Ocean and Coastal Management xxx (xxxx) xxx-xxx

Contents lists available at ScienceDirect

Ocean and Coastal Management

journal homepage: http://ees.elsevier.com

Sample selection bias in fisheries technical efficiency studies using stochastic frontiers; presence and correction for an artisanal fishery in Northwest Spain

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ARTICLE INFO

Keywords
Sample selection bias
Fishing technical efficiency
Stochastic frontiers
Artisanal fleets management

ABSTRACT

Technical efficiency (TE) is a key topic in fishery economics due to its relevance in guiding fishing regulations and policy measures. In some territories, the presence of artisanal and small-scale fisheries (SSFs) is clearly decreasing but is still substantial, and regulators are concerned about their productivity and TE. A distinguishing feature of SSFs when compared to industrial fishing is that multi-gear artisanal vessels do not participate in certain fisheries: climate and other technical and non-technical determinants condition the decision to take part in a fishery. Consequently, data gathered from samples of multi-gear artisanal vessels may not be purely random (sample selection), leading to biased estimations and erroneous conclusions for management purposes. In contrast to other fields of economic and social analysis, this bias has not been generally considered when studying TE and productivity in artisanal fisheries and SSFs. With the aim to improve TE modelling in fisheries and propose a correction, this article tackles sample selection bias, its sources and its consequences on stochastic frontiers (SF)-based TE studies on fishing. To this end, as has been applied in non-fishery studies, an alternative method is proposed to test and, when applicable, correct an SF function affected by selection bias and that takes into account the estimates resulting from a connected participation probability model. An empirical exercise was conducted to estimate TE for an artisanal octopus fishery in Asturias (NW Spain) for the 2008–2009 season. The results show that participant vessels had undergone self-selection and that the SF adjusted for sample-selection produced marked differences in the estimates of the contributions of vessel length and fishing effort to productivity, together with smaller technical efficiency scores. In terms of policy implications, these results led to the identification of improved on-board conditions for crew members and a market-based policy of eco-labelling as preferable sustainable measures, among others, and allowed the most efficient local fleets to be correctly identified to apply for an eco-label. The method described herein offers an alternative when non-technical determinants (fishermen's attributes) are not subject to analysis, and it can be extended to other TE studies dealing with fisheries that use multi-gear artisanal and small-scale vessels.

1. Introduction

Since the early article published by Farrell (1957), the study of sectoral efficiency has played a key role in economic analysis (Fried et al., 2008). Many studies on technical efficiency (TE) and capacity in fisheries have applied frontier functions, particularly parametric stochastic frontier analysis (SF), as proposed by Aigner et al. (1977) and Meeusen and van Den Broeck (1977). These functions explain the deviations from the frontier for each productive unit by distinguishing between stochastic exogenous effects and the operational inefficiency of vessels. The determinants of catch levels in a fishery, the productivity of fishing factors, and the importance of technical inefficiency to explain catch variability are some of the key parameters used for the design and implementation of regulatory measures and policies for the sustainable management of fleets and stocks. As Álvarez (2001) pointed out, TE studies in fisheries were developed (particularly analyses based on stochastic frontiers) after Schmidt et al. (1984) established the advantages and possibilities of estimating SF.

Heckman (1979) pioneered studies addressing the problem of non-representative samples. Some selection bias may appear when data do not come from randomly selected samples but rather from self-selection and selection decisions taken by analysts. In both cases, regression functions confuse the parameters explaining the studied behaviour and the determinants of the probability of being in the sample, thereby causing systematic differences between the characteristics of the units selected in the sample and non-selected units. More recently, Greene (2010) remarked on the need to control for sample selection bias in efficiency analyses, specifically in those based on non-linear models

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https://doi.org/10.1016/j.ocecoaman.2020.105319
Received 19 November 2019; Received in revised form 18 May 2020; Accepted 28 July 2020
Available online xxx
0964-5691/© 2020.

such as SF, for which he proposed a new estimator based on maximum simulated likelihood. Some productivity studies have dealt with sample selection bias in different ways. While Kaparakis et al. (1994) and Collins and Harris (2005) simply acknowledged the problem of this bias in their articles, Kumbhakar et al. (2009) and Lai et al., 2009 carried out various corrections, and Bradford et al. (2001) and Sipiläinen and Lansink (2005) opted for a correction based on Heckman's two-stage estimation procedure (Heckman, 1979). More recently, Wollni and Brümmer (2012) and Bravo-Ureta et al. (2012) followed Greene's correction to solve this bias.

Within the literature on fisheries, sample selection bias has been taken into account in several studies on distinct fishing topics. However, despite some outstanding work (Squires and Kirkley, 1999; Kirkley et al., 1998) showing the authors' awareness of the problem of non-representative samples and selection bias, no study has focused on TE to date. Kitts et al. (2000) dealt with selection bias issues in their study on vessel owner participation in a fishing vessel buyout program in the U.S.A. Eggert and Lokina (2010) corrected the selection bias in the sample they used to analyse regulatory compliance of artisanal fishermen on Lake Victoria in Tanzania. Focusing on lobster fishery in the Galapagos Islands, Bucaram and Hearn (2014) showed the importance of controlling and correcting this bias when modelling the variables that explain entry–exit decisions and intensity of participation in a fishery. Flores-Lagunes and Schnier (2012) proposed a correction for sample selection problems in models to estimate the spatial dependence of fishing production. Nevertheless, literature on SF applied to fisheries (among others, Kirkley et al., 1995, 1998; Sharma and Leung, 1998; Grafton et al., 2000; Eggert, 2000; Álvarez et al., 2003; García Del Hoyo et al., 2004; Oliveira et al., 2015, 2016) has paid little or no attention to the potential impact of sample selection bias.

The present study focuses on the susceptibility of fishing TE to sample selection bias, and the required controls, particularly when non-technical determinants (fishermen's attributes) are not subject to analysis. This bias is of particular concern when SF-based models are applied to guide sustainable policies for fisheries involving highly flexible and adaptive multi-gear vessels, which are inherent to many artisanal and small-scale fisheries (SSFs). If potential sample selection bias is not detected and, if present, corrected, estimates of marginal factor productivities will be biased, and global and individual TE indexes will also be affected. Likewise, this bias will be transferred to other closely connected models, such as those proposed by Battese and Coelli (1995) or Squires and Kirkley (1999), thereby hindering a correct understanding of the causes of technical inefficiency. In a context of designing policies and regulatory measures for a fishery, such bias can lead to incorrect conclusions concerning the type of measures to be introduced or the effectiveness of those already implemented to reduce existing inefficiency. Situations of this type may arise, for example, in SF cross-section analyses in data-poor fisheries, which have frequently involved coastal, artisanal and small-scale fisheries (Squires et al., 2003; Esmaeili, 2006; Sesabo and Tol, 2007; Kim et al., 2011; Oliveira et al., 2016), and where multi-gear vessels may have undergone self-selection processes that determine their participation. Likewise, SF models using panel data to analyse TE are not free of sample selection problems either, above all when multi-gear vessels or boats belonging to a different fishing census are involved.

This study aims to analyse the potential incidence of sample selection bias in TE modelling for fisheries, a topic that has not been addressed to date, and determine how this affects the design of sustainable fishery management policies. To this end, the technical determinants of an artisanal fishery in Northwest Spain were examined and a correction method to the SF production function was applied in a similar way to previous studies in non-fishery contexts (e.g. Wollni and Brümmer, 2012; Bravo-Ureta et al., 2012). The paper is structured as follows: Section two presents the model developed by Greene (2010) to correct non-linear models for sample selection bias. In Section three, data sources and the main features of an empirical case are described, together with the specification of an SF model to quantify TE for the octopus artisanal fishery on the west coast of Asturias (NW Spain) in the 2008–2009 season, considering sample selection problems. Section four compares the results of quantifying input productivities and TE indexes from a corrected and an uncorrected SF model. Section five evidences the significance of unbiased results for the choice of sustainable management measures in the fishery of study. The importance of detecting and correcting sample selection bias in TE models for artisanal fisheries is also discussed, as well as the interest of extending this correction to other studies. Finally, conclusions are provided in Section six.

2. Methodology

Non-random missing data is attributable to the presence of a systematic pattern, depending on unobservable variables, which explains that an individual i (i.e., a person, firm, or any observed unit in the analysis) is sampled or not. In his seminal work, Heckman (1979) raised this bias as a specification error, pointing out its most frequent sources and proposing a correction procedure that has been widely applied since then in socioeconomic studies that estimate behavioural relationships. Assuming that the structure of interest can be written as $y = X\beta + \varepsilon$, but data for the dependent variable y are observable only when another latent variable d takes the value $d = 1$, then the previous expression can be written as (1):

$$\text{if } d = 1\ ; y_i = x_i\beta + \varepsilon_i \cdots \left(y_i \text{ observed}\right) \tag{1}$$

if $d = 0$; y_i unobserved.

In this situation, residuals ε will be correlated with d, and the estimation of β will be biased (Heckman, 1979). Heckman's general approach sets an objective equation (3) that usually represents a function whose dependent variable y is not observed under certain conditions, and a selection/participation equation (2) that encompasses a discrete choice model to measure the probability p_i of individual i being sampled and z_i is a set of observables that explain the probability of being included in the sample. The residuals are assumed to distribute as $w \sim N(0,1)$ and $\varepsilon \sim N(0,\sigma)$, being $corr(w,\varepsilon) = \rho$. When $\rho \neq 0$, missing data on y are not random and the regression equation for the observed sample in (3) will produce biased estimates when standard regression techniques are used.

$$p_i = z_i\delta + w_i \tag{2}$$

$$y_i = x_i\beta + \varepsilon_i\ ; \cdots if\ p_i > 0 \tag{3}$$

In its simplest form, the SF originally developed by Aigner et al. (1977) represents a function such as (4), with an error structure ε_i based on two components. The first v_i is a symmetric disturbance assumed to be independently and identically distributed as $N\left(0,\sigma_v\right)$; this error component captures the random effects influencing an economic activity but out of the firms' control (such as luck, climatic events, etc.) and measurement errors in the dependent variable y. The second component, u_i, is an asymmetric disturbance $\left(u_i \geq 0\right)$ for all i; it is assumed that u_i is distributed independently of v_i.[1] According to Aigner et al. (1977), this component of the error makes the productive units locate at the frontier (the efficient units when $u_i = 0$) or below it (the ineffi-

[1] The most frequently assumed distributions are a truncated at zero normal or an exponential distribution, but other one-sided distributions such as the exponential are also possible.

cient units).[2] Finally, y_i is the output of each firm i and x_i is a vector containing the inputs.

$$y_i = x_i\beta + \varepsilon_i \cdots\cdots \varepsilon_i = v_i - u_i \cdots\cdots i = 1, \ldots, n \qquad (4)$$

Greene (2010) drew attention to the sample selection problems in nonlinear models and extended Heckman's proposal for the specific case of estimating SF functions affected by sample selection: bias arises when the unobservables (v_i) of the production function (6) are correlated with the unobservables (w_i) in the selection equation (5).

$$d_i = 1 \ \left[z_i\delta + w_i > 0\right] \qquad w_i \sim N[0,1] \qquad (5)$$

$$y_i = x_i\beta + v_i - u_i \qquad \text{being } y_i \text{ observed only when } d_i = 1, \qquad (6)$$

$$v_i = \sigma_v V_i\,, \ \ where\ V_i \sim N[0,1] \quad \text{and} \quad u_i = \left|\sigma_u U_i\right| = \sigma_u\left|U_i\right|, \ \ where\ U_i \sim N[$$

$$\left(w_i, v_i\right) \sim N_2\left[(0,1)\ ,\ \left(1,\ \rho\sigma_v, \sigma_v^2\right)\right] \qquad (8)$$

Assuming that w_i and v_i follow a bivariate normal distribution as shown by (7) and (8), the parameter ρ informs of the presence or absence of selection bias. Greene (2010) suggests a two-step estimation procedure using maximum simulated likelihood (ML), where the variances estimated are adjusted by applying the Murphy–Topel correction to the variance-covariance matrix (Murphy and Topel, 1985). Given that observations with $d_i = 0$ do not provide the simulated log likelihood with information about the parameters, the form of the function to be maximised is simplified as shown in (9):

$$logL_{S,C}\left(\beta,\sigma_u,\sigma_v,\rho\right) = \sum_{d_i=i} log\frac{1}{R}\sum_{r=1}^{R}\left[\frac{exp\left(-\frac{1}{2}\left(y_i - x_i\beta + \sigma_u\left|U_{ir}\right|\right)^2/\sigma_v^2\right)}{\sigma_v^2\sqrt{2\pi}} \times \right.$$

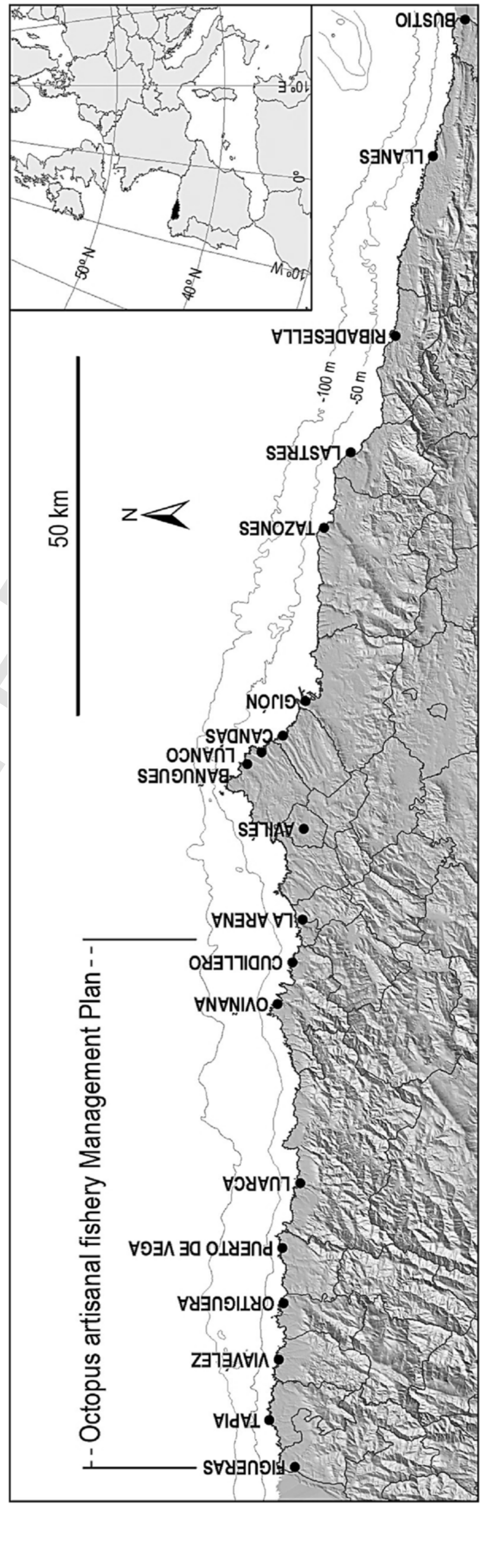
where $a_i = z_i\hat{\delta}$.

3. Case study: The artisanal octopus fishery on the west coast of Asturias (Northern Spain)

3.1. Description

Asturias is an Atlantic coastal region on the northern Atlantic coast of Spain whose fishing fleet is mainly artisanal (García-de-la-Fuente et al., 2013, 2016). Part of this fleet is based in eight harbours located in western Asturias[3] (Fig. 1) with a long tradition in octopus fishery; vessels operating this fishery target a single species, the common octopus (*Octopus vulgaris*), using artisanal traps (highly-selective fishing gear that barely produced by-catches or discards).[4]

The octopus is a very attractive species for artisanal vessels in the region (Fernández-Rueda and García-Flórez, 2007) because it reaches significantly higher first-sale prices than those registered by most sea products commercialised in the regional fishing guilds (Table 1). Due to the importance of this species, in 2000, the regional fishing authority approved an *Octopus Management Plan* (hereinafter OMP) for this fishery, with the aim to secure environmental (stock) and socioeconomic sustainability (increasing profitability levels and first-



2 As Schmidt and Sickles (1984) have later pointed out, while v_i disturbance is uncorrelated with regressors x_i, this is not necessarily assumed for u_i.

3 Namely Cudillero, Oviñana, Luarca, Puerto de Vega, Ortiguera, Viavélez, Tapia de Casariego and Figueras.

4 Recent technical references on the environmental sustainability of this fishery can be seen at https://fisheries.msc.org/en/fisheries/western-asturias-octopus-traps-fishery-of-artisanal-cofradias/about/.

Fig. 1. Fishing ports in Asturias (north-west Spain) and scope of the Management Plan for the artisanal octopus fishery (western part of the regional coast).

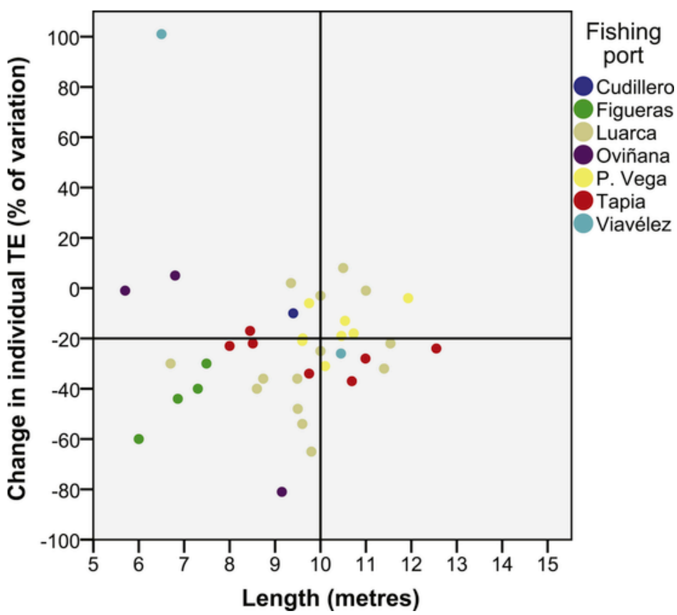


Fig. 2. Intensity of adjustment in individual TE indexes after correcting for sample selection bias, by total vessel length and fishing port.

sale prices). According to the OMP, the fishery remains open seven months a year (from 15 December to 15 July), when vessels are allowed to fish octopus under prior request to the fishing authority. Measures to control the fishing effort include an annual catch limit of 10,000 Kg per vessel and year,[5] a minimum capture weight of 1 kg per specimen caught, and a maximum number of 125 traps per crew member (limit of 350 per vessel). The fishery is operated mainly by small-scale multi-gear boats that catch octopus in shallow waters on fishing trips of a few hours (returning to port on the same day). But during its operating months, this fishery is also able to alternate octopus traps with other fishing métiers to exploit hake (*Merluccius merluccius*), red mullet (*Mullus surmuletus)*, mackerel (*Scomber scombrus*), and goose barnacle (*Pollicipes pollicipes*) (González-Álvarez et al., 2016). Octopus is a strategic resource for this fleet and for the entire region. In terms of landings, octopus catches on the west coast of Asturias accounted for around 77% of total octopus first sales in local fishing guilds of Asturias between 2007 and 2014. Previous studies (Pascoe and Herrero, 2004; Álvarez Ballesteros, 2018) similarly characterised the artisanal octopus fishery in Spanish Atlantic waters.

Due to the evolution of this fishery, in 2014 the regional fishing authority considered some new sustainable management measures. In this regard, to guide decision-making on potential measures, it commissioned a TE study of this fishery to gain a better understanding of the determinants of octopus catches within the OMP, and their importance for yield and the efficiency of the different local fleets. Most of the vessels in the fishery are small-scale multi-gear boats (average total length of 9 m in 2007–2014) registered as *multi-gear in the Cantabrian and Northwest fishing ground -CNW*[6] according to the Spanish Census of Active Fishing Fleet (Table 1). Since 2000, about 130 different vessels have participated in artisanal octopus fishery on the west coast of Asturias. Both total landings of octopus and the number of boats included in the OMP annually have decreased yearly since 2007. Although part of this negative trend is due to the general socioeconomic decline of artisanal fisheries in the region (García-de-la-Fuente et al., 2013) and the probable progressive reduction of the Atlantic stock[7] (Pascoe and Herrero, 2004; Álvarez Ballesteros, 2018), some active vessels remain in the fishery each season, while others leave after some years of fishing. Some boats simply fish in certain years (expectations about "how good" the octopus recruitment has been is a powerful driver for some vessels to enter the fishery[8]).

A first measure considered by the regional fishing authority consisted of introducing stronger restrictions on the fishing effort after 2014, by reducing the maximum number of fishing days per vessel and year to improve the environmental sustainability of the fishery. A second measure consisted of improving commercial profitability by increasing first-sale prices of octopus and the economic sustainability of the fishery. This measure involved supporting (with public resources) the most efficient fleets during the process of designing and implementing an eco-label. A third management measure considered new ways of improving the productivity and working conditions of crew members, as artisanal fisheries based on pots and traps have traditionally relied heavily on workforce and physical strength on-board (octopus fishery requires enough crew members to cast and haul the traps from the sea and to quickly harvest and re-bait). This action sought to improve socioeconomic sustainability.

3.2. Model specification

In the present case study, a cross-section stochastic frontier (SF) model (Aigner et al., 1977) for the 2008–2009 season (from 15 December 2008 to 15 July 2009) was initially specified (10) using a sample of $n = 39$ small-scale vessels that participated in the octopus fishery during that period. 2008–2009 was the only season for which precise data on the number of on-board crew members involved in fishing octopus were available.

The captures frontier reflects the maximum potential output (kilograms of octopus) that can be achieved given the productive inputs, the technology of production and the stock conditions. A relevant reason to select a SF for this specific case study is that SF methodology is highly suitable for capturing the effect of changes in the exploited stock, which is especially relevant for fisheries like the one analysed here, for which the abundance of its target species shows a high variability between fishing months and within the annual season (from December to July). In this case, a Cobb-Douglas production function was assumed as follows[9]:

$$\ln\ y_i = \beta\ \ln\ x_i + (v_i - u_i)\ ; i = 1, \ldots, n \tag{10}$$

[5] This level has never been reached by any boat.

[6] Category originally named *Artes menores en Cantábrico y Noroeste* in the Spanish census, corresponding to a large extent to the "Only passive gears" European census category.

[7] There are no population estimates of octopus for the region, as further studies are needed to clarify the status of the species and interconnections between subpopulations in this part of the Atlantic.

[8] A 3-year cycle characterises the abundance of octopus, so that a first successful fishing season is usually followed by moderate and low annual octopus catches respectively.

[9] Pascoe and Herrero (2004) also assumed a Cobb-Douglas standard production function for the artisanal octopus fishery in South Atlantic Spanish waters. In addition to this, the relatively small sample size, together with the introduction of several explanatory variables in the model, make the estimation of a translog function for this case study difficult.

Table 1
Information about the artisanal octopus fishery on the west coast of Asturias.

Fishing season	Number of vessels	% of artisanal multi-gear boats	Technical characteristics of the fleet (average)			Octopus landings (kg)	Octopus first-sale price (current €/kg)	Average first-sale price of sea products (current €/kg)
			Total length (m)	Gross tonnage (GT)	Power (kW)			
2007/08	61	98%	9.2	4.5	46.7	298,687	4.65	2.45
2008/09	39	97%	9.3	4.5	45.7	60,775	4.84	1.96
2009/10	39	97%	8.9	4	46.6	130,637	3.95	2.67
2010/11	49	98%	9.1	4.4	48.3	163,776	5.22	2.39
2011/12	44	98%	9.2	4.6	47.7	84,639	5.39	2.39
2012/13	44	95%	8.8	4.2	45.4	59,636	4.37	2.28
2013/14	38	95%	8.8	4.2	47.2	47,116	5.22	2.09

Under this SF, the TE for each unit i can be measured by the ratio between its real output and the output at the frontier level as (11):

$$TE_i = \frac{y_i}{\exp\left(x_i\beta + v_i\right)} = \frac{\exp\left(x_i\beta + v_i - u_i\right)}{\exp\left(x_i\beta + v_i\right)} = exp\left(-u_i\right) \quad (11)$$

For those vessels situated on the capture frontier, TE equals "1" (vessels operating efficiently). The SF function was initially constructed to model total octopus landings (kg) per vessel i in the 2008–2009 fishing season as a function of four independent variables, namely three technical fixed inputs that represent fishing power (vessel overall length, in metres; gross tonnage, in GT units; power, in kW), and fishing effort (the product of crew members' days at sea, in number) per vessel in 2008–2009.[10] The SF (12) has the classic structure with a symmetric error term (which represents stochastic factors affecting captures, v_i) and an asymmetric non-negative error term that accounts for inefficiency (u_i), for which an exponential distribution was assumed.

$$\ln\, y_i = \beta_0 + \beta_1\,\ln\, CrewDays_i + \beta_2\,\ln\, Lenght_i + \beta_3\,\ln\, Tonnage_i + \beta_4\,\ln\, Power_i + v_i - u_i \quad (12)$$

However, once this model had been built, some questions affecting this fishery were considered as potential sources of underlying sample selection bias that could also affect management decision-making for this fishery. As already described, inter-annual variations in the number of vessels operating this fishery are not random and combine a variety of factors that may influence their participation in the OMP each season (self-selection). Thus, an alternative SF model to (12) was set out to quantify the TE of the artisanal octopus fishery on the west coast of Asturias, taking into account potential sample selection bias. Accordingly, using data of the entire population, namely 90 vessels that operated this fishery at least one season between 2000 and 2014 and were active during 2008–09, a Probit model was estimated first to recover the probability of a vessel participating in the 2008-09 OMP. The dependent variable in the participation equation (2) shows the individual probability of participating in the octopus fishery in 2008–09. The Probit equation includes as regressors (z_i) some observables determining whether vessel i belongs or not to the sample, but not directly influencing y_i, previous experience in the OMP (number of octopus fishing seasons participated in from 2000-01 to 2007-08), difference in first-sale prices (in percentage) between octopus and the rest of the catches of a vessel,[11] and economic dependence on octopus fishery (ratio, in percentage, between vessel's income 2006–2008 from octopus and its total income from fishing).

Once the Probit model had been estimated, a new version of (12) was written to control for potential self-selection in the sample of vessels that participated in the octopus fishery during the period 2008-09 by ML, following Greene (2010), and calculating the variances of the estimates by applying the Murphy-Topel correction.

3.3. Data sources

Several data sources were used for this study. First, as mentioned earlier in this section, the OMP is a co-management tool for the species of interest. In this regard, local fishing guilds and regional authorities cooperate to define regulatory measures and monitor key parameters in the octopus fishery. Each season, small-scale boats officially registered as *multi-gear in the Cantabrian and Northwest fishing ground – CNW* (and, exceptionally, some bottom long-liners) based at the aforementioned eight fishing ports apply to the regional fishing authority for a license to operate in the OMP. Therefore, information on vessels participating in this fishery since 2000 was provided by the General Directorate of Maritime Fishing. OMP monitoring and control activities carried out by the regional fishing authority enabled the authors to access specific data on octopus landings (kilograms) and days at sea per vessel for the 2008–2009 season.

Second, technical information on vessels in the OMP since 2000 was obtained from the Spanish Census of Active Fishing Fleet. Updated yearly by the Ministry governing fishing affairs, this census collects a vast array of technical and administrative data on each vessel (such as age, length, power, gross tonnage, etc.). Third, information on registered crew on-board regional fishing vessels in 2009–2010 was provided by the Marine Social Institute (ISM), a public agency belonging to the Ministry of Employment and Social Security that manages the National Insurance contributions of Spanish sea workers. However, these figures had to be checked because the crews of artisanal vessels commonly vary during the year, depending on the fishing métier carried out. The only information to check and complete ISM data for the octopus fishery came from a research sampling carried out within the European Project "PRESPO: Sustainable Development of Atlantic

[10] The possibility of introducing days at sea and crew members as two separate variables was ruled out, due to the low variability of workforce in the sample (values of 1, 2, 3 or 4 fishermen).

[11] It can be considered an indicator of fishing strategy. Octopus first-sale prices in 2006, 2007 and 2008 are averaged *per* vessel and compared (as ratio) to the average price reached by the rest of its landings over January–July 2009: percentages near or over 100% represent vessels focused on medium-priced commercial species (like octopus), while low percentages correspond to those dedicated to high-priced species (with higher first-sale prices than octopus).

Arc Artisanal Fisheries", specifically focused on completing and improving current knowledge on artisanal fisheries in South-European Atlantic Areas (including Asturias) (García-de-la-Fuente et al., 2013, 2016).

Finally, a database on sea product first-sales auctioned in the quayside local fish markets of Asturias are annually compiled by the regional fishing authority, registering extensive information on each transaction (vessel, species, first-sale price, weight auctioned, etc.). As these micro-data are not public, a specific query was submitted for the purpose of this study to obtain monthly information for the 2006–2009 period.

4. Results

First, an SF function was estimated to explain individual levels of octopus landings $\hat{y}_i$ (kg per vessel in the 2008-09 season) and to quantify the TE of the artisanal octopus fishery on the west coast of Asturias, without considering sample selection bias (Table 2). The statistics of global adjustment (Log likelihood) showed that the model was valid; the null hypothesis H_0: $\gamma = \sigma_u^2 / (\sigma_u^2 + \sigma_v^2) = 0$ was rejected at 1% of significance, thereby revealing that technical inefficiency exists and that it is stochastic. The estimated value for the parameter gamma (0.85) indicates that the effects associated with inefficiency contribute significantly (rather than luck, stock variations, sea and weather conditions, etc.) to the observed variability in octopus catches. Given this observation, it is relevant to introduce management measures to improve efficiency. Three of the four regressors were relevant to explain the landing of a given vessel. Fishing effort ($\hat{\beta}_{lnCrewDays} = 1.0034$) registered the largest elasticity and its estimated parameter was positively significant at 1%. Technical inputs such as total vessel length or tonnage were statistically significant (p-values under 10%), but contrary to what was expected (total vessel length is assumed to be the main parameter that determines the number of fishing traps that can be transported on the boat during a trip), the estimated parameters had a negative sign for the length and a positive sign for the gross tonnage. As expected in these types of métiers, the engine power of the vessel was not relevant to explain octopus catches.

Second, an alternative SF function that considered potential sample selection bias was estimated. In a first stage, an ML estimation of a vessel's participation in the 2008-09 OMP was carried out (Table 3). Statistics of global adjustment show that the model was valid and the regressors were relevant to explain the probability of a vessel operating in the fishery. Two of the three regressors considered in the Probit model were statistically significant (P-values under 1% or 10%). Thus, previous experience fishing octopus (*Prev_seasons*) and the difference in the first-sale prices of octopus compared to other species (*Price_dif*) increased the probability of a vessel participating in the western octopus fishery during 2008–09.

Table 2
Estimation results of the stochastic frontier model without correction for sample selection bias (Initial_SF).

Variables	Coefficients [a]	S.E.
Constant	5.5282***	1.1121
ln_CrewDays	1.0034***	0.0001
ln_Length	−1.0641*	0.6252
ln_Tonnage	0.3594*	0.2117
ln_Power	0.0054	0.0913
Log likelihood	−43.8197	–
σ	0.6015***	0.0045
γ	0.8531***	0.6784
N	39	–

[a] Model adjusted by ML (dependent variable: kilograms of octopus landed per vessel in the season 2008-09, in logarithm). Legend: * if $p < 0.1$; ** if $p < 0.05$; *** if $p < 0.01$.

Table 3
Probit model: vessel probability of participating in the octopus fishery during the 2008-09 season.

Variables	Coefficients [a]	S.E.
Constant	−1.5456***	0.3412
Prev_seasons	0.2075***	0.0607
Price_dif	0.7974*	0.4513
Econ_depend	0.0032	0.0095
Log likelihood	−47.6019	–
Pseudo R^2	0.2270	–
N	90	–

[a] Binomial Probit model adjusted by ML (dependent variable: fish octopus). Legend: * if $p < 0.1$; ** if $p < 0.05$; *** if $p < 0.01$.

These results evidence underlying selection problems for the application of the initial TE model. Therefore, the estimated Probit model was used to obtain participation probabilities ($\hat{p}_i$) per vessel. To test and control this bias, the corrected SF model was then re-estimated (Table 4). The first noticeable result was that the estimate of ρ was statistically significant at 1%, thereby revealing sample selection bias. Re-estimated regressors (except engine power) were statistically significant at 1%. The estimated coefficient for vessel length differed greatly between the original and the corrected SF equation ($\hat{\beta}_{lnLength} = 0.6927$) and had a positive influence on octopus catches, as expected. In contrast, gross tonnage registered the lowest elasticity and a negative sign, which would appear to be more coherent. The interaction of crew number and fishing days now had even less influence than before on the level of catches, although fishing effort was confirmed as the most determining input to the yield.

These outcomes suggest that selection bias will also affect the measurement of TE in this fishery. Therefore individual and global TE indexes were calculated and compared with the original SF (Initial_SF) and the corrected SF (Adjusted_SF). Sample selection bias led to a marked overestimation of the global TE in the octopus fishery for the 2008–2009 season (Table 5): an average score of 0.613 when the Initial_SF was used and 0.492 when the model was adjusted to control for selection bias, following Greene (2010). According to both models, no boat is placed on the production frontier, although the two most efficient vessels kept their first and second place, respectively, and increased their TE scores, reaching almost 1 under the corrected model (TE scores of 0.98 and 0.94). Nevertheless, individual TE varied considerably for most of the vessels: 18 of the 39 boats dropped positions

Table 4
Estimation results of the stochastic frontier model with correction for sample selection bias (Adjusted_SF).

Variables	Coefficients [a]	S.E. [b]
Constant	3.5167***	0.2761
ln_CrewDays	0.8181***	0.0128
ln_Length	0.6927***	0.1774
ln_Tonnage	−0.2263***	0.0547
ln_Power	−0.0214	0.0237
Log likelihood	−53.1353	–
σ_u	1.1795***	0.0112
σ_v	0.0456***	0.0089
$\rho_{(w,v)}$	0.9999***	0.0021
N	39	–

[a] Model adjusted by ML (dependent variable: kilograms of octopus landed per vessel in the season 2008-09, in logarithm). Legend: * if $p < 0.1$; ** if $p < 0.05$; *** if $p < 0.01$.
[b] Adjustment based on Greene (2010) and standard errors correction according to Murphy and Topel (1985).

Table 5
Average TE indexes of local fleets when SF model is adjusted to control for sample selection bias.

Fishing port	Original TE (Initial_SF)	Corrected TE (Adjusted_SF)	Place in the ranking (Initial_SF)	Place in the ranking (Adjusted_SF)
Cudillero	0.361	0.324	7	6
Figueras	0.430	0.256	6	7
Luarca	0.663	0.522	3	6
Oviñana	0.701	0.638	2	1
P. Vega	0.707	0.593	1	2
Tapia	0.524	0.389	5	4
Viavélez	0.554	0.588	4	3
Average TE in the fishery	**0.613**	**0.492**	–	–

in the TE ranking before adjusting the SF, while 14 improved their initial positions.

Finally, small boats showed a more pronounced decrease in TE (Fig. 2). This is attributed to selection bias, causing the efficiency of the shorter boats to be overestimated. On average, TE scores for vessels under 10 m of overall length were reduced by 25%, compared to an average variation of −18% for vessels ≥10 m. The original SF model also enhanced TE indexes of some local fleets with moderate efficiency, such as those based in the fishing ports of Luarca, Figueras and Tapia (Table 5). After correction of the SF, the local fleet based in the port of Oviñana became the most efficient in the octopus fishery in the 2008–2009 season (overtaking the local fleet of Puerto de Vega, apparently the most efficient under the original SF model).

5. Discussion

5.1. Relevance of unbiased estimates in the sustainable management of the fishery

As the octopus case study has shown, the correction applied here proved useful to control selection bias in two key elements of the TE model: the relevance of certain fixed inputs to determine catch levels and the measurement of the TE of global and local fleets. The method applied in the present case study considered to be a versatile solution when non-technical determinants of productivity are not the object of the analysis; it can also be extended to TE analyses of artisanal fisheries and SSFs based on Data envelopment analysis (DEA), as for example those developed by Tingley et al. (2003) and Idda et al. (2009). The model used in the present study, based on cross-section data, may have some limitations to achieve consistent individual estimates of individual (Schmidt and Sickles, 1984). However, this case study presented truly reflects the reality of "data-poor" contexts characterising some artisanal small-scale fisheries where the availability of time series of reliable information is seriously limited (Ruano-Chamorro et al., 2017; Filous et al., 2019).[12] Although future improvements in the level of information can be used for more robust exercises, such as those based on panel data, the main objective of the present study was to evidence the susceptibility of selection bias in TE studies and reveal the implications of such bias for policy design and sustainable fishery management.

The main purpose of efficiency estimates in this empirical case was to guide sustainable fleet management decisions and the choice of new measures at a local-regional level. Sample selection bias would cause a marked underestimation of the importance of total vessel length for this artisanal fishery, which is the key fixed input (daily octopus catches do not require vessels with large tonnage but rather sufficient length to transport dozens of traps). On the other hand, SF correction prevented overestimation of fishing effort (crew productivity in fishing days) for this fishery. As expected,[13] fishing effort in terms of crew days was the most determining factor of catch volume in this case study, which would discourage the adoption of management measures based on reducing the fishing days allowed. However, correcting the bias implies a reduction in the estimate of labour productivity. Although both models suggest that limiting the number of fishing days per season could have a strong negative impact on catches and income derived from this fishery, labour elasticity is lower than one, according to the corrected SF model, so there is margin to increase productivity by improving labour productivity and crew member conditions (i.e., by supporting or subsidising the installation of mechanical haulers on-board, or the use of artificial bait).

Additionally, the corrected SF pointed to vessel length as being almost as determinant in the level of catches as fishing effort, an issue that had been remarkably underestimated by the initial model. Nevertheless, vessel length is a fixed productive factor that cannot be modified in the short-medium term, so market-based policies emerge as another strategy to improve global sustainability in this fishery.

But, in order to provide public support of an eco-label for this artisanal fishery, the most efficient local fleets had to be identified. The local fleet of Puerto de Vega had traditionally been considered the most productive in the regional octopus production, and apparently, it also proved to be the most efficient fleet under the original SF model. Nevertheless, the adjusted SF provided an unbiased interpretation of the efficiency of the local fleets, placing that of Oviñana in first place in the local ranking of TE, followed by the ports of Puerto de Vega (second position) and Viavélez (third position). In view of these results, in 2015, the Fisheries Local Action Group (FLAG), to which the ports of Viavélez and Puerto de Vega belong, jointly with the Regional Government, decided to certificate this fishery under the renowned Marine Stewardship Council (MSC) standard of environmental sustainability.[14] Vessels belonging to three of the four most inefficient local fleets according to the corrected SF estimates (Cudillero, Luarca and Figueras) decided not to join this eco-labelling certification in 2015.

5.2. Susceptibility to sample selection bias in technical efficiency models for artisanal fisheries

A multi-specific and multi-gear character is inherent to many artisanal fisheries and SSFs (González-Álvarez et al., 2016; Pranovi et al., 2016; Falautano et al., 2018). The empirical case studied in this article showed that the fleet participating in the artisanal octopus fishery during the 2008–2009 season had undergone a self-selection process. It reflects a typical scenario of some Southern European artisanal and small-scale fleets, where changes in the biological or economic conditions of a species results in a rapid redistribution of vessel fishing effort among an optimal combination of métiers. Along this line, previous TE studies on artisanal fisheries using cross-section datasets for SF models could also have been affected by self-selection issues in the samples used (Squires et al., 2003; Esmaeili, 2006; Sesabo and Tol, 2007; Kim et al., 2011; Kareem et al., 2012; Ka-

12 Unlike industrial and large-scale vessels, the sampled boats lacked vessel monitoring systems (VMS) or on-board logbooks, which provide basic, continuous and detailed information on their fishing activity.

13 Crew members are key for the yield of many artisanal fisheries, particularly those consisting of pot and trap métiers that highly depend on workforce, as Tingley et al. (2005) have pointed out.

14 In February 2016 the *Western Asturias Octopus Traps Fishery of Artisanal Cofradias* became the first octopus fishery in the world to be certified under the MSC eco-label for sustainable fishing (https://fisheries.msc.org/en/fisheries/western-asturias-octopus-traps-fishery-of-artisanal-cofradias/@@view)

reem et al., 2012, 2012). Some artisanal and small-scale vessels make short-term fishing decisions in a different manner. In this regard, highly flexible and adaptive multi-gear vessels alternate their annual activity between different métiers depending on market prices or stock size (in case of cyclic stocks, some seasons only the most efficient vessels decide to participate in the fishery).

Despite the advantages of carrying out SF modelling using panel data (Schmidt and Sickles, 1984), very few SF studies on data-poor artisanal and small-scale multi-gear fisheries have been able to follow this approach, because the availability of long time series with reliable information about output, inputs and fishing effort is often seriously limited. In fact, in some of the few studies based on panel datasets (Fousekis and Klonaris, 2003; Lokina, 2008), the authors admit that the available time series is so short that the model actually has a marked cross-section dimension. In this context, the method proposed here is feasible provided the sample is large enough and suitable for the use of parametric statistics to assess technical aspects of fisheries. However, if the samples are small and highly qualitative, this approach may not be suitable and other quantitative-qualitative alternatives based on mixed-methods that also consider non-technical determinants of productivity (attributes such as skills, knowledge, in-shore work, etc.) may be preferable to redress bias, while also detecting nuances that can incorporate non-technical aspects.

Complexity and data limitations to model TE and fishing capacity in some poor-data artisanal and small-scale multi-gear fisheries have been well described by Tingley et al. (2003) and Idda et al. (2009), among others. Indeed, even in the present case study, an artisanal fishery that has been monitored in recent times, detailed information on fishing effort (i.e. number of hauls per fishing trip, real number of traps used per vessel) and vessel specific time-varying inputs (i.e. consumption of bait and fuel, daily distance covered between the port and the fishing area) were unknown. Neither were data at trip level available. Indeed, fishing effort is a structural problem worldwide (even when management plans are in place), and in some cases this implies attitudes towards fishing and values that also have to be taken into account in fishery assessments.

Nevertheless, the outcomes detailed in Section 4 support the relevance of testing sample selection bias in TE studies of fisheries involving multi-gear vessels and for which panel data are available (Griliches et al., 1978). Frequently, the output of some units in the sample is not registered for the whole period involved due to definitive or temporal *attrition* of the fishery (Heckman, 1979).[15] However, regardless of whether the attrition rate is high or low, the randomness of missing data should be first ensured. Noteworthy examples that illustrate these risks can be found in García Del Hoyo et al. (2004) and Oliveira et al. (2015), again related to artisanal fisheries and SSFs. Another interesting situation, similar to the empirical case addressed in this article, is described by Pascoe and Herrero (2004) when using DEA and a panel dataset to obtain fish stock indexes for the artisanal octopus fishery in the south of Spain. The fleet involved —small artisanal vessels— have changed their fishing strategy to adapt to the decrease in octopus stock, thus progressively reducing their participation and diversifying fishing effort to alternative fisheries. In examples such as the aforementioned one, if vessels do not leave the panel dataset in a random way (i.e., the vessel is out of service, undergoing repair work, skipper's illness, etc.), a systematic pattern depending on unobserved characteristics affects disturbances in the model, so exogeneity assumptions will fail and the effect of sample selection bias will grow (Hausman and Wise, 1979). Alternatively, any attempt to cut observations from the unbalanced panel dataset to obtain a balanced set (by dropping *attriters* from the sample) will imply selection bias in the sample used for efficiency analyses.

Finally, it must be outlined that other reasons to control for sample selection bias go beyond aspects exclusively linked to multi-gear artisanal fisheries and SSFs. A first relevant question is to prevent a “ripple effect” distorting the results of other connected models. The use of SF estimates resulting from a selection-biased panel data sample to model the effects of inefficiency (in a simultaneous estimation, as proposed by Battese and Coelli, 1995) or to explore managerial determinants (so-called *skipper´s skill*, Squires and Kirkley, 1999) will lead to mistaken conclusions about the causes of fishing technical inefficiency and the appropriate measures of its reduction. A second key question is that sources of underlying selection bias are not exclusive to artisanal fisheries. SF using cross-sectional data have been widely applied to analyse the TE of fisheries operated by vessels belonging to different censuses and metiers. In situations such as those studied by Sharma and Leung (1998), Grafton et al. (2000), Pascoe et al. (2001) and Jamnia et al. (2015), self-selection problems could also have been present. In fact, Pascoe et al. (2001) eliminated vessels under 10 m of total length from the samples because they are considered to be “highly opportunistic” (they switch gear regularly).

6. Conclusions

Technical efficiency (TE) studies in fishing should pay attention to sample selection bias when analysing data-poor fisheries operated by highly flexible and adaptive multi-gear vessels (as is the case in many artisanal fisheries and SSFs). This study explored sample selection bias in an artisanal octopus fishery in northwest Spain, an empirical case where the TE analysis aims to guide the adoption of sustainable management practices. To this end, a SF non-linear model, developed by Greene (2010), was used to correct for sample selection bias, and this correction was applied to a cross-section SF for the 2008–2009 fishing season, a similar approach used by previous studies in non-fishery contexts. The method proposed here is suitable when assessing technical aspects of artisanal fishing (attributes or non-technical determinants were not the object of analysis). The results showed that participant vessels underwent a self-selection process. The corrected SF function was able to control selection bias in two key elements: input productivities and the measurement of the TE of global and local fleets. Sample selection bias led to a marked overestimation of the global TE in the octopus fishery for the 2008–2009 season. In this regard, an average score of 0.613 was obtained when the initial SF was used and 0.492 when the model was adjusted to control for selection bias, following Greene (2010). The unbiased SF avoided a significant underestimation of the importance of vessel length and an overestimation of fishing effort to explain catch levels. On the basis of these findings, the improvement of the on-board conditions of crew members and a market-based measure of eco-labelling emerge as the preferable policies to achieve a sustainable fishery, among others (such as reducing fishing days allowed per vessel and season). Unbiased TE indexes also allowed us to gain accurate knowledge of the efficiency of local fleets at port level, which was used to identify the most efficient local fleets as potential beneficiaries of public funding to support the eco-labelling process.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

[15] They may leave the fishery during a period of time and take it up later.

Acknowledgements

The authors would like to thank the General Directorate of Maritime Fisheries of Asturias (Regional Ministry) for providing the data needed for this analysis.

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