0.32	-0.08
	(-2.28)*	(-0.53)	(-9.21)*	(-8.79)*
$g_i \cdot x_i$	-0.13	-0.04	0.00	0.00

	(-1.04)	(-0.51)	(-0.28)	(0.46)
$g_i \cdot T$	0.14	0.07	-0.05	0.02
	(2.06)*	(3.22)*	(-2.66)*	(2.87)*
$x_i \cdot T$	0.01	-0.05	0.03	-0.00
	(0.87)	(-2.95)*	(2.57)*	(-1.54)

(II) Inefficiency Model:

	P1	***P2***	***P3***	***Total Panel***
Constant	0.05	1.19	0.07	0.36
	(0.05)	(0.16)	(0.07)	(0.36)
Firm´s Haul (a^j)	0.25	0.15	-0.43	0.2
	(2.17)*	(1.71)$^{++}$	(-1.69)$^{++}$	(2.13)*
Firm´s Storage Cap. (h^j)	-0.52	-0.01	0.96	-0.09
	(-3.22)*	(-0.09)	(2.84)*	(-0.67)
Firm´s Number Ships (n^j)	0.33	-0.24	-0.49	-0.24
	(2.29)*	(-2.75)*	(-2.78)*	(-3.45)*
Industry Haul (a^I)	0.36	0.48	0.06	0.5
	(1.39)	(1.66)$^{++}$	(0.24)	(3.39)*
Industry Number Ships (n^I)	-1.46	-0.44	0.04	-1.4
	(-2.27)*	(-0.81)	(0.04)	(-3.94)*
Age (g_i)	1.96	0.37	0.12	0.16
	(4.1)*	(3.52)*	(1.41)	(3.78)*
Experience (x_i)	0.00	-0.29	0.07	0.02
	(0.07)	(-3.5)*	(1.58)	(0.68)
Biomass (b)	0.05	0.01	-0.12	0.13
	(0.29)	(0.03)	(-0.51)	(1.35)
Effort (e_i)	-0.92	-0.92	-0.06	-0.98
	(-6.74)*	(-3.75)*	(-0.28)	(-11.76)*
D87	0.05	0.01	.	-0.04
	(0.25)	(0.07)		(-0.37)
D88	0.33	-0.12	.	-0.02
	(2.06)*	(-0.85)		(-0.19)
D89	-0.77	-0.38	0.35	-0.47
	(-3.25)*	(-2.21)*	(0.81)	(-3.76)*
D90	0.26	0.08	0.23	0.3
	(2.01)*	(0.77)	(0.87)	(3.93)*
Parameters				
Nº observations	391	707	149	1255
σ_S^2	0.16	0.12	0.07	0.21
	(12.1)	(8.28)	(10.9)	(17.8)
γ	0.82	0.9	0.88	0.88
	(19.8)	(36.5)	(16.36)	(49.06)
Log-likelihood	-71.7	-2.9	47.5	-198.7
MTE	0.66	0.68	0.80	0.72

Note: in parenthesis values of t statistics; *: significant at 95%, $^{++}$: significant at 90%; $MTE = \Sigma_{it} \exp(-u_{it})/(NT)$

Annex 2
Operating Vessels in 2001, at the Southern-Central Jack Mackerel fishery
(Vessels which are also part of our estimation sample)

Ship	(1) Panel	(2) Construction Year	(3)[a] Efficiency Score	(4) Storage Capacity (m^3)	(5)[a] Fishing Days per Year
1	2	1992	0.94	750	177
2	2	1991	0.92	650	229
3	2	1967	0.88	710	145
4	2	1993	0.84	700	110
5	2	1993	0.83	700	212
6	2	1992	0.82	710	159
Average [a]	2	1974	0.68		144
Min. [a]		1942	0.05		30
Max. [a]		1993	0.96		253
1	3	1979	0.95	1255	161
2	3	1978	0.94	1300	193
3	3	1979	0.92	970	148
4	3	1993	0.91	1000	165
5	3	1992	0.91	710	176
6	3	1993	0.86	910	178
7	3	1993	0.86	1000	147
8	3	1993	0.86	850	197
9	3	1994	0.83[b]	1200	213[b]
10	3	1978	0.81	1000	182
11	3	1992	0.80	850	180
12	3	1993	0.79	1000	126
13	3	1977	0.78	1200	162
14	3	1967	0.76	1000	187
15	3	1976	0.75	1700	200
16	3	1990	0.74	960	243
17	3	1978	0.73	910	184
18	3	1993	0.67	1065	158
19	3	1993	0.64	1200	171
20	3	1978	0.60	850	102
Average [a]	3	1981	0.80		166
Min. [a]		1950	0.57		31
Max. [a]		1994	0.96		253

[a]/ Average 1994-95.
[b]/ Calculated using information for 1995. This vessel was built in 1994 and only reached full operational capacity in 1995.