Accounting for fishing vessel time allocation at sea when measuring efficiency

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Abstract

Rising fuel and input costs are having a significant impact on the profitability of the fishing sector and increasing the need for vessels to improve operational efficiency. In particular, smaller vessels that do not have the economies of scale must maximize input-output efficiency to remain viable. There is also the consideration that improved fuel efficiency in fishing vessels will reduce the carbon footprint of the sector. Measuring vessel and fleet efficiency is important for these reasons, but it is also important to correctly measure efficiency to determine how best to manage a fleet and determine how ecosystem, regulatory and market changes will impact fleet viability and operability. This paper uses stochastic frontier analysis (SFA) to assess the efficiency of fishing vessels in the Irish demersal otter trawl nephrops fishery. Clear evidence of efficiency-heterogeneity across vessels in the fishery is reported, even when controlling for vessel-specific characteristics, such as vessel length, age and engine power. The drivers of efficiency are also investigated and we find that the use of vehicle monitoring systems (VMS) data allows for more spatially and temporally detailed information to improve fleet efficiency analysis.

Keywords nephrops, coastal, fishery, stochastic frontier analysis, efficiency, firm

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1 Introduction

Fishing effort is a critical factor to account for when analysing and managing fisheries, since generally, it must be controlled to ensure a fisheries sustainability. In fisheries economics, effort is incorporated into the theory of production and production functions. It is central to determining the efficiency of fishing vessels, since it partially determines the rate at which fishery inputs produce landings. The efficiency of fishing vessels, and the level of heterogeneity within a fleet, can itself have important management implications. For example, when a fishery suffers excess capacity issues, a common management response is to decommission a portion of the fleet. This alleviates fishing pressure on the stock and also allows vessels remaining in the fishery to attain positive economics fishing rents. However, the real variable that managers are trying to reduce in this scenario is not only capital, but also fishing effort, and to do this effectively, they need to understand the efficiency with which capital is utilised.

Effort can be defined as,

$$(1)\ E_t^i = E(T_t^i, FP_t^i)$$

Where T_t^i is the time vessel i spends fishing in period t and FP_t^i is vessel fishing power in the same period for the same vessel. Thus, the way in which time is measured and defined heavily influences the estimation of effort. Andersen (1999) points out a critical difference in thinking between biologists and economists when defining time and calculating effort. Biologists, primarily concerned with the impact of fishing on stock biomass, prefer to measure time as the period in which fishing gear is in use and directly giving rise to catch. Economists, concerned with production, costs and revenues tend to measure time as the period in which any time is expended in making a fishing trip. This is the case because non-fishing time allocations such as travel time, search time and handling time all have economic implications and effect fishing decisions and behaviour (Hilborn et al., 1992; Hannesson 1993). For this reason, economists have historically used the number of days absent from port or ‘days at sea’ as the measure of time in estimating effort. Out of necessity, biologists have also tended to use total time at sea in calculating fishing effort due to the difficulty of determining how much time at sea is purely allocated to fishing (Andersen, 1999). The failure of the ‘days at sea’ measure to capture the specific fishing period of interest for biologists is clear. However for economists, who wish to consider all legs of a fishing trip, using days at sea as an ad hoc measure of time prevents a distinction between vessels' different time allocations while at sea. Vessels may spend different amounts of time fishing, while at sea. Some may choose to travel between locations, while others may decide to continue to fish in an already visited site. Vessel skippers may make trade-offs between fuel and labour costs; for example the decision to stall at sea through a storm or to return to port until fishing can continue. All of these choices have implications for input usage and the level of output, and thus have implications for a vessel's efficiency level. Omitting such information when determining vessel efficiency and the drivers of efficiency, possibly undermined the reliability of efficiency measures currently used by fisheries economists.

Recent technological improvements have increased the capacity of fisheries managers to monitor vessels' activities at sea and to distinguish between different time allocations. Vehicle Monitoring Systems (VMS) collect positional data from fishing vessels, and combined with catch data from logbooks, allow fishery managers and researchers to map spatially resolved catch and effort data Gerritsen and Lordan (2011). Furthermore, applying a given speed rule to a vessels positional data while at sea allows for a distinction between the time spent fishing and time spent travelling between ports and fishing sites. Once integrated with catch data from logbooks, estimates of catch per unit of effort can be improved upon, than had they been estimated using days at sea.

In this paper, we use a stochastic production model to determine the degree of efficiency-heterogeneity in the Irish nephrops trawl fleet. We use the measures of efficiency resulting from this analysis to get at the drivers of efficiency within the fleet. In particular we pay specific attention to the issue of vessels' time allocations while at sea; our goal is to determine whether the improved temporal detail of VMS data (compared to days at sea measures of time) can improve fishery managers' understanding of vessel and fleet efficiency and help inform management decisions that are reliant on efficiency measures. Beyond that, the temporal detail of the data allows us to pose interesting questions relating to efficiency in this particular fishery.

Section 2 provides a background to the Irish nephrops trawl fishery. Section 3 discusses the data and variables used in the stochastic frontier model. The methodology description in section 4 explains stochastic frontier analysis (SFA) and how it is applied in this case. Section

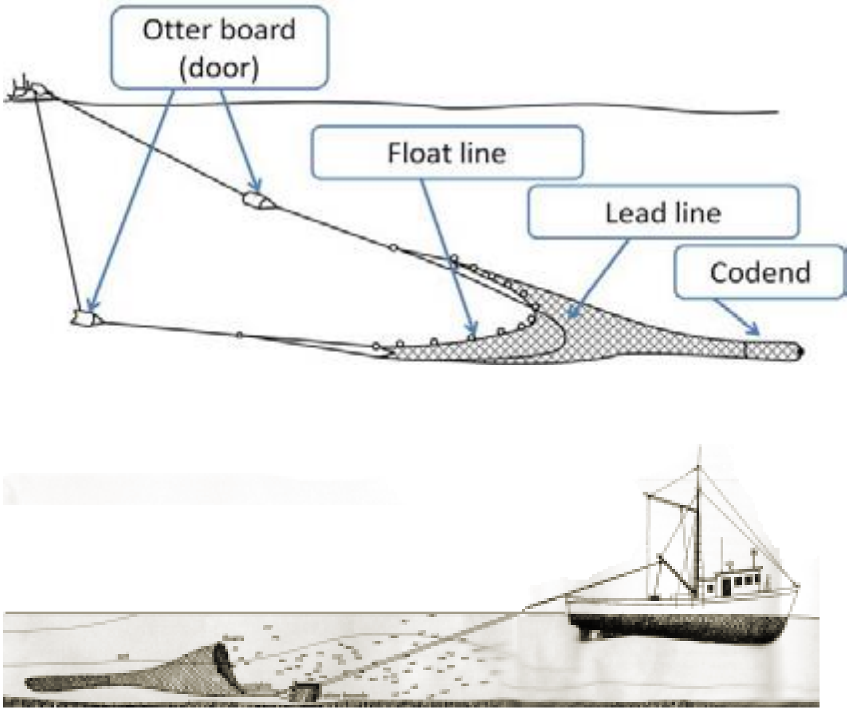
5 presents the results of the SFA and further analysis. Concluding remarks and a brief discussion are provided in section 6.

2 The Irish nephrops trawl fishery

Nephrops norvegicus, also known as the Norway Lobster or Dublin Bay Prawn, is a demersal species of the lobster genus primarily distributed in the north-eastern Atlantic Ocean and Mediterranean Sea. It can grow up to 25 cm in length and is found at depths of between 20 to 800 metres in benthic habitats characterised by sedimentary substrates which it uses to dig burrows (Lordan et al., 2012). Commercially, it is the most valuable demersal species in Ireland with a harvest value of €80m at first sale at Irish ports in 2012 which accounted for 30% of total European landings. Around Ireland nephrops can be found in ICES subareas VI and VII; west of Scotland, in the Irish sea, along the west coast and to the south and southeast in the Celtic sea. Distribution is concentrated at key sites where depth and benthic habitat is ecologically suitable.

Trawling is the main method of harvesting nephrops in Irish waters and of the 275 demersal otter trawlers that operate out of Irish ports, around 80 are dedicated to nephrops fishing (ref). This type of trawling requires a means of holding the mouth of the net open while towing, and a system of wires to connect the net and gear to the vessel (Galbraith and Strange, 2004). Vessels are fitted with winches on deck to move and store the trawling wires or warps and otter boards' are used to spread these connecting wires and hold the net open, horizontally (see Figure 1). Large spherical floats, built to withstand implosion at extreme fishing depths are attached to the upper edge of the net mouth (floatline) and these provide vertical lift to the net while weight is placed on the edge of the net in contact with the seabed (footrope). The net itself is usually funnel shaped with extended sides that form wings for guiding fish into the net. Bottom trawl nets sometimes have a top canopy to prevent fish from escaping over the top of the net.

Figure 1: Otter Trawl Rig System



Irish fishing waters are governed as part of the EU's Common Fisheries Policy (CFP) since 1983. Measures include setting Total Allowable Catch limits (TAC), limiting the number of days at sea (fishing effort), restricting the use of certain fishing gear (Technical Conservation Measures (TCM)) and reducing overcapacity in the EU fishing fleet (through fleet decommissioning). All of these methods are employed in the management of the Irish nephrops fishery. As recently as 2013, the EU granted Irish fishing fleet a 6% increase in the quota for nephrops (breakingnews.ie, 2013). Since then, both in 2014 and 2015, due to falling stock biomass, quotas have been reduced (Irish marine times, 2014&2015). In the Aran Islands, the major nephrops fishery on the west coast, the Irish Fish Producers Organisation (IFPO) have introduced a self-imposed limit on effort in which a 5 day limit is applied to vessels over 20 metres in length during April and May, and vessels below this length are restricted to 20 days per month. It is estimated that these actions will reduce nephrops catches in the area by 17% (Irish marine times, 2015). From the SFA analysis, it will be interesting to note whether more efficient vessels stand to gain a greater share of potentially greater catches in the future, as a result of the voluntary temporary reduction in days at sea.

3 Data and variables

3.1 VMS data

Since 2005 all fishing vessels of 15 metres in length or more have been legally obliged to fit a vehicle monitoring system transponder (VMS) (EC, 2003). These transponders transmit a fishing vessel's position every two hours whilst at sea. By using the distance between a vessel's sequential location points to calculate travel speeds, analysts can calculate which elements of a vessels time at sea are dedicated to travelling to and from fishing locations and which elements are actually spent fishing Gerritsen and Lordan (2011). Vessels are also required to record retained catch in daily logbooks (EEC, 1983) and sales notes data is also collected by the Irish Department of Agriculture, Fisheries and Food (Gillespie and Hynes, 2011).

By combining positional data of vessels' VMS records with electronic logbook data for each vessel, analysts can create an unprecedentedly detailed representation of the spatial distribution of historical species catches as well as the corresponding fishing location choices made by fishermen. The latter is useful because it allows those vessels concentrating in bona fide nephrops sites to be identified. In the case of Irish nephrops fisheries, of the 275 demersal otter trawls in operation in Irish waters, 80 were found to be dedicated to nephrops fishing.

3.2 Variables

The focus of this paper is on analysis in determining the drivers of efficiency, thus which variables are to be used in defining the production frontier is largely a feature of the results sections. Nevertheless it will add clarity to describe core variables in this section. The reasons behind *why* they are be used in the ensuing model is left to the results section of the paper (section 5).

As earlier stated, Irish nephrops fishing sites lie in three specific areas around Ireland; the Atlantic Ocean to the west, the Celtic sea to the South and the Irish sea to the East. There may be efficiency differences in vessels operating within different seas, so it was deemed necessary to control for this in our analysis of the drivers of efficiency through creation of sea dummy variables. Summary statistics of key variables across three different sea types are reported in Table 1. In Table 2 they are presented by vessel length category.

Briefly,

- Liveweight (kg) is the kilogram weight of nephrops harvested, weighed and recorded in the vessels daily catch log book.
- Effort (kw hrs) is the number of hours a vessel is estimated to have spent fishing while at sea multiplied by the kw engine capacity of the vessel.
- Labour (man hours) is the number of hours a vessel is at sea multiplied by the number of crew members estimated to be on-board given the vessel length category into which the vessel fits.
- % non-fishing time is the ratio of hours *not* spent fishing while at sea, relative to total hours at sea.
- Vessel tonnage is the weight in tonnes of a vessel.

  Days at sea is self-explanatory. There may be rounding up or down errors, but ultimately, we use hours as our time variables and are considering the weakness of using days at sea as opposed to more temporally exact VMS time measures.

Table 1 Means of selected variables by sea region

	All		Atlantic		CelticSea		IrishSea		F-test	
Liveweight (kg)	2986	(2838.49)	2764	(2744.48)	2041	(2456.53)	3911	(2911.91)	2,458.00	***
Effort (kw hrs)	37171	(2838.49)	48769	(50470.19)	43579	(32551.11)	23276	(16250.58)	207.85	***
Labour (man hours)	1120	(2838.49)	1472	(1161.28)	1311	(839.1)	701	(426.9)	47.42	***
% non-fishing time	0.41	(2838.49)	0.43	(0.16)	0.43	(0.11)	0.37	(0.18)	2,458.00	***
Vessel tonnage	136	(2838.49)	177	(65.65)	118	(54.58)	120	(52.53)	47.42	***
Days at sea	6.27	(2838.49)	7.58	(0.16)	7.70	(0.11)	4.13	(0.18)	280.66	***

Source: VMS data

Table 2 Means of selected variables by vessel length categories

	All		12-18 m		18-24 m		24-40 m		F-test	
Liveweight (kg)	2986	(2838.49)	671	(1102.17)	3154	(2809.95)	3315	(2986.26)	78.56	***
Effort (kw hrs)	37171	(36267.3)	9334	(10492.76)	32369	(20304.56)	62133	(59715.69)	246.45	***
Labour (man hours)	1120	(898.11)	267	(188.75)	919	(446.49)	2050	(1306.02)	661.99	***
% non-fishing time	0.41	(0.16)	0.58	(0.17)	0.38	(0.15)	0.42	(0.15)	169.20	***
Vessel tonnage	136	(63.09)	51	(22.59)	120	(42.09)	216	(47.27)	1,532.58	***
Days at sea	6.27	(3.97)	3.34	(2.36)	5.73	(2.79)	8.99	(5.73)	239.53	***

Source: VMS data

4 Methodology

The research question examined in this work concerns the technical efficiency of vessels and the relationship of this measure to a suite of possible 'drivers' of efficiency. The two most common approaches to estimating the drivers of technical efficiency are Data Envelopment Analysis (DEA) and Stochastic Frontier models (SF). Each approach has strengths and weaknesses.

4.1 The Stochastic Frontier approach

Both DEA and SF methods estimate production frontiers representing the maximum level of output for a group of firms, with individual firm inefficiency represented as the potential proportional increase in output to the frontier. The approaches differ in that DEA is a deterministic process and by definition does not account for any statistical noise in the data. Any deviation in observed output from the maximum feasible frontier output is fully attributed to inefficiency. In fishing data, such noise could be due to many factors such as weather or spontaneous stock collapse.

Stochastic frontier analysis explicitly takes account of statistical noise when calculating technical inefficiency. The approach defines the production technology for a particular industry using a stochastic production frontier, whereby output is expressed as a function of inputs, a random error component and a one-sided technical inefficiency component which captures deviations below the frontier output level. However, the SF approach is not without its shortcomings. One of the main issues associated with the specification of an SFA model is that it requires the specification of a functional form, and this can be an onerous assumption. Another assumption is the particular shape which the inefficiency term's probability density function takes on, and there is not theory to guide this particular researcher here. However, the SF method has been selected for this particular application since statistical noise is very prevalent in fishing datasets, and in particular an initial examination of the data confirmed the existence of statistical noise in this dataset.

4.2 Other modelling details

The approach taken involves estimating a production directly from the available technical data. This is known as the 'primal approach'. An alternative is to estimate a cost function, and then use duality theory to derive the production function which it implies, i.e. the 'dual approach'. The latter is useful because cost functions will often be more consistent with theoretical regularity conditions, and because cost data is often more forthcoming than the technical details of production. However, in this application the data does not contain any cost information, and the estimated production function meets the usual regularity conditions. A further benefit of this approach is that it removes the need to make any behavioural assumptions, e.g. cost minimisation.

Furthermore, the data does not contain information on the stream of services obtained from capital. This forces the analysis to take a short run orientation, whereby capital is assumed to be fixed; hence no measure of capital is included in the production frontier. The frontier is of the KLEM variety of production functions which was popularised by Berndt, E. R., & Wood, D. O. (1975). This style of model has been applied in fisheries as well (Eggert & Tveterås. 2013), and seems the obvious choice given that there is no land input to be considered. Therefore, the specified model fits both the usual theoretical framework applied in fishery economics as put forth by Gordon (1954)—where catch is a function of 'effort' or 'fishing power' and time—and also the general production economics framework with 'effort' being a measure of energy and time now measuring labour. The short run nature of the frontier allows the exclusion of capital (a fixed input), and the selection of a relatively homogenous group of vessels (nephrops fishing) allows the exclusion of materials from the model because gear will be uniform across vessels, varying only in scale, but not by type. What variability there is in the scale of gear used will largely be captured by a vessel's kW engine power and length.

The functional form assumed for this work is the usual Cobb-Douglas form.

The estimation of stochastic production frontiers using cross-sectional data was simultaneously proposed by Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977). Using a Cobb-Douglas production technology, the stochastic frontier is written as:

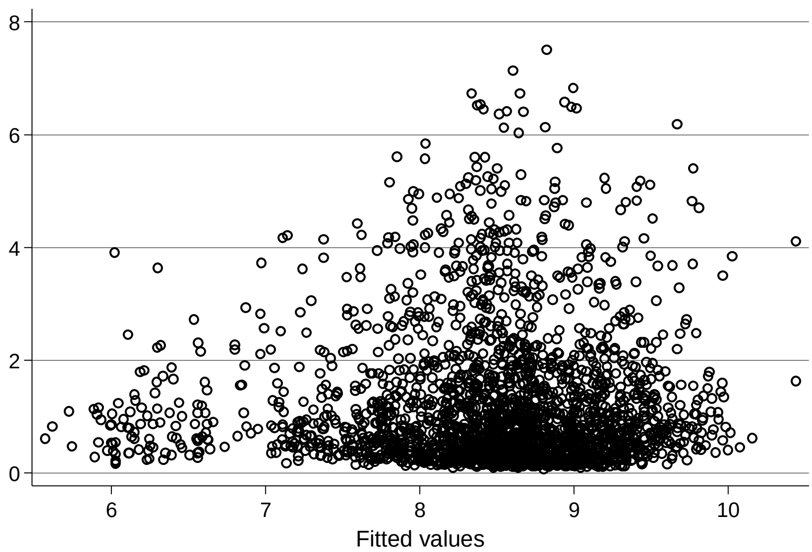
$$lny_i = \mathrm{B}_0 + \sum_{k=1}^{K} \mathrm{B}_k \ln x_{ki} + e_i \quad \text{where} \quad e_i = v_i - u_i \qquad \textbf{(1)}$$

where y_i is the farm's output level and x_i is a vector of production inputs; in this application x_i will be energy (effort), and labour (labour measure in man-hours). The composite error term e_i consists of a statistical noise component v_i and u_i which is a non-negative technical inefficiency component. We assume the Cobb-Douglas functional form for this model to ease interpretation of the coefficients and to ensure that theoretical regularity conditions will hold globally, i.e. for all points in the estimated function.

The model is usually estimated by maximum likelihood after assuming a distribution for both components. The distribution of u_i is assumed to be a truncated normal distribution to allow the estimation of the drivers of efficiency. This is accomplished through a simultaneously estimating an auxiliary function of u_i on a vector of 'drivers' (z).

A practical concern when estimating this model is the effect of heteroscedasticity in both the u and v components of the error term. Figure 2 displays the estimated u parameter plotted against the model's predicted values for catch, i.e. it is a residual plot. Figure 3 displays the same for the noise parameter. Both of these scatterplots present strong evidence of heteroscedasticity in these parameters.

Figure 2 Heteroscedasticity in the inefficiency parameter



Source: Authors' calculations

According to Kumbhakar et al (2014, pg. 323), '[ignoring] heteroscedasticity could lead to inconsistent parameter estimates.' Hence, the 'doubly heteroscedastic' vintage of SF model is employed. Since the heteroscedasticity and the mean of u are estimated as functions of the same vector of 'drivers' (z), this is considered a model of non-monotonic inefficiency á la Wang (2002). Therefore, the noise component is modelled as

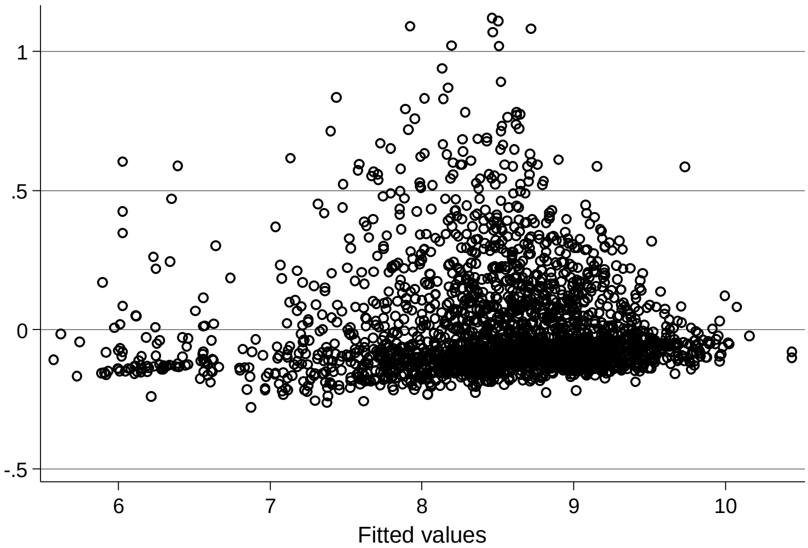
$$v_i \sim N(0, \sigma^2_{v,i}) = N(0, \exp(\omega_{v,0} + z'_{v,i}\omega_v)) \quad \textbf{(2)}$$

and the inefficiency term is modelled as

$$u_i \sim N^+(\mu_i, \sigma^2_{u,i}) = N^+(\delta_0 + z'_i\delta, \exp(\omega_{u,0} + z'_{u,i}\omega_u)) \quad \textbf{(3)}$$

where δ is a vector of parameters associated with the mean of u, and ω are the parameters associated with the variance of either u or v.

Figure 3 Heteroscedasticity in the stochastic parameter



Source: Authors' calculations

5 Empirical results

Parameter estimates are presented in Table 3 below. This table provides variable coefficients (which can be interpreted as output elasticities), White's robust standard errors, z-statistics and the p-values they imply, as well as confidence intervals for the point estimates of the coefficients. The results are split into the multiple (simultaneous) stages over which the model estimates its parameters. The frontier model itself is presented first, followed by the efficiency effects model, and finally the model of heteroscedasticity in the inefficiency (u) and noise (v) parameters.

5.1 The frontier model

Variables forming the production function 'kernel' are the measure of effort in kilowatt-hours (ln(effortwkhours)) and the measure of labour in man hours (ln(totalhrs)). Both are statistically significant at the 99 percent confidence level and are consistent with microeconomic theory in that they have the expected positive signs. The Cobb-Douglas functional form guarantees that the other regularity conditions concerning quasi-concavity of the estimated frontier will be met so long as these non-negativity constraints hold[1].

The coefficients indicate that effort is more influential than labour in determining catch. It is estimated that a one percent increase in effort raises catch by 0.51 percent, which contrasts with a figure of 0.38 percent for total hours. The fact that these two variables are highly correlated suggests one should approach this particular conclusion with some care however. An estimate of returns to scale can be calculated by summing these two coefficients; in this case the resulting figure is less than unity, implying decreasing returns to scale.

Three control variables are estimated alongside the production function, all of which are statistically significant at the 99 percent confidence level. Two of these are dummy variables which describe the sea region in which each trip took place. The third is the proportion of man-hours that are not directly related to fishing relative to total man-hours associated with the trip. Including these control variables allows the model to identify the effects of the variables of the production function after correcting for these confounding effects.

[1] See Pollak and Wales, 1992 for a treatment of the Cobb-Douglas regularity conditions

Table 3 Model results

Dependent variable: $\ln(\text{liveweight})$	Coef.	Robust Std. Err.	z-stat	P>z	[95% Conf. Interval]	
			Frontier			
$\ln(\text{effortkwhours})$	0.51	0.04	12.98	0.000	0.43	0.59
$\ln(\text{totalhrs})$	0.38	0.06	6.83	0.000	0.27	0.50
$\ln(\text{nfishprop})$	-0.18	0.05	-3.46	0.001	-0.27	-0.08
Sea dummy2	-0.30	0.08	-3.97	0.000	-0.45	-0.15
Sea dummy3	0.56	0.05	10.59	0.000	0.45	0.66
Constant	0.44	0.28	1.58	0.114	-0.10	0.98
			Efficiency Effects Model (μ)			
$\ln(\text{vesseltonnage})$	10.06	4.79	2.10	0.036	0.68	19.44
$\ln(\text{nfishprop})$	7.52	2.55	2.94	0.003	2.51	12.52
$\ln(\text{daysatsea})$	4.85	1.98	2.45	0.014	0.97	8.73
Sea dummy2	-9.48	8.77	-1.08	0.279	-26.67	7.70
Sea dummy3	9.92	3.74	2.65	0.008	2.58	17.25
Constant	-66.67	28.03	-2.38	0.017	-121.61	-11.72
			Heteroscedasticity in inefficiency parameter (σ_u)			
$\ln(\text{vesseltonnage})$	-0.57	0.26	-2.15	0.031	-1.09	-0.05
$\ln(\text{nfishprop})$	-0.32	0.11	-2.98	0.003	-0.54	-0.11
$\ln(\text{daysatsea})$	-0.24	0.12	-1.97	0.049	-0.48	0.00
Sea dummy2	0.71	0.34	2.06	0.040	0.03	1.39
Sea dummy3	-1.22	0.13	-9.65	0.000	-1.47	-0.98
Constant	5.97	1.25	4.78	0.000	3.52	8.41
			Heteroscedasticity in noise parameter (σ_v)			
$\ln(\text{nfishprop})$	0.75	0.20	3.78	0.000	0.36	1.14
Sea dummy2	-0.07	0.23	-0.31	0.756	-0.53	0.39
Sea dummy3	-0.80	0.21	-3.87	0.000	-1.21	-0.40
Constant	-1.04	0.24	-4.41	0.000	-1.50	-0.58
$\boldsymbol{E(\sigma_u)}$	4.57				4.50	4.64
$\boldsymbol{E(\sigma_v)}$	0.36				0.36	0.36
$\boldsymbol{N}$	=	2459				
Wald $\chi^2_{(5)}$	=	1156.55				
$\boldsymbol{P > \chi^2}$	=	0.0000				

When the model is specified in this way, the effect of fishing within a given sea region alters the intercept of the production frontier, but not the slope. Considered intuitively, it is as though there is a once-off cost to moving a given vessel from the base sea region (the Atlantic) to the Celtic Sea, and a once-off benefit to moving said vessel to the Irish Sea. Furthermore, the effect of increasing the proportion of non-fishing time in total man-hours by one percent reduces catch by 0.18 percent.

5.2 The auxiliary models

Several variables were investigated for inclusion in the efficiency effects model. The procedure for inclusion in the model was a reverse stepwise procedure. This is a straightforward approach where the largest list of possible efficiency drivers is included in the estimation of the auxiliary efficiency effects model. Subsequently, the variable with the largest p-value are dropped, and the model is re-estimated until the remaining variables are all statistically significant at a minimum of the 90 percent confidence level. There are two exceptions to this rule; if a given variable is statistically significant in the estimate of μ, i.e. in the primary efficiency effects model, then it is included in the model of σ_u, i.e. the heteroscedasticity model of u, and vice versa. The other exception concerns the dummy variables for sea region, which are specified as a set. If one dummy is statistically significant, the whole set is retained in the model. Finally, the specification of the model of heteroscedasticity in v need not match the specifications of either σ_u or μ.

It is important to note that the while magnitudes of the effects in the various models are not directly interpretable since they are estimated using the minimum likelihood estimator, the signs and p-values are informative. Negative signs in the primary efficiency effects (μ) indicate efficiency improvements (because distance to the frontier is reduced). While the focus of the analysis is on the proportion of non-fishing time while at sea, some additional controls are specified as well. These allow the interpretation of the non-fishing time variable to be related to a given size vessel (in terms of tonnage), within a given sea region and for a given duration of trip (relative to the vessel and measured in days). The sign on the proportion of non-fishing time is positive, as are the signs for all the control variables barring the sea dummy for the Celtic Sea. A positive sign suggests that increasing non-fishing time as a proportion of the journey tends to reduce the technical efficiency associated with that trip, even after accounting for the specified control variables. However, the interpretation is complicated by the heteroscedasticity in the u parameter, as discussed below.

The sign of the coefficients in both of the heteroscedasticity models indicate that a variable increases variability in u or v if it is positive and decreases variability in the relevant parameters if it is negative. For the heteroscedasticity in u model the estimated parameters have signs which are the opposite of those in the model of μ (which has an identical specification). So in this application, wherever a variable has an efficiency worsening effect, it happens that it also reduces the variability in u, and vice versa. Since u is assumed to have a strictly positive distribution, this will also affect the mean of the u parameter (μ) and will often mean that a negative sign increases efficiency here as well. A similar argument applies to the heteroscedasticity in v, albeit the effect is less direct. Therefore, the overall marginal effects on technical efficiency must be calculated separately, and this is done below in Table 4. The table shows the effect of the specified z variables, i.e. the drivers of TE, on the TE score when averaged over all the vessels in the sample. It can be seen that a one percent increase in the proportion of time spent in non-fishing activities reduces TE by 5 percent on average.

Table 4 Marginal effects of efficiency drivers

ln(vesseltonnage)	- 0.01
ln(nfishprop)	- 0.05
ln(daysatsea)	- 0.03
Sea dummy2	20.57
Sea dummy3	30.44

Source: Authors' calculations

The model yields not only average figures for TE scores, but also observation specific measures of TE. Therefore, it is possible to create descriptive profiles of vessels groups on the basis of these scores. Table 5 reports such profiles using continuous variables when partitioning the sample into thirds in terms of the least efficient to most efficient vessels.

Table 5 Profiles of TE classes (continuous measures)

	Low TE	Mid TE	High TE
Mean TE score within group	0.13	0.47	0.75
Vessel. Age (years)	19	21	21
Vessel tonnage (tonnes)	147	136	125
Mean distance to landing port (km)	71	53	37
Days at sea	7	6	5
Effort (hours)	103	90	77
Effort (kw hrs)	44813	38106	28583
Liveweight (kg)	834	2826	5302
Fishing time (man-hours)	787	675	547
Non-fishing time (man-hours)	587	431	332
Proportion of non-fishing time	0.43	0.41	0.38

Source: Authors' calculations based on VMS data and model output

As can be seen from table, a clear pattern emerges whereby the larger, newer, and more powerful vessels tend to be the *least* technically efficient. These vessels require larger crews, and they also tend to travel further from their landing ports, thus increasing effort and time expended. Another consequence is that the proportion of time they spend steaming to and from the fishing ground is larger, hence their proportion of non-fishing to total time is higher.

Table 6 Profiles of TE classes (counts by engine power categories)

	70	100	200	300	400	500	600	700	Total
Low TE	1	13	102	167	331	148	10	48	820
Mid TE	1	38	116	168	354	97	4	42	820
High TE	1	25	86	274	369	59	0	5	819
Total	3	76	304	609	1054	304	14	95	2,459

Source: Authors' calculations based on VMS data and model output

The data also contain some ordinal variables which describe the vessels. Cross-tabulations of these variables also reveal a relationship between vessel characteristics and technical efficiency. One can see from Table 6 that the low TE group skews towards the larger engine sizes, and as more efficient vessels are considered, the distribution of engine sizes moves towards the left.

Table 7 shows that most observations were in the mid-range of TE when considering vessels of the smallest size, most were in the high TE group for vessels of mid-size, and most were in the low TE group for vessels in the largest size category.

Table 7 Profiles of TE classes (counts by vessel length categories)

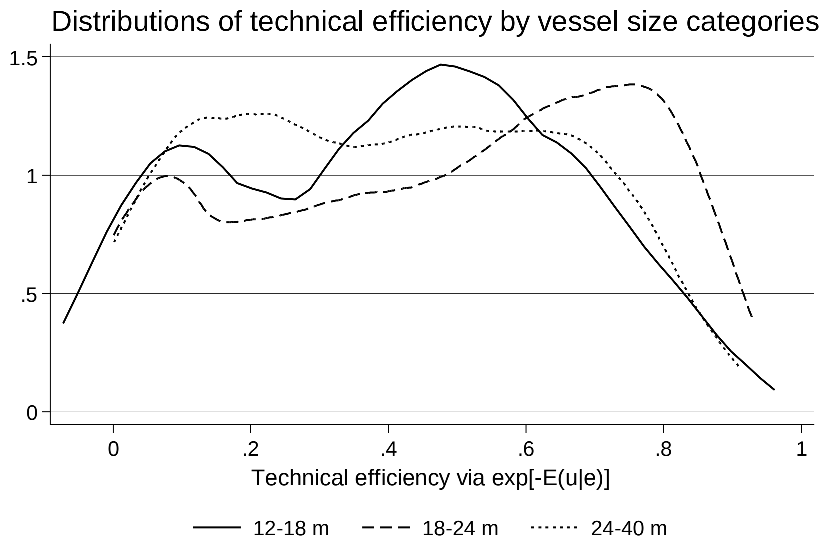
	12-18 m	18-24 m	24-40 m	Total
Low TE	65	513	242	820
Mid TE	84	547	189	820
High TE	53	644	122	819
Total	202	1,704	553	2,459

Source: Authors' calculations based on VMS data and model output

The tables above give descriptions of the vessels in terms of mean values, but it is also possible to analyse entire distributions of TE across the sample. Figure 4 plots kernel densities of trip level TE for each vessel size category. Substantial variability within each vessel category is observed. However, it is clear that the 24-40 m vessel group (the fine dashed line) is shifted to the left, the 12-18 m group (the solid line) has taken an intermediate position, and the, 18-24 m group (the longer dash) has the most rightward distribution. This demonstrates that although there is plenty of variability within vessel categories, the intermediate size grouping tends to fair best, whilst the largest vessels tend to be the least technically efficient in practice.

There is a subtle point to make about Figure 4; the distributions all display some level of bi-modality, i.e. there appears to be two distinct classes of vessel *within* vessel size categories. Therefore, a simple analysis of vessel size will miss important detail regarding the technical efficiency of the fleet, and policy prescribed on this basis may be ill-targeted.

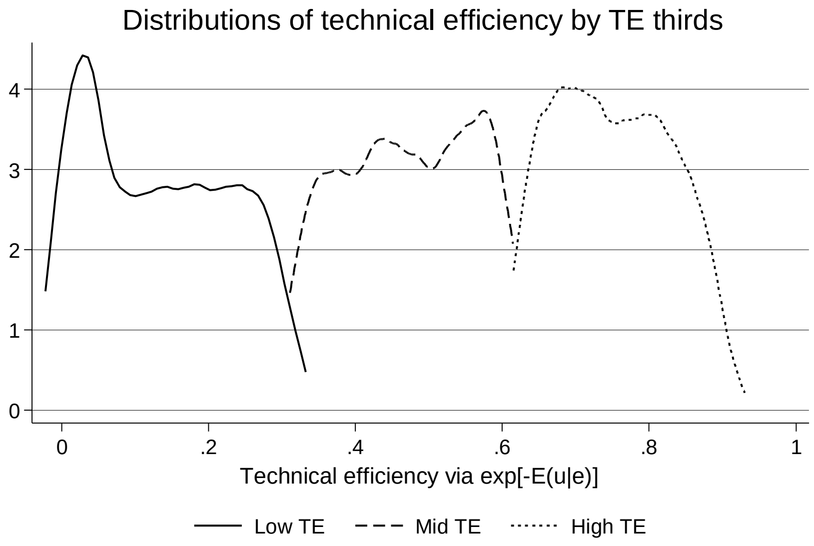
Figure 4 Analysis of TE by vessel size



Source: Authors' calculations

Figure 5 investigates the TE scores further by viewing the distribution of TE within each TE group, i.e. the sample partitioned on the basis of TE scores. Both the MidTE and the HighTE groups are distributed relatively evenly across their ranges, but the LowTE group has a noticeable spike at its lower TE scores. The data's variables exhibit no obvious pattern in relation to this subgroup, and this, combined with the bi-modality, supports the specification of a latent class model in future work.

Figure 5 Analysis of TE within each TE group



Source: Authors' calculations

6 Conclusion

In this paper we put forward the idea that fleet efficiency analysis can be improved by considering more temporally explicit measures of fishing activity. With this in mind, we applied SFA to VMS data for the Irish nephrops trawl fleet to analyse the drivers of efficiency and determine whether improved deductions about vessel efficiency can be made by considering variables like non-fishing hours and kw fishing hours, as opposed to using generic variables like days at sea kw hours. Tentatively, we found that increasing non-fishing time as a proportion of the journey tends to reduce the technical efficiency associated with a fishing trip. The results also indicated that larger, newer, and more powerful vessels tend to be the *least* technically efficient and that intermediate sized vessels tended to be the most efficient. This is certainly an interesting result and worthy of further explorations. Gordon (1952) asserts that,

> ‘*A fisherman starting from port and deciding whether to go to ground 1 or 2 does not care for marginal productivity but for average productivity, for it is the latter that indicates where the greater total yield may be obtained’*

Is it the case that for larger vessels, this assertion holds, and in chasing greatest yields they operate less efficiently? Along this vein, is it the case that medium sized vessels in the 18-24 metre category, being less capable of catching as many fish as larger vessels (be it from capital or quota limitations) and thus being less profitable, must prioritise greater efficiency in how they utilise their inputs to attain output. Or is it simply that by being less large scale, they are not as capable of chasing ‘average catches’ and do not attain the same profits or level of inefficiency that vessels in the larger category do. These are early stage questions on which we hope to shed more light in future work. Further patterns observed in the data were of interest and we hope to investigate these in the future as the research evolves.

A further question we feel future research may be able to investigate is around the issue of the voluntary limit on days at sea set by fishermen in the Aran Islands nephrops fishery off the coast of Galway. It may be interesting to determine whether more efficient vessels stand to gain the most from this. Or indeed, will it be less efficient vessels, such as the large scale variety (24-40 meters), which chase average increases in catches as opposed to marginal increases. On this basis, are there connotations for how stakeholder-based and voluntary fishing limits are debated and agreed upon amongst fishermen? These are questions we hope future research in this area might be able to answer.

This paper is a tentative one and in its early stages, thus there are a number of limitations in the analysis and the data which we have plenty of scope to address. Data limitations forced our hand in some of the modelling choices we made. In particular, there were no data concerning fish stocks, and this ruled out any sort of dynamic model. This made the use of an SF model all the more important, as stock collapse or extreme fluctuations are a potential stochastic shock which should not be included in the inefficiency term.

Another limitation was related to the time dimension of the data. The data were observed per trip per vessel, but there were no dates or times contained in the dataset. This made it impossible to aggregate the data in any way below the annual level. Since the data span only two years, this drastically reduced the variability in our regressors, and this prevented panel models from being estimated. It would be very advantageous to estimate such a model, because there is a concern regarding the possibility of endogeneity in the model. Specifically, the estimated production frontier predicts catch on the basis of effort and time, but it may be the case that both effort and time are actually determined by the catch/tonnage of the vessel on a particular trip, i.e. vessels remain at sea and continue to expend effort until they reach a minimum level of catch.

Dates must have been present in an expanded version of the data, as it was VMS readings which gave rise to the fishing time variables, but such measurements were not available for this application. We hope to secure date information, and possibly additional years' data as well; at that point a panel model will be possible.

The choice of a Cobb-Douglas functional form was a simplifying assumption we made to ease parameter interpretation and to ensure global conformity with theory across the range of the function. Furthermore, the choice of a truncated normal distribution for the inefficiency term is based on standard practice in the efficiency literature. However, both of these assumptions need to be rigorously tested, this will be carried out in subsequent versions of this paper

Lastly, some concerns have been raised in the literature concerning the appropriateness of the use (and form of) effort variables in fishery production functions (Hoff & Rodgers, 2006). We have followed standard practice in our approach here, but subsequent work will examine this aspect of the modelling more closely. Many of the caveats and limitations we have mentioned are issues that can realistically be resolved and we are actively addressing these as the research evolves.

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