Aquat. Living Resour. 20, 231–239 (2007)

DOI: 10.1051/alr:2007036
www.alr-journal.org

Aquatic
Living
Resources

Implications of human capital enhancement in fisheries

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Received 21 March 2007; Accepted 27 July 2007

Abstract – Decommissioning programmes have been used in many countries in an attempt to reduce the level of overexploitation in fisheries. The extent to which human capital enhancement may offset capacity reductions, however, has not been previously examined. The study uses a stochastic production frontier model to estimate the impact of differing skipper, vessel and technology characteristics on the productivity of a set of UK trawlers operating in the English Channel. The results suggest that productivity improvements resulting from increased education and training could exceed those from increased technological adoption. Increased investment in human capital enhancement could potentially offset, at least to some degree, the effects of decommissioning in the fishery. The study highlights an apparent oversight in fisheries policy analysis. Considerable attention is paid to the potential problem of technological creep and input substitution. However, enhancing human capital may have a greater impact on stocks than technological adoption in established fisheries.

Key words: Technical efficiency / Fisheries / Human capital / Decommissioning / Education / Training / Economics

Résumé – Implications de l'augmentation du capital humain dans le secteur des pêches. Des programmes de sortie de flotte de navires ont été utilisés dans de nombreux pays, dans le but de réduire le niveau de surexploitation dans le secteur des pêches. Cependant, la compensation des réductions de capacité de pêche par l'augmentation du capital humain n'a pas été examinée antérieurement. Cette étude utilise un modèle stochastique de production pour estimer l'impact des caractéristiques des capitaines, des navires exploités et de la technologie utilisée, sur la productivité d'un groupe de chalutiers britanniques opérant en Manche. Les résultats suggèrent que les améliorations de la productivité, résultant d'un meilleur niveau d'étude et de formation, peuvent dépasser celles résultant de progrès technologiques. La croissance de l'investissement dans le capital humain peut potentiellement compenser, au moins à un certain degré, les effets des programmes de sortie de flotte. Cet article met en évidence un apparent désintérêt pour cette question dans les politiques des pêches, une attention considérable ayant été donnée au problème de la dérive technologique et des effets de substitution entre *inputs* (intrants). Cependant, l'augmentation du capital humain peut avoir un impact plus important sur les stocks que l'adoption d'une technologie dans une pêcherie établie.

1 Introduction

The propensity for fisheries to become overexploited if not managed is well recognised. Where fisheries are already overexploited, some form of capacity reduction programme is often implemented. Such programmes aim at reducing the total level of inputs in the fishery, usually through reducing the number of fishing vessels. The most common capacity reduction method is decommissioning, also known as buyback, where the vessel and/or licence is purchased, subsequently removing it from the fishery (Holland et al. 1999). Decommissioning programmes are generally accompanied by a licence limitation programme, otherwise new vessels would re-enter the fishery following the buyback. Although buybacks do not address the underlying problems that cause overexploitation in the fishery (i.e. the lack of explicit property rights), they are politically acceptable policies that may result in some conservation and economic benefits, at least in the short run (Weininger and McConnell 2000).

Holland et al. (1999) concluded that decommissioning programmes were not an effective method for addressing the problems that they are meant to solve. Firstly, as the least efficient vessels are most likely to exit the fishery first (Holland et al. 1999; Pascoe and Coglan 2000), the proportional reduction in harvesting capacity is often less than the reduction in the fleet size. As with other input controls, there is an incentive for remaining fishers to substitute other inputs. For example, those remaining fishers have greater incentives to increase their fishing intensity through fishing harder, particularly as average catch rates (and hence the marginal value product of effort)

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Article published by EDP Sciences and available at http://www.alr-journal.org or http://dx.doi.org/10.1051/alr:2007036

are likely to be higher with fewer boats in the fishery. Similarly, Weininger and McConnell (2000) and Clark et al. (2005) demonstrated that decommissioning programmes provide substantial incentives for investment by the remaining vessels, particularly if vessel owners anticipate the scheme. New technologies also improve the efficiency of the vessels, and technological creep offsets the conservation benefits of the capacity reduction.

The focus on efficiency changes following decommissioning programmes has largely been on the adoption of new technologies or input substitution. However, another potential area for productivity change is in the skill of the fisher directly. Fisheries production requires a combination of natural, physical and human capital, where the skill of the fisher represents the human capital component of the fishing activity. This can be influenced by education, training and experience, as well as background and environmental conditions.

In the UK, as in many other countries, considerable investment is undertaken in training the industry in order to increase their productivity. This is despite considerable investment in decommissioning vessels by the UK government in an attempt to reduce overcapitalisation of the industry, see Pascoe and Coglan (2000) for details on these programmes. In 2004, the Sea Fish Industry Authority – the main organisation in the UK responsible for training the seafood industry, invested £1.8 M in training for the industry as a whole. Of this, around one third was targeted at commercial fishers directly, with training delivered largely through a network of regional industry training organisations (SFIA 2005). This was further supported by £0.9 M of training grants from other sources, including regional development agencies, local councils, Learning and Skills Councils and the European Union (SFIA 2005).

Training programmes in the UK involve both safety training as well as boat handling skills. The latter are delivered as NVQs (National Vocational Qualifications), with several levels of qualification being available from basic deckhand to skipper. Other boat handling training is also provided that does not lead to any formal qualification.

In order to examine the relative contribution of different forms of education and training to productivity, the contribution of other inputs to production must also be considered and factored out. These include the vessel characteristics (e.g. size, engine power) and the technology employed. A stochastic production frontier (SPF) approach was adopted as the most suitable methodology for separating out the effects of input utilisation, technology and factors that influence the level of human capital. The SPF model is estimated in two components. The first component represents the production function, and includes the capital inputs and their level of utilisation. The second component is an efficiency model that can include quantitative and qualitative variables that may explain differences in the efficiency of fishing vessels.

A stochastic production frontier model was estimated for a group of fishing trawlers operating in the English Channel was estimated. An inefficiency model was incorporated that includes skipper characteristics, including factors relating to types of training, as well as differences in the level of technology employed in order to determine how these factors affect efficiency. An earlier version of the technical analysis is presented by Tingley et al. (2005). The results of the analysis is used to compare the impact of human capital enhancement (e.g. education and training) with those of technology on potential output, and the implications of policies that support such enhancement programmes on sustainability of fish stocks.

2 Fishing efficiency: human capital versus technology

The level of human capital embodied in the skipper and crew has long been recognised as a key component of the production process. Empirical estimates of the level of human capital, more commonly referred to as “skipper skill” in fisheries, have been based on the estimation of technical efficiency – a measure of the relative efficiency of the vessel once the effects of the main capital inputs have been removed. Technical efficiency can be affected by many components. Pascoe and Coglan (2002) found that differences in boat characteristics explained around one third of the variation in technical efficiency of English Channel trawlers, and attributed the remainder to unmeasureable characteristics such as skipper skill and differences in technology that could not be quantified. Other studies have also suggested that much of the difference in technical efficiency between vessels may be due to differences in skipper skill (e.g. see Kirkley et al. 1998; Sharma and Leung 1999; Squires and Kirkley1999).

Traditionally, labour economics has measured skill separately in terms of either education level or level of experience, although more recently composite indexes of education and experience have been developed (Portela 2001). Education has generally been assumed to be associated with increased efficiency as it broadens the producers’ minds and enables them to acquire and process relevant information (Ali et al. 1996). However, more recently, years of education has been considered only a poor measure of skill due to the variety of training courses (in terms of both quality and content) that may constitute the educational experience (Ingram and Neumann 2006). A number of studies have indicated that skill development may involve more than just formal education, and may also involve participation in extension programmes (e.g. Ali et al. 1996; Seyoum et al. 1998) or vocational/on-the-job training (Ravn and Sørensen 1999).

Experience is often considered an alternative to education in the development of human capital, the idea of learning-by-doing (Arrow 1962; Young 1991). The general assumption in such cases is that skill, and therefore productivity and efficiency, increases with experience (Portela 2001). In the context of this study, greater experience also provides greater opportunities to engage with the rest of the fishing community and thereby gain skills through observation and discussions. Age is often used as a proxy for experience (e.g. Card and Lemieux 1996), although some studies suggest that skill may diminish with age in relative terms through reduced incentive to continue to develop and learn (Maurer 2001). Similarly, some empirical studies using years of experience as a measure of skill have found that efficiency decreases with experience, the explanation provided being that those in the industry longer are less willing to adapt (Wilson et al. 1998).

Family history has also been found to influence skill, although studies of this have largely been limited to educational development of children. Several studies (e.g. Connor et al. 2005) have linked reading skills of children to the characteristics of the family, prominently of which is the families' participation in these activities. This implies that immersion in a culture of undertaking an activity can have a positive impact on the child's ability to undertake that activity. Ingrim and Neumann (2006) also found a small, but statistically significant, transmission of occupation-specific skill capital within families for a wide range of occupations. In the context of the fisheries, it could then be expected that children brought up in families with a fishing history would develop a greater aptitude to fishing, which may translate to greater skill. Further, intergenerational knowledge transfer could also enhance skills.

Few attempts have been made at examining the effects of technology on the level of efficiency in fisheries. In agriculture, extension programmes aimed at introducing new techniques have been found to have a significant impact on efficiency (e.g. Ali et al. 1996; Seyoum et al. 1998), although these programmes also provide training in the use of the technology. Vocational training in fisheries is also largely linked to the use of improved search or navigational technology (or new gears in some cases) so separating the effects of training from the technology is difficult.

The adoption of improved search technology may give some skippers an advantage over those using less efficient technologies. However, these advantages may not be substantial. Robins et al. (1998) found that boats operating in the Australian northern prawn fishery using GPS (Global Positioning Systems) had 4 per cent greater fishing powers than those boats who without GPS. The use of both a GPS and plotter was found to increase fishing powers by 7 per cent. However, the use of increased technology may result in a different set of skills becoming important, such as those required to use the equipment and catch the fish once found. Robins et al. (1998) found a "learning effect", as fishing powers continued to increase by 2 to 3 per cent over the first three years of using the equipment.

3 The fisheries of the English Channel

The English Channel contains a number of multi-species multi-gear fisheries dominated by high value fish and shellfish species such as sole, lobster and scallops. Around 4000 registered boats operate in the fishery ranging in size from 4 m to over 30 m, of which around half are based in the UK. The fleet consists primarily of UK and French boats, although a small number of Belgian beam trawlers operate part of the year in the Eastern Channel, and a small fleet from the Channel Islands operate in their adjacent inshore waters. Most of the UK boats are relatively small, owner-operated, multi-purpose vessels, using a range of different fishing gears over the year. Total employment in the UK component of the fishery was estimated to be about 4300 excluding indirect employment in industries linked to the fishing industry.

Fishing fleets operating in the Channel can be broadly classified based on their main gear type. Many vessels are multipurpose, and operate using several different gears over the year. However, vessels predominantly use either trawl gear (otter trawl, mid-water trawl, beam trawl or dredge) or static gear (line, nets and pots), with only a small number using both trawl and static gears over the year.

Table 1. Average output and boat characteristics.

	Trawl gear	
	Mean	Coefficient of variation.
No. boats	18	
Revenue (£)	144,613	87%
Days fished	171	41%
Engine power (kW)	217	67%
Length (m)	14	42%

The trawl fleet size has decreased substantially over the last two decades following a series of decommissioning programmes. These were aimed at reducing the number of larger vessels (i.e. greater than or equal 10 m in length), and were largely implemented as part of the Multi-Annual Guidance Programme, part of the structural policy of the European Common Fisheries Policy, see Pascoe and Coglan (2000) for details. Between 1994 and 2004, the number of trawlers greater than 10 m in length operating in the English Channel declined from 330 to 175. Despite this reduction in fishing capacity, stocks of several key species have declined to dangerously low levels.

3.1 Data

The data set used in the analyses was comprised of both logbook and economic survey data. Monthly logbook revenues from all activities of the boats in the sample (i.e. over all gear types for multi-gear vessels) were aggregated into annual revenues over the period 1993-98, and combined with survey estimates of revenue for 1999 and 2000. As the latter two years data represented the complete activity of the vessels, the annual revenues derived from the log book data were aggregated over all fishing activities in which the vessel participated. The revenues in each year were inflated to 2000 values using a Fisher price index for the period 1993-98, and changes in the fish component of the retail price index in 1999 and 2000 to bring the revenues to 2000 values. Although only annual data were available for the last two years of the period examined, most of the factors assumed to affect efficiency did not vary over the year so a greater frequency of data would not have improved the analysis.

For the purposes of the analysis, only boats using trawl gear (beam trawlers, otter trawlers, midwater trawl and scallop dredges) were considered. Most boats in the study used at least two of the gear types covered by the grouping. Data on a total of 18 boats were used, representing roughly 10 per cent of the current fleet. A summary of the key characteristics of the fleet segments is given in Table 1.

A key input into standard fisheries production functions is the level of stock. In multi-species fisheries such as the Channel, deriving a composite stock index is not straightforward. The method developed by Pascoe and Herrero (2004) was used to determine the stock effect. This produces an estimate of the

Table 2. Skipper details by main gear type.

Trawl gear	No. Obs	Average Age (years)	Average Experience (years fished)	Average History[a]
Otter Trawl[b]	14	43	23	0.8
Beam Trawl	2	31	16	3.0
Dredge	2	50	30	0.5

[a] Values for family fishing history as follows: 0 = no history 1 = father/uncles and close family 2 = father and grandfather 3 = more than three generations.
[b] Includes one mid-water trawler.

Table 3. Proportion of observations using technology, and with education and training.

	Proportion
Technology	
Navigational Aids	79%
Autopilot	62%
Fish finders	89%
Education and training	
Formal education ("O" levels or above)	39%
Boat handling qualifications	44%
Other vocational training	6%

effects of changes in stock size on the level of output at the individual observation level (thereby allowing for differing effects due to differing characteristics of the vessel). The output measures were adjusted based on this stock effect. An additional feature of the stock effect measure in this case was that it would also correct for any systematic differences between the survey and logbook revenue estimates. A small number of observations with particularly large stock effects were excluded. As not all catch is recorded, it was assumed that a large adjustment to these data probably reflects an underestimate of the original value and hence it (and the adjusted estimate) may not be reliable.

The data were normalised by dividing the value of each observation by the mean for each variable. This results in a normalised mean of 1, and a logged mean of zero, for each variable.

3.2 Skipper characteristics and technology data

A difficulty identified in the previous study of English Channel trawlers (Pascoe and Coglan 2002) was that information on skipper characteristics and levels and use of onboard technology was not available. A survey of vessels operating in the English Channel was undertaken in order to obtain these characteristics for at least a subset of the fleet with which a more detailed study of factors affecting efficiency could be undertaken. Information collected included skipper characteristics such as age, number of years fishing experience and the number of generations of family fishing history (Table 2). Information on education and training, as well as use of on-board technology (and the number of years that the skipper had been using it) was also collected (Table 3). Vocational training was separated into two components – training directly relating to boat handling (e.g. the skipper or deckhand "ticket") and other training. The latter largely related to safety at sea and also use of navigational equipment, but also included training relating to enhancing quality on board such as through improved handling of the catch.

4 Factors affecting efficiency

The level of efficiency of a particular firm is characterised by the relationship between observed production and some ideal or potential production. The measurement of firm specific technical efficiency is based upon deviations of observed output from the best production or efficient production frontier. If a firm's actual production point lies on the frontier it is perfectly efficient. If it lies below the frontier then it is technically inefficient, with the ratio of the actual to potential production defining the level of efficiency of the individual firm

A general stochastic production frontier model can be given by:

$$\ln q_j = f(\ln x) + v_j - u_j \tag{1}$$

where q_j is the output produced by firm j, $\boldsymbol{x}$ is a vector of factor inputs, v_j is the stochastic error term and u_j is the estimate of the technical inefficiency of firm j. Both v_j and u_j are assumed to be independently and identically distributed (iid) with variance $\sigma_v^2$and σ_u^2 respectively.

The production frontier was specified as a translog frontier production function, given as

$$\ln V_{j,t} = \beta_0 + \sum_i \beta_i \ln X_{j,i,t} + \frac{1}{2} \sum_i \sum_k \beta_{i,k} \ln X_{j,i,t} \ln X_{j,k,t} - u_{j,t} + v_{j,t} \tag{2}$$

where $V_{j,t}$ is the output measure in period t and $X_{j,i,t}$ and $X_{j,k,t}$ are the inputs (i,k) to the production process. As noted above, the error term is separated into two components, where $v_{j,t}$ is the stochastic error term and $u_{j,t}$ is the estimate of the technical inefficiency. The output used in the model was the average real revenue, adjusted for the stock effects following the method of Pascoe and Herrero (2004). The inputs used in the model were days fished and engine power (kW). Information on overall length was excluded as it was highly correlated with engine power. As the data were pooled, gear specific dummy variables were also incorporated to test the effect of specific gear types on the model. One vessel characterised primarily as an otter trawler also used mid-water trawl gear, so an additional dummy variable was used to identify this vessel.

In order to separate the stochastic and inefficiency effects in the model, a distributional assumption has to be made for u_j. While a range of distributional assumptions are available, one approach is to define the inefficiency as a function of the firm specific factors such that:

$$u = z\delta + w \tag{3}$$

where $\boldsymbol{z}$ is the vector of firm-specific variables which may influence the firms efficiency, δ is the associated matrix of coefficients and $\boldsymbol{w}$ is a matrix of iid random error terms. The parameters of the inefficiency model are estimated in a one-step procedure (Battese and Coelli 1995) along with the parameters of the production frontier.

An earlier version of the analysis is presented in Tingley et al. (2005). The earlier version was estimated using unnormalised values of the input levels. An advantage of normalising the values is that the coefficients of the input variables in the production function directly represent the production elasticities. Further, the functional form of the production function component of the model (outlined below) is derived as a Taylor series expansion of a constant elasticity of substitution (CES) production function evaluated with at a mean of zero. Hence, it is more appropriate to estimate the model using normalised data. Further, the use of normalised data allows further testing of the validity of the model (Sauer et al. 2006) as outlined below.

4.1 Inefficiency model

The inefficiency model includes variables that are less tangible inputs into the production process. For the purposes of simplification, these can be grouped into three categories: vessel characteristics; on board technology and skipper related aspects.

The number of crew per metre overall length was considered a vessel characteristics that may affect efficiency, as proportionally more crew on the boat would enable the catch to be sorted faster and the nets to be re-set sooner. The vintage of the boat was also assumed to affect efficiency, as older designs were presumable less efficient than modern vessels built with modern materials (Pascoe and Coglan 2002). Incorporating a larger engine was also thought to affect efficiency as the boat would be able to reach the fishing grounds faster as well as tow the gear faster. While engine power was a variable in the production function, the ratio of engine power to boat size was incorporated into the inefficiency model to test the effects of this on efficiency.

The information collected on technology use was too detailed to use in its entirety due to degrees of freedom problems. The technology was aggregated into three categories – navigational aids (GPS, radar), auto-pilots and fish finding aids (sonar, sounders). Communication technology was not included as nearly all boats had some form of communication device for safety purposes. While this could also affect efficiency (through skippers working together and passing on information about catch rates in different areas), identifying how the technology was used was not possible. Information was collected as to when the skipper adopted the technology, and dummy variables were used to represent the use of these technologies.

Skipper characteristics incorporated into the analyses included age in 2000, the number of years experience, the number of generations of family fishing history, formal education ("O" level or above, where "O" level (now known as the General Certificate of Secondary Education, or GCSE) is the first formal education level in the UK), vocational education (e.g. training in safety, use of radar, VHF etc and quality enhancement) and boat handling training (e.g. skipper ticket, crew hand, etc.). For the education and training variables, dummy variables were used with a value of 1 if training had taken

Table 4. Correlation between explanatory variables in the inefficiency model.

	Activity	Crew/m	Boat vintage	OL/kW	Nav. Aid	Sounder/ sonar	Auto pilot	Skipper age	Exper- ience	History	Formal Ed.	Voc ed.	Boat qual.
Activity	1.00												
Crew/m	0.02	1.00											
Boat vintage	−0.03	−0.37	1.00										
OL/kW*	0.01	0.25	0.34	1.00									
Nav. Aid	−0.27	−0.05	−0.31	−0.17	1.00								
Sounder / sonar	−0.06	−0.13	−0.49	−0.50	0.39	1.00							
Autopilot	0.30	−0.03	−0.27	−0.12	0.26	0.19	1.00						
Skipper age	−0.33	0.40	0.25	0.14	−0.36	−0.28	0.04	1.00					
Experience	−0.30	0.36	0.24	0.20	−0.38	−0.26	0.06	0.86	1.00				
History	0.05	−0.28	−0.25	−0.42	0.06	0.24	−0.05	−0.22	−0.15	1.00			
Formal Education	−0.16	0.02	0.20	0.18	0.20	−0.10	0.19	−0.11	−0.09	−0.29	1.00		
Vocational Education	0.31	0.14	0.35	0.41	−0.66	−0.77	−0.31	0.24	0.22	−0.22	−0.19	1.00	
Boat Handling qual.	−0.16	−0.22	0.27	−0.14	0.27	−0.05	0.28	0.09	0.05	0.06	−0.03	−0.22	1.00

* Overall length (OL) of the vessel.

Table 5. Specification tests.

	$L(H_0)$	$L(H_1)$	λ	Significance
Trawl gears				
$\beta_{i,k} = 0$	2.577	7.086	9.018	2.91%
$\gamma = 0$	−39.263	7.086	92.699	< 1%[a]
$\delta_1 = \delta_2 = \ldots = \delta_n = 0$	−39.264	7.086	92.699	< 1%
$\delta_0 = 0$	5.517	7.086	3.139	7.64%

[a] based on the critical value determined by Kodde and Palm (1996).

place and 0 if it had not. The level of engagement (in addition to total years fished) in the fishery could also be assumed to affect skipper skill. A measure of activity was estimated based on the total time expended in the fishery over the period of the data (i.e. the total number of days fished over the period of the data). An assumption was made that those fishers who spend more time in the fishery would be more efficient than those who spent less time in the fishery.

Separating out the effects if each component requires orthogonality in the data. The correlation coefficients between the key explanatory variables in the inefficiency model are presented in Table 4. In most instances, the correlation between variables is very low, suggesting problems of collinearity in the analysis are likely to be relatively minor. Exceptions to this include relatively high correlation between vocational training and navigational aids and sonar, and high correlation between experience and skipper age. The implications of these high correlations the results are considered in the interpretation of the results below.

4.2 Results

The model was estimated using FRONTIER 4.1 (Coelli 1996). As with all econometric analysis, the results are highly dependent on specifying the correct functional form of the model. The model was original specified as a translog production frontier. The hypothesis that the correct functional form of the model is Cobb-Douglas was imposed by removing the squared and cross product terms from the translog production function (i.e. H_o: $\beta_{i,k} = 0$) and re-estimating the model. This was rejected at the 5 per cent level of significance (Table 5). The presence of inefficiency was also confirmed using the one-sided generalised likelihood ratio-test (H_o: $\gamma = 0$, Table 5). The test to determine whether inefficiency variables were jointly not significant (H_o: $\delta_I = 0$, Table 5) was also applied. This hypothesis was rejected at the 1 per cent level. A test for the significance of the constant term in the inefficiency model was also undertaken based on the initial results. This could not be rejected at the 5 per cent level of significance Table 5.

The estimated parameters of the production frontier and inefficiency model are given in Table 6. Both the unrestricted and restricted (i.e. $\delta_0 = 0$) models are presented. Following Sauer et al. (2006), the models were tested for monotonicity (Table 7) and curvature at the mean (i.e. $(x, y) = 1$; $\ln(x) = 0$). Both models demonstrated positive marginal products (i.e. $\mathrm{d}y/\mathrm{d}x$), although the second derivatives were positive rather than negative, suggesting increasing marginal productivities. Further, the signs on the derived eigenvalues were mixed, indicating an indefinite bordered Hessian and violating the curvature conditions proposed by Sauer et al. (2006). The former is perhaps less of a problem than Sauer et al. (2006) suggests. On average, the vessels examined were relatively small, and increasing returns might be expected over the range of the data. Violation of quasi-concavity, however, suggests that the potential to underestimate inefficiency exists. However, as inefficiency was estimated based on an inefficiency model rather than individual independent estimates, apparent efficiency resulting from curvature problems is likely to be largely captured as random error

The effects of the various factors on the level of efficiency of the boats can also be seen in Table 6. The direction of effect on efficiency is the opposite of the sign in the inefficiency model in Table 6. A factor that increases inefficiency (i.e. has a positive sign in the inefficiency model) would decrease efficiency, and vice-versa. In most cases, the coefficients in both inefficiency models were similar in sign, although the significance of the coefficients varied depending on the assumption regarding the constant.

From the restricted model in Table 6, older boats were found to be no more or less efficient than newer boats, counter to the earlier study (Pascoe and Coglan 2002). Implicit in the assumption of Pascoe and Coglan (2002) that newer boats would be more efficient was the assumption that newer boats were better equipped with newer technology. Explicitly accounting for technology in this study removes this link.

A number of results were likely to be representative of a direct productivity effect rather than efficiency effect *per se*. Increasing the engine power relative to the boat size increased efficiency. As in the production frontier, a larger engine is associated with increased output. However, a larger engine is usually associated with a larger boat. These results suggest that, ceteris paribus, increasing engine size may result in increased productivity.

The impact of technology on efficiency was also unanticipated, with navigational and fish-finding technologies having no apparent impact on efficiency, and the coefficient on the autopilot being significant only at the 10 per cent level. The apparent non-significant impact of the other technologies may be an artefact of their relatively high rate of adoption (between 80 and 90 percent).

The level of activity over the period examined had no significant impact on the efficiency of the vessel. Although the coefficient on skipper age was not significant, the coefficient on experience was had a significant negative impact on efficiency. Given the high correlation between age and efficiency, it is most likely that this result is reflecting skipper age rather than experience *per se*. It is reasonable to conclude that efficiency decreased with age, although the rate of efficiency decline with age is less certain as a result of the collinearity between these variables. From the correlation coefficients (Table 4), there appears to be a tendency for technological adoption to decrease with age, although the correlation is relatively weak.

Of key interest to this study is the relationship between education and training and the level of efficiency. Efficiency increased with formal education and boat handling training, but was not significantly affected by other vocational training.

Table 6. Production frontier and inefficiency model results.

	Base model			Restricted model ($\delta_0 = 0$)	
	coefficient	*t*-ratio		coefficient	*t*-ratio
Production frontier					
Constant	0.510	4.216	***	0.530	5.753 ***
lndays	1.274	12.577	***	1.280	12.024 ***
lnkW	1.976	6.982	***	1.941	7.117 ***
$\ln^2$days	−0.086	−0.923		−0.071	−0.800
$\ln^2$kW	1.100	2.414	**	1.101	2.462 **
lnday x lnkW	0.012	0.120		0.036	0.369
Beam dummy	−2.782	−3.703	***	−2.744	−3.801 ***
Dredge dummy	0.413	2.098	**	0.576	2.594 **
Mid-water dummy	1.235	3.709	***	1.119	3.627 ***
Inefficiency model					
Intercept	−2.378	−1.621		-	-
ln(Crew/m OL)	−0.612	−2.181	**	−0.326	−1.478
ln(boat vintage)	−0.644	−2.062	**	−0.379	−1.435
ln(kW/m OL)	−0.677	−2.220	**	−0.601	−2.167 **
Navigational Aid	−0.070	−0.650		−0.096	−0.952
Sounder/ sonar	−0.193	−0.571		−0.280	−1.121
Auto-pilot	−0.846	−2.681	***	−0.510	−1.920 *
lnactivity	0.342	1.139		0.002	0.011
ln(Skipper age)	0.245	0.572		−0.318	−1.081
ln(Experience)	0.795	3.203	***	0.687	3.355 ***
History	−0.215	−3.621	***	−0.202	−3.639 ***
Formal education	−0.381	−2.038	**	−0.575	−3.240 ***
Boat Handling	−0.192	−1.179		−0.304	−1.784 *
Other vocational	0.050	0.074		0.235	0.359
σ^2	0.072	4.872	***	0.074	5.178 ***
γ	0.776	3.264	***	0.840	6.332 ***
log likelihood	7.086			5.517	
N. Obs.	112			112	

*** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

Efficiency was positively related to a history of family involvement in the fishing industry. Experience of the earlier generations in such cases is likely to be passed down, which may be more valuable training than vocational education.

5 Discussion and conclusion

The results of the analyses conformed to many established perceptions. Formal education was found to be positively related to efficiency, consistent with most studies of efficiency that use formal education as a proxy for skill. While education level could reflect innate ability (e.g. intelligence level) rather than knowledge enhancement, other studies have found that increases in the level of educational attainment have been positively correlated with increased productivity (e.g. Temple 1999). The use of trawl gear requires an understanding as to how the resource moves with changes in seasonal and climatic conditions, so requires greater skipper input. Knowledge, however, can be provided though other means than formal education. Family history (which can impart an education on to the skipper based on knowledge passed down from previous generations) was found to be significant in affecting the efficiency of the trawl gear vessels. This result is not unique to fisheries.

Table 7. Tests for monotonicity.

	Base model		Restricted model ($\delta_0 = 0$)	
	Days	kW	Days	kW
$\dfrac{\partial y}{\partial x_i} = a_i > 0$	1.274	1.976	1.280	1.941
$\dfrac{\partial^2 y}{\partial x_i^2} = a_{ii} + a_i(a_i - 1) < 0$	0.263	3.029	0.287	2.927

Note: $(\bar{y}, \bar{x}) = 1$; $\ln \bar{x} = 0$. Derived from Sauer et al. (2006).

While education and training could be obtained outside the local community, family history is directly related to the existence of a continuing fishing community, which contain considerable social capital. Efficiency was found to increase by roughly 22 per cent, *ceteris paribus*, for each generation that the family had been involved in fishing. European fisheries policy has (implicitly) incorporated an objective of maintaining fishing communities for cultural reasons. However, given the results of this study, there may well be productivity as well as cultural arguments for maintaining fishing communities. This has less to do with information sharing and knowledge dissemination than maintaining families in fisheries. Previous studies on information sharing suggest that broad-based pooling of information does not occur, but rather is limited to close knit groups of fishers with long standing relationships (Curtis and McConnell, 2004). These relationships are most likely to exist in well established fishing communities. Preserving fishing communities will encourage future generations to remain in the industry, maintaining existing familial and other long standing relationships and potentially enhancing future productivity.

Undertaking boat-handling training increased productivity of the individual by approximately 35 per cent (i.e. $e^{-\delta} = e^{0.304}$), although this was only significant at the 10 per cent level. This suggests that the boat handling training being provided is largely effective in improving productivity. While other vocational training did not appear to increase productivity, this may have been an artefact of the data set used. A key area of vocational training was use of radar and other electronics. However, those who had undertaken this training had also not tended to be using these technologies, and, conversely, those using the technologies had not tended to have undertaken the training (as indicated by the negative correlations observed in Table 4). It is possible that a larger data set including more skippers who had both undertaken training and were using the technologies might have produced a more synergistic impact on efficiency.

Extrapolating from these results, if all vessels without an autopilot subsequently adopted an autopilot, productivity of the fleet as a whole could be enhanced by roughly 21 per cent. However, efficiency gains from education and training may far exceed this. Assuming that education enhances skill (rather than just reflecting innate ability), then if all skippers with lower levels of education (i.e. below "O" level, where "O" level is the first formal education level in the UK) gained higher levels of formal education (i.e. "O" level or above), productivity of the fleet could increase by 42 per cent. Similarly, if all remaining skippers took advantage of the boat handling training opportunities, the fleet productivity could increase by a further 19 per cent. Consequently, the potential productivity improvements from human capital development may exceed those from technological adoption. This latter result is partially a function of the high adoption rate of technology relative to education and training. It does, however, present an ethical quandary to fishery managers. While training is beneficial to the individual fishers, it may be detrimental to the industry as a whole. That is, the increase in effective fishing effort arising from enhanced capability will have similar impacts on fish stocks as that arising through technological creep.

The objective of enhancing fishing incomes through training appears at odds with the conservation objectives underlying the decommissioning programmes being implemented in the UK. This apparent contradiction is largely an artefact of the dependence of input controls for the management of the fishery. With more rights based measures such as individual transferable quotas, incentives exist for the industry to self adjust. In such cases, enhanced human capital may lead to longer term economic as well as conservation benefits.

Acknowledgements. The authors would like to thank the reviewers and editor for their useful comments.

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