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IMPACTS OF VESSEL CAPACITY REDUCTION PROGRAMS ON EFFICIENCY IN FISHERIES: THE CASE OF AUSTRALIA'S MULTISPECIES NORTHERN PRAWN FISHERY

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ABSTRACT

Capacity reduction programs in the form of buybacks or decommissioning programs have had relatively widespread application in fisheries in the US, Europe and Australia. A common criticism of such programs is that they remove the least efficient vessels first, resulting in an increase in average efficiency of the remaining fleet. The effective fishing power of the fleet, therefore, does not decrease in proportion to the number of vessels removed. Further, reduced crowding may increase efficiency of the remaining vessels. In this paper, the effects of a buyback program on average technical efficiency in Australia's Northern Prawn Fishery are examined using a multi-output distance function approach with an explicit inefficiency model. The results indicate that average efficiency of the remaining vessels was greater than that of the removed vessels, and that average efficiency of remaining vessels also increased as a result of reduced crowding.

Keywords: Buyback programs, technical efficiency, fisheries management, multi-output distance function.

INTRODUCTION

Overcapacity is often considered a key factor underlying unsustainability in fisheries. While overcapacity itself is a symptom of insufficient property or user rights in a fishery, recognition that excessive fleet size has a detrimental effect on both the resource and economic performance of the fishery has increased since the implementation of the FAO International Plan of Action for the Management of Fishing Capacity (FAO, 2004). Capacity reduction programs have been undertaken in many countries to address this, principally through some form of buyback (or decommissioning) program. Examples include the British Columbia Salmon fishery, the Oregon Columbia River Gillnet salmon fishery, the Washington State salmon fishery, the Canadian Atlantic groundfish fishery, the Norwegian purse seine fishery, several European fisheries (including Danish fisheries, United Kingdom fisheries under the EU Multi Annual Guidance Programs) and nearly all Australian commonwealth-managed fisheries. The overarching objectives of vessel or licence buyback programs are improved profitability of the fleet and enhanced sustainability of the fishery through reduced boat numbers, capital and ultimately fishing effort. However, despite their widespread application, their effectiveness is less than clear cut (Holland *et. al.*, 1999).

Buyback programs vary depending on goals and design, with some purchasing vessel licences and others purchasing the vessels also (or requiring their removal from fishing)¹. Holland *et al* (1999) identify three objectives: conservation of the fish stock, improvement of economic efficiency and provision of direct aid to fishers who want to exit the fishery. However, results can be mitigated in the long run if capital or effort is not permanently removed from the fishery. For example, if programmes extract historic or actual catch from the fishery, rather than potential catch, or fail to prevent to prevent capital or effort from returning to the fishery (Holland *et. al.*, 1999). To this end buyback programmes are normally implement in conjunction with post-buyback entry restrictions related to effort or inputs (in an explicitly attempt to prevent "input stuffing") (Holland *et. al.*, 1999; Weninger and McConnell, 2000).

Whilst it is possible to limit physical and/or measureable inputs (e.g. days at sea) these are not the only determinant of catch capacity. A number of studies have found that characteristics such as skipper skill and technology are factors that affect boats efficiency (Kirkley *et. al.*, 1995, 1998;

Pascoe and Cogan, 2002). Efficient skippers may re-enter the fishery and thereby improve the catch of previous less productive vessels. Further, buyback programs generally attract the least efficient vessels and skippers, so that the reduction in effective effort is substantially less than the fleet reduction would suggest (Pascoe and Cogan, 2000; Walden *et al.*, 2003). There is also an incentive for remaining fishers to enhance their efficiency. Vessels that remain in the fishery have strong incentives to invest in inputs that are not controlled in order to capture any rent generated by the buyback program (Weninger and McConnell, 2000). Paradoxically, buyback programs in the UK were paralleled with industry training with an explicit objective of improving the efficiency of the sector (Cogan and Pascoe, 2007).

In this paper, we examine the impact of a recent buyback program on the average efficiency in vessels in Australia's northern prawn fishery. We estimate a multi-output distance function with an explicit inefficiency model that includes vessel numbers as an explanatory variable to estimate the impact of reduced fleet size on efficiency. A translog multi-output distance function is employed as an earlier study in the fishery found that inputs and outputs were non-separable (Pascoe *et al.*, 2010), and hence a multi-output production function is more appropriate than a production function with a single (aggregated) output.

THE NORTHERN PRAWN FISHERY

The northern prawn fishery is one of Australia's most valuable fisheries in terms of total landed value, and is the most valuable fishery managed by Australian Commonwealth government. The fishery has an explicit management objective of maximizing economic returns (Dichmont *et al.*, 2010). In 2007-08 the gross value of product was around \$74m (AUD) (ABARE, 2009). The fishery is currently managed using a combination of input controls, primarily seasonal closures and individual transferable gear units. The latter places restrictions on the amount of headrope that vessels can tow. Over the last decade, the fleet size has more than halved, from 133 vessels in 1998 to 52 in 2008. In 2005 and 2006, 43 vessels left the fishery as part of a \$150 million national government buyback scheme. In return for government assistance to restructure, the fishery had to agree that it would move to management through ITQs.

The fishery occurs over two "seasons" each year, and, within the Gulf of Carpentaria, can effectively be considered as two separate fisheries – namely a "banana prawn fishery" and a "tiger prawn fishery". The analysis focuses on the tiger prawn season. The key species caught in the tiger prawn fishery are brown tiger prawns (*Penaeus esculentus*), grooved tiger prawns (*P. semisulcatus*) and two endeavour prawn species (*Metapenaeus endeavouri* and *M. ensis*). Most of the catch of these species takes place during the second season during the tiger prawn fishery. Tiger and endeavour prawns are caught also as bycatch during the first season, although there are strict limits on the quantities that may be retained to prevent targeting of these species at that time. Two species of banana prawns (white *Fenneropenaeus merguensis* and red leg *Fenneropenaeus indicus*) are also caught as bycatch (or opportunistically) in the tiger prawn fishery, along with king prawns. In addition, a number of other prawn species (e.g. king prawns, *Melicertus* spp.) as well as fish, cephalopods and other crustaceans are caught as by-products.

Technical efficiency in the banana prawn component of the fishery has previously been examined (Kompas *et al.*, 2004), as has the tiger prawn component of the fishery (Pascoe *et al.*, 2010), although the latter did not consider the factors affecting vessel efficiency. In this paper, we focus on the tiger prawn component of the fishery as this has been the main focus of management.

TRANSLOG MULTI-OUTPUT DISTANCE FUNCTIONS

As with Pascoe et al (2010), we adopt the translog multi-output distance function, which was found to be the most appropriate functional form. The translog distance function with M ($m = 1, 2, \dots, M$) outputs Y ; K ($k = 1, 2, \dots, K$) inputs X ; and for I ($i = 1, 2, \dots, I$) firms can be given by:

$$\begin{aligned}
\ln D_i &= \alpha_0 + \sum_m \alpha_m \ln y_{m,i} + 0.5 \sum_m \sum_n \beta_{m,n} \ln y_{m,i} \ln y_{n,i} \\
&+ \sum_k \alpha_k \ln x_{k,i} + 0.5 \sum_k \sum_l \beta_{k,l} \ln x_{k,i} \ln x_{l,i} \\
&+ \sum_k \sum_m \beta_{k,m} \ln x_{k,i} \ln y_{m,i} + v_i
\end{aligned} \tag{1}$$

where D_i is the distance from the production possibility frontier ($0 \leq D_i \leq 1$), $y_{m,i}$ and $x_{k,i}$ are the outputs and inputs respectively, and v_i is a stochastic error term, assumed to be $N[0, \sigma]$. The distance function assumes joint production and non-separability of outputs from inputs. If the alternative assumption of separability is valid, then production is effectively forced to be joint (Livernois and Ryan, 1989). The validity of the assumptions of both non-jointness and separability can be explicitly tested.

The output distance function is homogeneous of degree one in outputs (Shephard, 1970). In order to maintain the homogeneity conditions, the constraints $\sum_m \alpha_m = 1$, $\sum_n \beta_{mn} = \sum_m \beta_{km} = 0$ need to be imposed, while symmetry restrictions require $\beta_{mn} = \beta_{nm}$ and $\beta_{kl} = \beta_{lk}$. The homogeneity restrictions can be imposed through normalizing the function by one of the outputs (e.g. $y_{l,i}$), and the model can be expressed as a standard production frontier by moving the distance measure to the right hand side of the equation. This results in:

$$\begin{aligned}
-\ln y_{l,i} &= \alpha_0 + \sum_{m \neq l} \alpha_m \ln y_{m,i}^* + 0.5 \sum_{m \neq l} \sum_n \beta_{m,n} \ln y_{m,i}^* \ln y_{n,i}^* \\
&+ \sum_k \alpha_k \ln x_{k,i} + 0.5 \sum_k \sum_l \beta_{k,l} \ln x_{k,i} \ln x_{l,i} \\
&+ \sum_k \sum_{m \neq l} \beta_{k,m} \ln x_{k,i} \ln y_{m,i}^* + v_i - \ln D_i
\end{aligned} \tag{2}$$

where $y_{m,i}^* = y_{m,i}/y_{l,i}$ and the distance measure is equivalent to the inefficiency term (i.e. $-u_i = -\ln D_i$). For estimation purposes, the negative sign on the dependent variable can be ignored (i.e., we use $\ln y_{l,i}$ rather than $-\ln y_{l,i}$). This results in the signs of the estimated coefficients being reversed, but is more consistent with the expected signs of conventional production functions, and provides a convenient means of qualitatively assessing the results.

Improvements in technology over time result in a shift in the relationship between inputs and outputs. Technical change over the period of the data can be captured by including a time variable, t , into the model. This can be given by:

$$\begin{aligned}
\ln y_{l,i} &= \alpha_0 + \sum_{m \neq l} \alpha_m \ln y_{m,i}^* + 0.5 \sum_{m \neq l} \sum_n \beta_{m,n} \ln y_{m,i}^* \ln y_{n,i}^* \\
&+ \sum_k \alpha_k \ln x_{k,i} + 0.5 \sum_k \sum_l \beta_{k,l} \ln x_{k,i} \ln x_{l,i} \\
&+ \sum_k \sum_{m \neq l} \beta_{k,m} \ln x_{k,i} \ln y_{m,i}^* \\
&+ \gamma_1 t + \gamma_2 t^2 + \sum_k \gamma_k t \ln x_{k,i} - \ln D_i + v_i
\end{aligned} \tag{3}$$

The rate of technological change during each period can be determined by $\partial \ln y_{l,i} / \partial t = y_{l,i} (\gamma_1 + 2\gamma_2 t + \sum_k \gamma_k \ln x_{k,i})$, where $y_{l,i} = \exp(\ln y_{l,i})$.

A distributional assumption has to be made for $\ln D_i$ to separate the stochastic and inefficiency effects in the model. In this study, inefficiency is modelled explicitly as a function of known characteristics and exogenous effects, such that:

$$\ln D_i = \mu + \sum_l \delta_l z_{l,i} + w_i \tag{4}$$

where μ is the mean inefficiency level, Z is a set of L ($l=1, \dots, L$) firm-specific variables which may influence the firm's efficiency, δ_l is the associated inefficiency parameter coefficient, and w_i is an iid random error term (Battese and Coelli, 1995).

A criticism of the multi-output distance function approach is the potential for endogeneity bias resulting from outputs appearing as covariates in the distance function, as well as the normalisation of the outputs by the dependent variable (Atkinson *et. al.*, 2003; Felthoven and Morrison Paul, 2004; Kumbhakar and Lovell, 2000). This criticism is often disputed, with some arguing that the output ratios (y_m/y_l) are more likely to be exogenous than values of y_m used in other multi-output transformation functions (Kumbhakar and Lovell, 2000), and hence distance functions may be less susceptible to endogeneity bias than alternative multi-output models. Further, as the distance function represents a radial expansion of all outputs, given the set of inputs, the ratio $y_{m,i}/y_{l,i}$ remains constant and hence can be assumed to be exogenous (Morrison Paul and Nehring, 2005). This latter argument, however, is also seen as weakness of distance functions, because it implies that any increase in efficiency increases all outputs by the same proportion and that any random shock affects all outputs equally (Orea *et. al.*, 2005). For the case of a fishery, where catch composition depends on the relative abundance of the different species in the area fished and the selectivity of the fishing gear deployed, radial expansion is a reasonable assumption (and indeed is implicit in all single output fisheries production frontiers where a composite output measure is used).

DATA

Daily logbook data over the period 1995 to 2007 were combined with information on vessel characteristics. While a longer period of logbook data was available (back to 1970), the analysis was restricted to post-1995 due to substantially different management structures being in place before 1995. Within the data set, each logbook record was classified as either relating to the tiger prawn or banana prawn fishery. Only observations that were coded as relating to the tiger prawn fishery were used, eliminating almost all of the first season and the activity in the west of the fishery (the Joseph Bonaparte Gulf). The daily data were aggregated into weekly values, with the first day of week 1 each year being 1 January. Weekly, rather than annual, values were considered more appropriate given the sequential nature of the fishery.

Logbook information only records the catch of prawns as tigers, endeavours, bananas and kings. Data from scientific surveys taken from each area over each week of each season were used to separate the total catch of tiger prawns into their separate species (Venables and Dichmont, 2004). Equivalent species split information was also available to separate endeavour prawns to species. However, the data for the two endeavour species were combined because reliable stock information at the species level was not available for endeavour prawns, and as they form only a relatively small proportion of the total catch. All other species (banana, king and other prawns) were aggregated into an “other” category, representing between 2 to 10 per cent of the total catch each week.

The inputs in the production function were headrope length, engine power (kW) and hours fished over the week. From 2006, vessels were able to use quad gear (4 nets – two off each beam) rather than twin gear (2 nets – one off each beam) although they incurred a penalty in terms of headrope length if they did so. A dummy variable was used to capture the effects of this for vessels that used quad gear.

Weekly biomass estimates for the two tiger prawn species are estimated directly through regular stock assessments (Dichmont *et. al.*, 2003), but only a single composite endeavour prawn biomass estimate was available at a weekly level. The biomass estimates were converted to an index with the base being the average over the period as a whole. For the “other” prawn species, average catch per unit of effort (CPUE) was used as a proxy measure of stock abundance in order to derive the stock index. The use of CPUE as a stock index in production functions raises several issues (Pascoe and Coglán, 2002). However, given the relatively small contribution to total catch of the “other” species, it is unlikely that any problems associated with the use of the index will substantially influence the results.

Catch of each species was divided by the stock index to produce an index of partial exploitation rate. This involves an implicit assumption that the stock elasticity is equal to 1, consistent with the stock assessment process that assumes catch rate is linearly related to biomass. Zero catches of any species were nominally changed to a value of 0.01 kg to avoid problems when logging the data. This affected less than 1% of the observations for each of the three main species, but almost two thirds of the records for the “other” catch category. The final panel data set included 24,259 observations from

164 vessels that operated over the 13- year period. The data were logged and normalized such that the mean (logged) value was zero. A time variable was included to capture technical change. This was an annual variable rather than weekly because it is most likely that changes in technologies would occur between the seasons rather than during them.

The inefficiency model included information on the vintage of the vessel (i.e. estimated as 2007 minus the year built), the total number of boats fishing each week and each year, the moon phase expressed as an index of luminosity ranging from 0 (new moon) to 100 (full moon), and a series of dummy variables representing ownership structure (i.e. owner operator, single vessel company with an employed skipper, small company with 2 to 5 vessels and large companies with more than 5 vessels) were included in the inefficiency model (Equation 4). Several studies have suggested that inefficiency is linked to the vintage of the vessel (Pascoe and Coglán, 2002; Sharma and Leung, 1999). The number of boats fishing could contribute to crowding, thereby reducing individual vessels' efficiency. Conversely, there is a belief in the fishery that a critical number of vessels is necessary to find the prawns which are dispersed over a large area. Hence, reducing vessel numbers may reduce overall vessel efficiency given information sharing amongst crews. Moon phase is believed to affect catch rates, with catch rates being generally higher at or following the new moon (Salini *et. al.*, 2001). Individual vessel dummy variables were also incorporated into the inefficiency model as fixed effects, as the Battese and Coelli (1995) approach does not take full advantage of the panel nature of the data.

A summary of the main vessel information included in the analysis is presented in Table 1. There has been a slight shift in catch from brown to grooved tiger prawns over the period of the data examined, reflecting changes in seasonal closures and other overt management actions to reduce the fishing mortality on brown tiger prawns. Vessel engine power generally increased over time, while the average vintage decreased as older boats were replaced with newer boats. The average number of vessels fishing each week declined, reflecting the general decrease in the total number of vessels in the fishery.

Table 1. Summary of data used in the analysis

	Average vessel catch per week (kg)				Average Hours fished per week	Average vessel characteristics			Number of active boats
	Brown tiger	Grooved tiger	Endeavour	Other		Engine	Head-rope	Vintage	
1995	669	833	437	92	80	316	13	26	125
1996	736	952	420	88	76	305	13	24	127
1997	691	1007	413	94	81	325	13	24	129
1998	655	1083	494	91	79	329	13	23	130
1999	576	1147	351	88	76	331	13	23	129
2000	590	1123	375	87	75	337	13	22	121
2001	445	1241	422	86	75	345	12	22	116
2002	283	1390	325	89	77	361	12	21	114
2003	245	1455	397	92	80	366	11	20	98
2004	209	1434	452	92	79	368	11	20	96
2005	384	1251	284	91	79	379	10	19	89
2006	428	1201	342	92	79	382	10	19	77
2007	406	1256	373	88	76	379	11	18	51

RESULTS

The most appropriate functional form for the production function was determined in the previous study (Pascoe *et. al.*, 2010), so additional specification tests are not repeated. It has been shown that there is a trade-off between flexibility and theoretical consistency when using flexible functional forms such as the translog (Sauer *et. al.*, 2006). The previous study imposed monotonicity and curvature on the model through using a Bayesian estimation process (Pascoe *et. al.*, 2010). However, as we are particularly interested in estimating an inefficiency model in this paper, we are unable to

impose the same constraints. Instead, following Sauer *et al.* (2006), the models were tested *ex post* for their monotonicity and curvature properties at the mean (i.e. $(x,y)=1$; $\ln(x)=0$). The first derivatives were positive and the second derivatives were negative for all inputs, as expected, and consistent with the monotonicity requirement. Further, the determinant of the hessian of the second order derivatives with respect to the inputs was negative, indicating that it is negative semi-definite and hence the convexity conditions hold.

Most parameters of the translog model were significant at the 1 per cent level (Table 2) and similar to those estimated by (Pascoe *et al.*, 2010).² The coefficients for the different species were negative, implying that the output of all species increases as the level of inputs increase, as would be expected. An estimate of the goodness of fit of the production function component of the model was derived by comparing the predicted values with the actual values of the dependent variable. The correlation between the predicted and observed values was $r = 0.936$, from which $\bar{r}^2 = 0.913$, indicating the model is able to capture most of the variation in the dependent variable.

Given that $\ln(\bar{x}) = 0$, the coefficients for the inputs represent their production elasticities at the mean level of all inputs. The elasticity relating to fishing effort was not significantly different from 1, as expected. The elasticity relating to engine power was relatively low. While engine power can increase the area swept per unit of time, other factors – such as time fished and headrope length – have a greater impact on total catch. Increasing headrope length was estimated to produce a less than proportional increase in catch (elasticity = 0.723 at the mean, with standard error of 0.068). (Kompas *et al.*, 2004) found a similar, but lower production elasticity (elasticity = 0.62) for headrope in the banana prawn component of the fishery.

Efficiency, technical change and total factor productivity

Inefficiency was positively related to the total number of boats licensed in the fishery, and negatively related to number of boats fishing in any one period (Table 2). One interpretation of this is that former may be considered to indicate crowding effects with more boats licensed increasing efficiency, while the latter may indicate information sharing so that fewer boats operating at any one point in time may reflect less information flow. Traditional fisheries models assume that crowding externalities occur as a result of congestion on the fishing grounds, and that a reduction of fishing vessels will result in an increase in efficiency through a reduction in crowding (Smith, 1969). Evidence of the negative effects of crowding externalities on technical efficiency has been observed in other fisheries (Pascoe *et al.*, 2001). Within a year, efficiency may decrease with vessels numbers. In a geographically large fishery such as the northern prawn fishery, fishers are unable to effectively search themselves, and rely on information collected by other vessels. Reducing vessel numbers reduces the total area searched and the amount of information collected. An alternative interpretation of the second result relates to the direction of causality – potentially the least efficient vessels are the last to stop fishing for the year so the small set of vessels still operating at the end of the season is characterized by less efficiency on average.

Efficiency was also negatively related to the level of lunar illumination and the vintage of the vessel. The effects of moon luminosity and the vintage of the vessel on efficiency were as expected. Similarly, the relationship between moon phase and prawn catch rates was as expected, with lower catch rates being experienced on the full moon as prawns tend to burrow deeper to avoid the light (and the corresponding higher risk of predation) (Salini *et al.*, 2001). Likewise, other studies have identified a link between vintage of the vessel and its level of technical efficiency (Pascoe and Coglán, 2002; Sharma and Leung, 1999), with newer vessels generally having more efficient designs than older vessels.

Vessel ownership was also a significant factor affecting efficiency. In general, vessels belonging to larger companies were more efficient than those belonging to smaller companies, which in turn were more efficient than owner-operators. This may reflect the greater level of information sharing that can occur within a larger company fleet, but may also reflect fleet management skills, with the larger companies having better fleet managers. Alternatively, the larger companies may be able to attract and keep the better skippers and crew.³

Although the decline in boat numbers between 1995 and 2007 may have had a negative impact on technical efficiency, the removal of older vessels through buyback and consolidation, and replacement

of some older vessels by newer vessels resulted in a net increase in average technical efficiency in the fishery. The mean technical efficiency in 2007 was 0.793, compared to a mean technical efficiency score of 0.736 over the period 1995-2000.⁴ Although the mean efficiency scores appear to differ only marginally, the distribution of scores shifted to the right (Figure 1), with a higher proportion of vessels having high technical efficiency scores (i.e. ≥ 0.8).

Table 2: Model parameter estimates

	Coefficient	Standard error	t-statistic	
<i>Production frontier</i>				
Constant	0.756	0.013	56.769	***
Ln(Brown tiger)	-0.417	0.002	-252.757	***
Ln(Endeavour)	-0.249	0.002	-139.349	***
Ln(Other)	-0.037	0.001	-29.357	***
Ln ² (Brown tiger)	-0.051	0.000	-128.073	***
Ln ² (Endeavour)	-0.039	0.000	-91.883	***
Ln ² (Other)	0.001	0.000	3.377	***
Ln(Brown)*Ln(Endeavour)	0.053	0.001	73.754	***
Ln(Brown)*Ln(Other)	-0.001	0.000	-2.940	***
Ln(Endeavour)*Ln(Other)	-0.006	0.000	-13.448	***
Ln(Hours fished)	1.032	0.019	54.485	***
Ln(Engine power)	0.257	0.054	4.797	***
Ln(Headrope)	0.723	0.068	10.699	***
Ln ² (Hours fished)	0.170	0.005	37.393	***
Ln ² (Engine power)	0.048	0.077	0.627	
Ln ² (Headrope)	-0.339	0.098	-3.454	***
Ln(Hours)*Ln(Engine power)	-0.057	0.043	-1.314	
Ln(Hours fished)*Ln(Headrope)	-0.121	0.053	-2.269	***
Ln(Engine power)*Ln(Headrope)	-0.031	0.158	-0.194	
Ln(Brown tiger)*Ln(Hours fished)	-0.049	0.003	-18.547	***
Ln(Brown tiger)*Ln(Engine power)	-0.089	0.006	-14.223	***
Ln(Brown tiger)*Ln(Headrope)	0.095	0.008	12.570	***
Ln(Endeavour)*Ln(Hours fished)	-0.018	0.003	-6.790	***
Ln(Endeavour)*Ln(Engine power)	0.061	0.008	8.046	***
Ln(Endeavour)*Ln(Headrope)	-0.083	0.010	-8.554	***
Ln(Others)*Ln(Hours)	0.051	0.002	29.368	***
Ln(Others)*Ln(Engine power)	-0.022	0.004	-5.701	***
Ln(Others)*Ln(Headrope)	-0.015	0.004	-3.382	***
Time	0.040	0.004	9.373	***
Time ²	-0.003	0.000	-7.964	***
Time*Ln(Hours fished)	0.004	0.003	1.280	
Time*Ln(Engine power)	-0.017	0.009	-1.979	***
Time*Ln(Headrope)	-0.050	0.011	-4.611	***
Quad gear (dummy variable)	0.208	0.066	3.143	***
<i>Inefficiency model</i>				
Constant	-7.471	0.275	-27.200	***
Ln(Moon illumination)	0.574	0.043	13.278	***
Ln(Number of boats each week)	-2.716	0.090	-30.319	***
Ln(Vintage)	1.389	0.100	13.876	***
Ln(Number of boats over the year)	5.856	0.150	39.051	***
one boat (employed skipper)	-0.335	0.037	-9.179	***
2-5 boats	-0.250	0.057	-4.363	***
>5 boats	-0.696	0.055	-12.678	***
<i>Model statistics</i>				
σ^2	3.357	0.113	29.715	***
γ	0.980	0.001	1124.745	***
Log Likelihood	-14166			

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

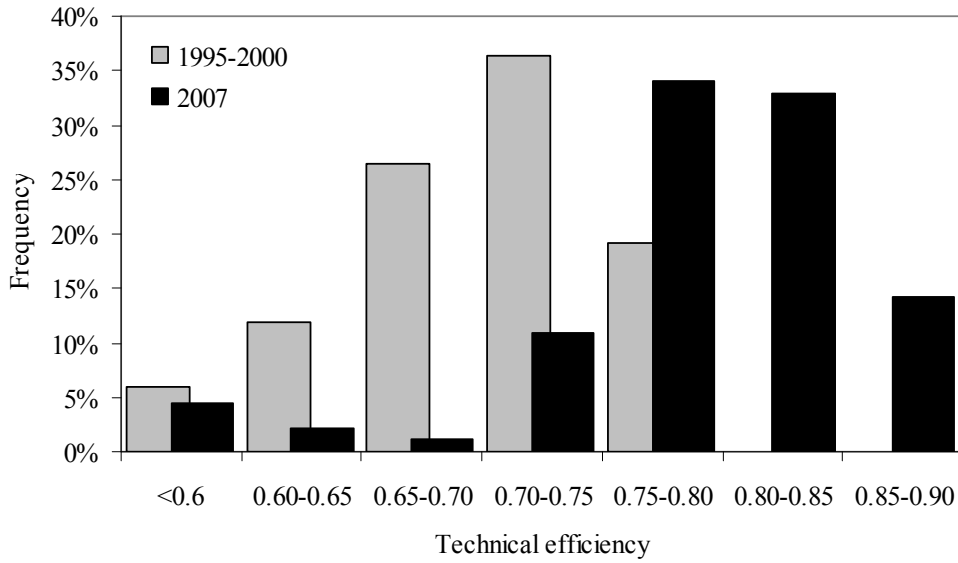


Figure 1. Among-vessel distribution of technical efficiency scores

The rate of technological change each year generally declined over the period of the data, and has been negative since 2001 (Figure 2). The cumulative effect is still an increase in productivity in 2007 compared to 1995. This corresponds to the change to an effort unit system of management (based around gear units related to total headrope length) around this time (2001), and the progressive reduction in the amount of headrope length that vessels were able to use over the period 2001 to 2007. Further, season length also decreased in order to reduce total effort in the fishery and aid the recovery of one of the species. Both these factors may have slowed the rate of technical change (which still remained positive albeit increasing at a slower rate). Total factor productivity (the product of technical change and efficiency change) has remained fairly constant over the period of the data (Figure 2).

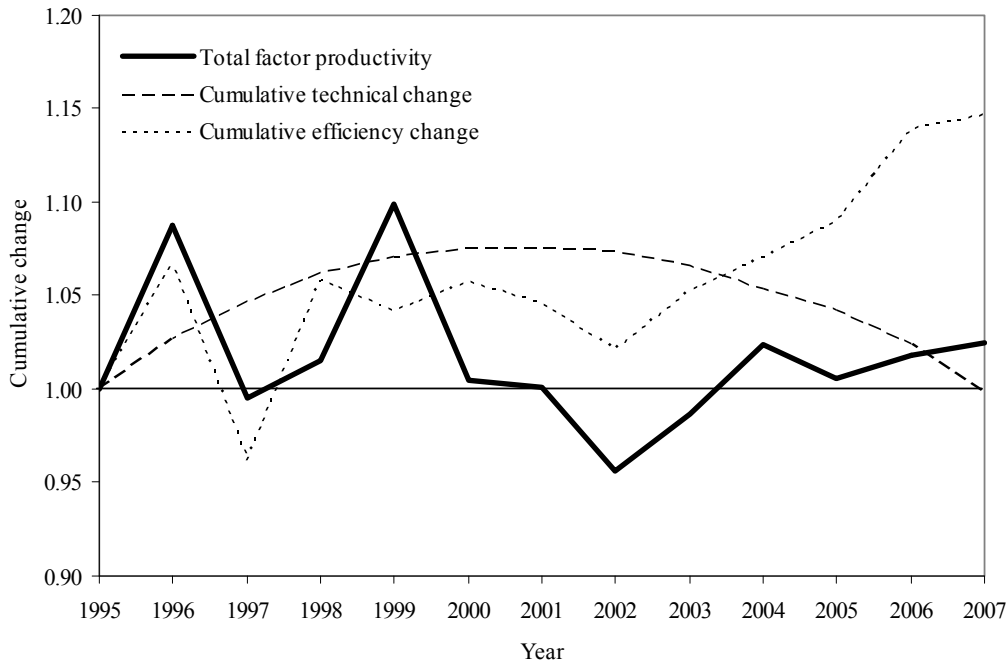


Figure 2. Technical change, efficiency change and total factor productivity

DISCUSSION AND CONCLUSIONS

The main objective of this study was to determine what, if any, impact a buyback program has on the efficiency of the fleet. The results of the analysis largely confirm that the average efficiency of a fleet is likely to increase as a result of a buyback program, mainly as the least efficient vessels exit the fishery first. Further, we found that the average efficiency of those boats that remained also increased, largely due to the reduced crowding effect and consequently higher catch rates.

The industry have suggested that a smaller fleet size may lead to reduced efficiency as the total area being searched at any one time is less, and the probability of finding prawns reduced as a consequence. The results of the analysis support this argument to a degree, as the number of vessels operating at any one time was positively related to efficiency (or rather negatively related to inefficiency). However, the impact of greater vessels numbers overall on efficiency was negative, as the crowding externality was greater than the positive searching externality. Consequently, while individual vessels and firms may have more difficulty finding prawns post buyback, their higher catch rates due to less competition will result in an overall gain. Further, the reduced fleet size has enabled the restrictions on headrope length to be substantially relaxed, such that vessels are able to use a more efficient mix of inputs. This effect is not captured in the analysis as these changes occurred after the period of the data examined.

The key motivation of the buyback program was to enhance the economic performance of the fleet as it was recognised that the restrictions placed on the vessels were severely impeding their efficiency. Australia has an explicit objective of maximising the returns to society from its Commonwealth managed fisheries (Dichmont *et. al.*, 2010), and this program was aimed at helping the fishery achieve this by reducing capacity and enabling some of the restrictions. Restrictions in previous years were imposed primarily to offset improvements fishing power over time (Bishop *et. al.*, 2004). Given the way the model is structured, the subsequent removal (or at least reduction) of these restrictions is likely to manifest itself as technical progress rather than efficiency change. Headrope length changes are captured directly in the production function, but other restrictions are not implicitly included in the model but instead are captured in the time trend (representing technical change). Total factor productivity is likely to change as a result of both technical and efficiency change, the former arising from the reduced controls on inputs and the latter arising out of the reduced crowding.

An economic evaluation of the buyback program found substantial increases in profitability of the vessels remaining in the fishery in 2007-08 compared to the average performance prior to the buyback (Vieira *et. al.*, 2010). These results were slightly confounded by changes in fuel and prawn prices, as well as a better than average banana prawn season. Nevertheless, after accounting for these factors, fleet economic performance post buyback was still better than before.

The apparent benefits of the buyback program in the fishery may be short lived if the additional profits attract substantially greater investment into the fishery, as is often the case in fisheries post buyback (Holland *et. al.*, 1999). In the case of the northern prawn fishery, the fishery is to move to a system of individual transferable quotas in 2012, and it is expected that much of the benefits of the buyback will be retained in some form.

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REFERENCES

- ABARE, 2009, Australian Commodity Statistics 2008 ABARE, Canberra.
- Atkinson, S.W., C. Cornwell, and O. Honerkamp, 2003, Measuring and decomposing productivity change: stochastic distance function estimation versus data envelopment analysis, *Journal of Business and Economic Statistics*, 84(April), pp 284-294.

- Battese, George E., and Tim J. Coelli, 1995, A model for technical inefficiency effects in a stochastic frontier production function for panel data, *Empirical Economics*, 20, pp 325-332.
- Bishop, Janet, W. N. Venables, and You-Gan Wang, 2004, Analysing commercial catch and effort data from a Penaeid trawl fishery: A comparison of linear models, mixed models, and generalised estimating equations approaches, *Fisheries Research*, 70(2-3), pp 179-193.
- Coglan, Louisa, and Sean Pascoe, 2007, Implications of human capital enhancement in fisheries, *Aquat. Living Resour.*, 20(3), pp 231-239.
- Dichmont, C. M., A. E. Punt, A. Deng, Q. Dell, and W. Venables, 2003, Application of a weekly delay-difference model to commercial catch and effort data for tiger prawns in Australia's Northern Prawn Fishery, *Fisheries Research*, 65(1-3), pp 335-350.
- Dichmont, Catherine M., Sean Pascoe, Tom Kompas, and Andre E. Punt, 2010, On implementing maximum economic yield in commercial fisheries, *Proceedings of the National Academy of Science* 107(1), pp 16-21.
- FAO, 2004, Progress on the Implementation of the International Plan of Action for the Management of Fishing Capacity, In *Technical Consultation to Review Progress and Promote the Full Implementation of The IPOA to Prevent, Deter and Eliminate IUU Fishing and the IPOA for the Management of Fishing Capacity*, Rome, Italy, 24-29 June, FAO, Rome.
- Felthoven, Ronald G., and Catherine J. Morrison Paul, 2004, Multi-output, nonfrontier primal measures of capacity and capacity utilization, *American Journal of Agricultural Economics*, 86(3), pp 619-633.
- Holland, Dan, Eyjolfur Gudmundsson, and John Gates, 1999, Do fishing vessel buyback programs work: A survey of the evidence, *Marine Policy*, 23(1), pp 47-69.
- Kirkley, James, Dale Squires, and Ivar E. Strand, 1995, Assessing Technical Efficiency in Commercial Fisheries: The Mid-Atlantic Sea Scallop Fishery, *American Journal of Agricultural Economics*, 77(3), pp 686-697.
- _____, 1998, Characterizing Managerial Skill and Technical Efficiency in a Fishery, *Journal of Productivity Analysis*, 9(2), pp 145-160.
- Kompas, Tom, Tuong Nhu Che, and R. Quentin Grafton, 2004, Technical efficiency effects of input controls: evidence from Australia's banana prawn fishery, *Applied Economics*, 36(15), pp 1631 - 1641.
- Kumbhakar, Subal C., and C. A. Knox Lovell, 2000, *Stochastic frontier analysis*, Cambridge University Press, Cambridge, UK.
- Livernois, J. R., and D. L. Ryan, 1989, Testing for Non-jointness in Oil and Gas Exploration: A Variable Profit Function Approach, *International Economic Review*, 30(2), pp 479-504.
- Morrison Paul, Catherine J., and Richard Nehring, 2005, Product diversification, production systems, and economic performance in U.S. agricultural production, *Journal of Econometrics*, 126(2), pp 525-548.
- Orea, Luis, Antonio Alvarez, and Catherine J. Morrison Paul, 2005, Modeling and measuring production processes for a multi-species fishery: alternative technical efficiency estimates for the Northern Spain hake fishery, *Natural Resource Modeling*, 18(2), pp 183-213.
- Pascoe, S., J. L. Andersen, and J. W. de Wilde, 2001, The impact of management regulation on the technical efficiency of vessels in the Dutch beam trawl fishery, *European Review of Agricultural Economics*, 28(2), pp 187-206.

- Pascoe, Sean, and Louisa Coglan, 2000, Implications of differences in technical efficiency of fishing boats for capacity measurement and reduction, *Marine Policy*, 24(4), pp 301-307.
- _____, 2002, The contribution of unmeasurable inputs to fisheries production: An analysis of technical efficiency of fishing vessels in the English Channel, *American Journal of Agricultural Economics*, 84(3), pp 585-597.
- Pascoe, Sean, André E. Punt, and Catherine M. Dichmont, 2010, Targeting ability and output controls in Australia's multispecies northern prawn fishery, *European Review of Agricultural Economics*, [in press].
- Salini, J., D. Brewer, M. Farmer, and P. Jones, 2001, Lunar periodicity of prawns and by-catch in trawls from the Gulf of Carpentaria, northern Australia, *Marine Biology*, 138(5), pp 975-983.
- Sauer, J., K. Frohberg, and H. Hockmann, 2006, Stochastic efficiency measurement: The curse of theoretical consistency, *Journal of Applied Economics*, 9(1), pp 139-165.
- Sharma, K.R., and P. Leung, 1999, Technical efficiency of the longline fishery in Hawaii: an application of a stochastic production frontier, *Marine Resource Economics*, 13(3), pp 259-74.
- Shephard, R.W., 1970, *Theory of Cost and Production Functions*, Princeton University Press, Princeton.
- Smith, V.L., 1969, On models of commercial fishing, *Journal of Political Economy*, 77(2), pp 181-198.
- Venables, William N., and Catherine M. Dichmont, 2004, A generalised linear model for catch allocation: an example from Australia's Northern Prawn Fishery, *Fisheries Research*, 70(2-3), pp 405-422.
- Vieira, Simon, Christopher Perks, Kasia Mazur, Robert Curtotti, and Michelle Li, 2010, Impact of the structural adjustment package on the profitability of Commonwealth fisheries, In *ABARE research report 10.01*, ABARE, Canberra.
- Walden, John B., James E. Kirkley, and Andrew W. Kitts, 2003, A limited economic assessment of the Northeast Groundfish Fishery buyout program, *Land Economics*, 79(3), pp 426-439.
- Weninger, Quinn, and K. E. McConnell, 2000, Buyback programs in commercial fisheries: efficiency versus transfers, *The Canadian Journal of Economics*, 33(2), pp 394-412.

ENDNOTES

¹ A criticism of buyback programs that do not remove the boat from fishing is that the capital can be exported elsewhere, such that the overcapacity problem is transferred rather than reduced. We do not address this problem in this paper.

² Vessel specific dummy variables are not presented in Table 2 due to their large number. However, most were significant.

³ Information on skipper was available for only some of the vessels.

⁴ The previous study using the Bayesian estimation approach and assuming a half normal inefficiency distribution found a higher average efficiency level of 0.855 (Pascoe *et al.*, 2010). Kompas *et al.* (2006) found a comparable average efficiency of 0.774 in the banana prawn component of the fishery for the first half of the data (1994-200).