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Original Article

Use of catch and effort data to monitor trends in economic performance in fisheries

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In many low-valued fisheries, the quantity and types of data that might be available to support fisheries management are often limited. Generally, information on the economic performance of the fishery is low in priority in these fisheries. Basic catch and effort information, however, may contain implicit information about economic performance of the vessels. From these data, technical efficiency scores and measures of capacity utilization can be derived. The technical efficiency score can provide a proxy measure of the distribution of economic performance, while changes in capacity utilization theoretically reflect changes in the economic conditions in the fishery. Given this, changes in these measures over time should also reflect changes in economic outcomes and performance. To test this, we use data from a data-rich fishery, including catch and effort information as well as detailed economic information (i.e. vessel-level profitability). Key technical performance measures are estimated using data envelopment analysis and compared with the economic performance measures. We show that these technical performance measures can provide useful indicators of changes in economic performance when economic information is not available.

Keywords: capacity utilization, economic performance indicators, fisheries management, technical efficiency.

Introduction

In many low-value fisheries, and in low-income coastal nations, the high cost of data collection relative to the value of the fishery limits the quantity and types of data that might be available to support fisheries management. Often, lowest in priority in the list of data to be collected is information on the economic performance of the fishery, as monitoring resource sustainability usually takes precedence. This has been identified as a common legacy problem of fisheries management, which is largely seen primarily as having a biological focus (Hanna, 2011). Considering economic performance aspects in fisheries management can provide useful information about behavioural incentives that underly fleet behaviour, as well as understanding the extent to which any economic objectives are being achieved. However, even in higher-value fisheries, a lack of investment in the collection and analysis of economic data is a common barrier to incorporating economics into fisheries management (Hilborn *et al.*, 2005; Emery *et al.*, 2017). Where economic data are collected, time delays in collection, processing, and publication often result in these data being out of date.

However, basic catch and effort information are more commonly collected in most fisheries. With increased use of electronic submission processes, these data are often real time or close to real time. Given revenue is related to the level and composition of catch, and costs are related to fishing effort, such data may reflect the real-time economic performance of the fleet. For example, Cambiè *et al.* (2012) suggested that indicators of vessel profitability might include simple technical performance measures such as average catch or revenue per capacity unit (i.e. vessel gross tonnage).

Productivity analysis provides a potential means to relate changes in catch and effort with changes in economic performance. Productivity analysis relates the level of output to the levels of inputs as a technical measure of performance. Differences in these measures between individuals and/or over time reflect changes in technical efficiency. That is, how well inputs are used by an individual fisher/vessel to produce outputs relative to others. A related measure, capacity utilization, estimates the extent to which fixed inputs (e.g. boats) are operating at their full capacity, with underutilization indicating the presence of excess capacity.

The estimation of technical efficiency from such data has also been undertaken for a wide variety of fisheries. For example, technical efficiency has been estimated for trawl fisheries (e.g. Hannesson *et al.*, 1981; Kirkley *et al.*, 1995; Kompas *et al.*, 2004; Färe *et al.*, 2006; Greenville *et al.*, 2006; Pascoe *et al.*, 2007; Vinuya, 2010; Guttormsen and Roll, 2011; Pascoe *et al.*, 2012, 2017, 2018; Solís *et al.*, 2015; Green, 2016), lobster and crab fisheries (e.g. Pascoe *et al.*, 2013a; Rust *et al.*, 2017; Schrobback *et al.*, 2023), small pelagic fisheries (e.g. García del Hoyo *et al.*, 2004; Estrada *et al.*, 2018), and tuna longline fisheries (e.g. Sharma and Leung, 1998; New, 2012; Nguyen *et al.*, 2022). Similarly, estimates of capacity utilization have been undertaken in a wide range of fisheries across the EU (e.g. Tingley *et al.*, 2003; Vestergaard *et al.*, 2003; Espino *et al.*, 2005; Pascoe and Tingley, 2006; Lindebo *et al.*, 2007; Tsitsika *et al.*, 2008; Idda *et al.*, 2009; Castilla-Espino *et al.*, 2014; Pinello *et al.*, 2016), Asia (e.g. Reid *et al.*, 2003),

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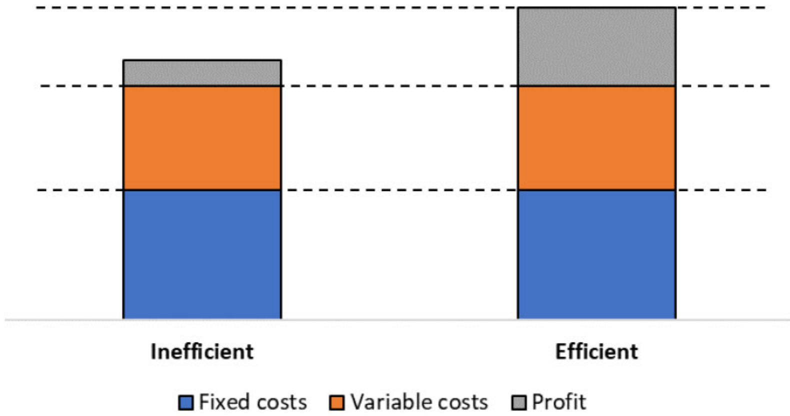

Figure 1. Difference in profits for an efficient and inefficient vessel using the same level of inputs.

the USA (e.g. Kirkley *et al.*, 2002; Felthoven *et al.*, 2009), Australia (e.g. Pascoe *et al.*, 2013b; Schrobback *et al.*, 2015; Rust *et al.*, 2017), and Canada (e.g. Dupont *et al.*, 2002; Squires *et al.*, 2010). A recent review of applications of efficiency and capacity utilization in fisheries is provided by Van Nguyen and See (2023).

While changes in efficiency and capacity utilization in many of these studies were undertaken to assess changes in management, or the importance of socio-demographic or technological drivers in the fishery, such measures also related theoretically to profitability (Diewert, 1971). Maximizing production given a set of inputs is the dual of minimizing costs given a set of outputs, based on Shephard's duality theory (Shephard, 1970). As a result, technical efficiency should provide a proxy measure of economic performance. Similarly, assuming profit maximizing behaviour of fishers, then changes in capacity utilization theoretically reflect changes in the economic conditions in the fishery.

In this paper, we use data envelopment analysis (DEA) to estimate technical efficiency and capacity utilization as benchmark performance metrics relating to Australia's Northern Prawn Fishery—a data-rich fishery in terms of both economic and catch-effort data. We then compare these metrics (hereafter termed technical performance measures) to other economic metrics (gross margins, boat cash profits, and full equity profits) to determine the extent to which technical performance measures may provide useful indicators of changes in economic performance. If technical performance measures are found to have similar trends to other economic metrics, these measures can be used as proxy for monitoring changes in fishery economic performance in the absence of detail economic data.

Material and methods

Theoretical link between technical efficiency, capacity utilization, and changes in economic performance

The concept of a production function derives directly from profit maximization (Diewert, 1971), where individual producers aim to choose the combination of inputs that produce the most output at least cost (Fuss and McFadden, 1978). From Shephard's duality theory (Shephard, 1970), maximizing production given a set of inputs is the dual of minimizing costs given a set of outputs.

The methods underlying productivity analysis have a long pedigree in economic analysis; Debreu (1951) and Koopmans (1951) introduced the concept of a production frontier, where deviations from the frontier reflected measures of the technical efficiency of the individual producer. Farrell (1957) developed a simple measure of the level of efficiency as the ratio of actual to potential (frontier) output. From these, a range of parametric (e.g. Aigner *et al.*, 1977) and non-parametric approaches (e.g. Charnes *et al.*, 1978; Färe and Grosskopf, 1983) have been developed to empirically estimate the frontier and measure these deviations.

The key measures examined in this study are output-oriented technical efficiency and capacity utilization. Output-oriented technical efficiency represents the extent to which outputs are being maximized given the set of all inputs used (i.e. fixed and variable), while capacity utilization represents the extent to which outputs are being maximized given the set of fixed inputs used. As capacity utilization also includes an element of technical efficiency, this is usually removed to provide an "unbiased" estimate of capacity utilization (Färe *et al.*, 1989).

These measures, while conceptually similar, have different implications in terms of vessel profitability. If a vessel is inefficient, it is producing less catch than an efficient vessel with the same level of inputs. This means it has lower revenue with same costs, and hence lower profits than if the vessel operated efficiently. This can be seen in Figure 1, where the inefficient vessel has the same fixed and variable costs as its equivalent efficient, but lower total revenue and hence lower profits.

Over time, it would be expected that if average technical efficiency increases, then average profitability of the fleet would also most likely increase. Conversely, if average technical efficiency decreases, then average profitability of the fleet also most likely decreases. We say most likely, as profitability of even efficient vessels may change due to changes in input and output prices. *Ceteris paribus*, however, we would expect this relationship to hold.

In resource-based industries, such as fisheries, economic performance will also vary with the level of the resource. In periods of high stock levels, catch per unit of fishing effort is expected to be higher than in periods of lower stock, and hence profits are also expected to be higher. This effect will manifest between time periods rather than between individual vessels,

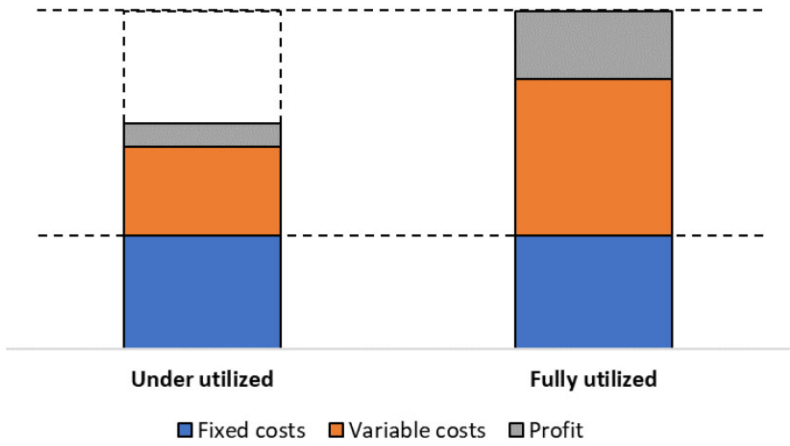

Figure 2. Difference in profits for a fully and under-utilized vessel.

as all vessels will be subject to similar, if not the same, stock conditions.

In contrast, capacity utilization is linked directly to the economic conditions in the fishery. While technical efficiency measures difference in output given a set of inputs (both fixed and variable), capacity utilization relates to output differences as a result of different levels of use of variable inputs, usually represented by some measure of fishing effort such as days fished. This in turn depends on the relative marginal cost of fishing and the marginal revenue from an additional unit of fishing effort. With evidence from many fisheries that fishers do aim to maximize individual profits (e.g. Dupont, 1993; Robinson and Pascoe, 1997; Pascoe and Robinson, 1998; Poos *et al.*, 2013; Alizadeh Ashrafi *et al.*, 2020; Alizadeh Ashrafi and Abe, 2021), it would be expected that fishers adjust their level of fishing effort (and hence capacity utilization) in response to changes in prices, catch rates, or costs.

The implications of capacity utilization as a measure of fisheries economic performance, then, is more nuanced than that of technical efficiency. Within a year, differences in capacity utilization between vessels may reflect differences in access to the resource. For example, ports nearer to the main fishing grounds would have lower access costs and potentially higher levels of capacity utilization (Tingley and Pascoe, 2005; Poos *et al.*, 2013). Hence, it would be expected that under-utilized vessels have lower levels of fishing profits, even though variable costs are also lower (Figure 2), and both may be maximizing their individual profits given their individual circumstances.

As with technical efficiency, changes in average capacity utilization for the fleet over time are also likely to provide information on fisheries economic performance. Over time, if average capacity utilization increases, then this most likely reflects improved economic conditions in the fishery and subsequently profitability, on average, of individual vessels is also most likely to have increased. Conversely, declines in average capacity utilization are most likely indicative of less favourable economic conditions in the fishery and consequently lower profits on average.

Fisheries management can also impact both technical efficiency and capacity utilization, and many previous studies of technical performance in fisheries have focused on the effects of management on these measures (e.g. Felthoven, 2002; Walden *et al.*, 2003; Greenville *et al.*, 2006; Pascoe *et al.*, 2012). Restrictions imposed by fisheries management that impact technical efficiency and/or capacity utilization will also have consequent implications for vessel profitability. The aim of this study, however, is not to assess the impacts of management on technical performance measures nor vessel profitability, but to explore the potential of the relationship between technical performance measures and economic performance as a proxy for monitoring changes in fishery economic performance when economic data are limited.

Data envelopment analysis (DEA)

We used data envelopment analysis (DEA) to assess the different technical performance measures. DEA is well established in the economics literature for productivity analysis (Färe *et al.*, 1989, 2000; Färe and Grosskopf, 2000), and in fisheries in particular (e.g. Reid *et al.*, 2003; Tingley *et al.*, 2003; Walden *et al.*, 2003; Vestergaard *et al.*, 2003; Herrero, 2005; Pascoe and Tingley, 2006; Maravelias and Tsitsika, 2008; Tsitsika *et al.*, 2008). Stochastic production frontiers are often considered better at estimating technical efficiency in fisheries due to the often high degree of "luck" involved in fishing, particularly when efficiency is conserved over a small time step (e.g. a day, week, or month) (Lee and Holland, 2000; Tingley *et al.*, 2005). With less frequent data (e.g. annual), however, short-term variations due to "luck" may be averaged out, with studies applying DEA to lower-frequency data being found to be less sensitive to stochastic error (Ruggiero, 2007). DEA is also generally considered better for capacity estimation in multi-species fisheries (Färe *et al.*, 2000; Pascoe *et al.*, 2003; Tingley *et al.*, 2003). As we are interested in both technical efficiency and capacity utilization, the use of DEA as a common measurement framework was considered the most appropriate.

The general form of the output-oriented DEA model is given by:

$$Max\ \Phi_1. \tag{1}$$

Subject to

$$\Phi_1 y_{1,m} \le \sum_j z_j y_{j,m} \quad m \in M, \tag{2}$$

$$\sum_j z_j x_{j,n} \le x_{1,n} \quad n \in N, \tag{3}$$

where Φ_1 is a scalar showing by how much the production of each firm can increase output, $y_{j,m}$ is amount of output m by firm j, $x_{j,n}$ is amount of input n used by boat j and z_j

are weighting factors. The set of inputs (N) can be separated into fixed and variable factors. For capacity estimation, only fixed inputs are considered in the analysis (i.e. included in the set N), while technical efficiency estimation involves the inclusion of both fixed and variable inputs. Variable returns to scale can be imposed by adding a further restriction of $\sum_j z_j = 1$. Without this restriction, constant returns to scale are imposed.

The same model is used for both estimation of technical efficiency and capacity utilization, the difference being the treatment of variable inputs. Capacity output is defined as Φ_1 multiplied by observed output (u), using fixed inputs only in the model. This also assumes that all inputs are used efficiently at their optimal capacity. Therefore, this measure represents the technically efficient capacity utilization (TECU), and is given by:

$$TECU = y \bullet (\Phi_1 y)^{-1} = \Phi_1^{-1}. \quad (4)$$

The measure of TECU ranges from 0 to 1, with 1 being full capacity utilization (i.e. 100% of capacity). Values <1 indicate that the firm is operating at less than its full output potential given the set of fixed inputs.

In practice, this measure reflects both technical efficiency and capacity utilization. It is likely to be biased downwards as part of the increase in output may be due to improved efficiency as well as improved capacity utilization (Färe *et al.*, 1989). Hence, an adjustment is necessary to separate out the capacity utilization component to correct for this bias. An adjusted or "unbiased" estimate of capacity utilization can be estimated by:

$$CU = TECU \bullet TE^{-1} = \Phi_2 \bullet \Phi_1^{-1}, \quad (5)$$

where Φ_2 represents the extent to which output can increase through using all inputs efficiently (i.e. including both fixed and variable inputs into the model analysis), and TE is the estimated level of technical efficiency, given by:

$$TE = \Phi_2^{-1}. \quad (6)$$

This "unbiased" measure also has other advantages. As noted previously, DEA is often criticized as a means of estimating efficiency as it does not account for random error. However, as any distorting effects of random error are similar (at least in terms of direction) in both Φ_1 and Φ_2, the ratio of the two is less affected by random noise (Holland and Lee, 2002).

From these measures, we can also derive an estimate of scale efficiency, which provides an indication as to how close the vessel is to its optimal scale. Productivity, expresses as total output per unit input, is greatest at the point where returns to scale are equal to 1 (Coelli *et al.*, 1998). A measure of scale efficiency is estimated as the ratio of technical efficiency with variable returns to scale (i.e. $\sum z_j = 1$) compared with technical efficiency with constant returns to scale imposed (Coelli *et al.*, 1998), which provides a measure as to how close a vessel is to the (technically) optimal scale (Orea, 2002).

Given information on prices of each of the species, allocative efficiency can also be estimated. This reflects the degree to which fishers are catching the revenue-maximizing combination of species. As we are considering data-limited situations (where even price information may be unavailable), allocative efficiency was not estimated for the main analysis. Allocative efficiency, however, is estimated and discussed further in the Supporting Information.

Dealing with stock in DEA

The fish stock is a significant input into the fisheries production process. Treatment of stocks in DEA models, however, is complex. A common approach is to estimate the technical performance measures in each time period separately on the assumption that all fishers face the same stock conditions equally (Tingley *et al.*, 2003; Schrobback *et al.*, 2023), or use DEA window analysis to compare vessels over different "windows" of time (e.g. Vázquez-Rowe and Tyedmers, 2013). This, however, makes assessing changes in technical performance over time difficult. Where stock information is available, these can be included as non-discretionary inputs (Andersen, 2005). For multi-species fisheries, a composite stock index may also be appropriate (Duy and Flaaten, 2016).

The impact of stock on the catch of each vessel is not necessarily homogeneous. Even within a single year, spatial and temporal differences in stock abundance and the response of fishers to these will manifest as part of the efficiency measure for the individual vessels. Excluding stock all together from the analysis and estimating efficiency over time provides a TE score that is a combination of both technical efficiency and stock condition (and its impact on production). This combined effect is expected to be of more relevance to economic performance and allows for differences in individual fisher skill as well as the effects of spatio-temporal variations in relative stock abundance on production to be captured. This combined measure also captures the impact of any changes in technology.

This measure is estimated by comparing observations across the entire time series. An estimate of the stock effect each year (and the influence of any technological change) can be derived by dividing this combined TE-stock measure by the TE measure estimated in each year separately.

Case study data

The analysis uses data from the Australian Northern Prawn Fishery (NPF). This multispecies fishery was selected as a case study as it is data rich in terms of both economic and catch and effort data. Further details on the fishery are given in the Supporting Information.

The fishery has a long history of efficiency and productivity analysis. Earlier studies tended to focus on the separate sub-fisheries. For example, Kompas *et al.* (2004, 2009) examined the relationship between input controls and technical efficiency levels for the banana prawn component of the fishery; Pascoe *et al.* (2010) examined targeting ability for individual species in the multispecies tiger prawn fishery using a multispecies distance function; Pascoe *et al.* (2012) examined the impact of the effort reduction (buyback) programme on efficiency in the tiger prawn fishery; Pascoe *et al.* (2018) examined changes in efficiency over the banana prawn fishing season and implications for setting the MEY trigger; and Van Nguyen *et al.* (2021) examined the sensitivity of model functional form on the efficiency estimates for the banana prawn fishery. Only one study to date has estimated efficiency across the whole fishery: O'Donnell (2013) used aggregate fishery level data to estimate measures of total factor productivity change, environmental change, technical efficiency change, and scale efficiency change over time in the fishery between 1974 and 2010.

Vessel level catch and effort data were obtained from Australian Fisheries Management Authority (AFMA) logbooks covering the period 1999–2000 to 2019–2020. For consistency with the available economic data, catch and effort for each vessel were aggregated to a financial year level, with separate catch values for common banana prawns, redleg banana prawns, tiger prawns (combining both brown and grooved tiger prawns), endeavour prawns (red and blue endeavour combined), and other prawn species (see Supporting Information). In total, 1521 observations were obtained, covering 160 different vessels that operated for at least 1 year in the fishery. Of the 52 vessels currently in the fishery, 35 operated over the full time period of the data (Supplementary Figure S1).

Vessel information also included details on the number of days fished, engine power, and vessel length. Information on hours fished was also available, but this was considered inaccurate for the earlier years in the time series so was not used in this study.

Price information was also compiled at a financial year (annual) level for each of the species. These were derived from reports by the Australian Bureau of Agriculture and Resource Economics and Sciences (ABARES) (e.g. Steven *et al.*, 2020) as well as industry-provided price data used in the stock assessment process and estimation of the trigger catch rates.

Economic data (vessel-level costs and earnings) over the same period were derived from ABARES economic surveys (e.g. Bath and Green, 2016; Bath *et al.*, 2019; and earlier reports). These covered the years 1999–2000 to 2016–2017. Data for earlier years were also available, although not used in the study (which was limited to the turn of the century). The economic data were available for a subset of the fleet. In total, 530 observations were available, which were subsequently matched with the efficiency analysis results from the catch and effort data. The key economic parameters of interest were gross margins (a short-term measure of vessel financial performance), boat cash profits (a medium-term financial measure of vessel performance), and boat full equity profits (a longer-term measure of economic performance).

All economic data were inflated to 2019–2020 real values using the Consumer Price Index (CPI), which reflects price changes over time of a standardized bundle of goods purchased by consumers. The real values of the derived profit measures are related to what they can be used to purchase, with the CPI reflecting this change in value over time. Alternative approaches could also have been applied, such as the use of the Gross Domestic Product (GDP) implicit price deflator, which reflects price changes of all goods that contribute to a country's GDP. A further alternative approach is to use a measure that reflects the changes in the costs of resources used in the industry (Turner *et al.*, 2019). ABARES (Bath *et al.*, 2019) produces an output and input price index for the fishery, which could have been applied separately to the cost and revenue data in the analysis. The implications of the use of different price indexes to assess changes in real profits were not assessed. While inter-annual changes may differ between the different indexes, empirical analysis suggests that these indexes tend to converge over time (e.g. Browne and Cronin, 2010; Myers *et al.*, 2018).

Analyses and results

Efficiency and capacity utilization over time

As we are interested in the degree to which technical performance measures may reflect changes in economic performance of the fleet over time, all individual vessel's catch and effort data were pooled, and the technical performance measures estimated across the whole time series rather than year by year. Changes in resource abundance will directly affect the level of output per unit of effort (i.e. the catch rate), with a direct impact on revenue and fishery profits, *Ceteris paribus* (Marshak and Link, 2021). *A priori*, by excluding stock as an input, changes in stock abundance (or other environmental drivers) are likely to manifest as changes in the measure of technical efficiency, as lower (or higher) levels of output are realized for the given combination of inputs employed. Similarly, any changes in technology will also be captured in this composite measure. The impact of stock (and technology) changes on the derived technical efficiency scores is illustrated in the Supporting Information.

Estimates of scale and allocative efficiency were also derived and are presented in the Supporting Information. Allocative efficiency was found to be significant in the subsequent regression analysis, indicating that this measure should also be estimated provided appropriate cost data are available. Scale efficiency was high across the time period, above 0.97 for at over 75% of the observations, suggesting the vessels were mostly operating at close to an optimal scale over the period of the data.

Changes in relative input and output prices over time will potentially affect capacity utilization; an increase in input prices relative to output prices would result in fishers fishing less (and vice versa), manifesting itself as reduced capacity utilization. The capacity utilization also indicates the presence of excess capacity, which may exist for economic reasons as above, or may be due to overcapitalization of the fishery—the classic too many boats chasing too many prawns (given the economic conditions in the fishery).

Given this, it would be expected that the technical performance measures would not only reflect information on changes in economic performance but provide a possible explanation for any changes in economic performance.

The distribution of the key technical performance scores over the full period of the data (comparing all observations across time) are presented in Figure 3. The horizontal dashed line in Figure 3 represents the last major buyback programme, in which the fleet was reduced from over 100 to 52 boats.

From Figure 3, the unbiased measure of capacity utilization was generally lower before the buyback than after, as might be expected, as the buyback removed some of the excess capital from the fishery. From 2007 to 2008, capacity utilization in the fishery was relatively high, with just small interannual variations. Technical efficiency levels were also generally higher after the buyback. The gradual increase in technical efficiency after the 2007–2008 reflects the recovery of the tiger prawn stocks.

Relationship with economic performance measures

A key objective of the study is to determine the extent to which these technical performance measures can provide information on economic performance in the fishery. Three key measures of economic performance were extracted from the available vessel-level economic data: full equity profits (revenue minus cash and non-cash costs, including capital costs), boat cash income (revenue minus all cash costs, including fixed and variable costs), and gross margins (revenue minus variable costs). The contribution of technical efficiency (which in

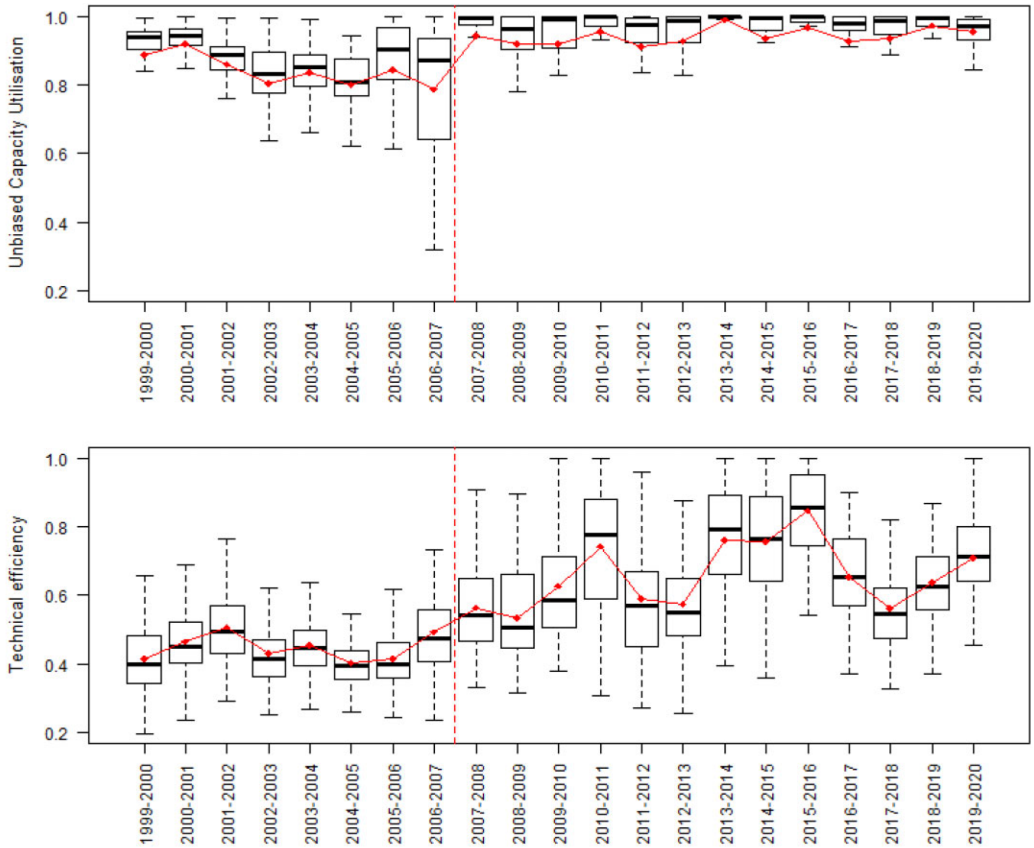

Figure 3. Distributions of key technical performance measures, NPF, 1999–2000 to 2019–2020.

this case captures the effects of changes in stock abundance and technology) and (unbiased) capacity utilization to these economic performance measures was assessed through panel data regression analysis, with the economic measure regressed against the technical efficiency and unbiased capacity utilization scores.

A range of different functional forms of the model were examined, with a log-linear form providing the best results. An additional advantage of the log-linear model is that coefficients on the explanatory variables represent the elasticity of the economic measure with respect to the technical performance measure. However, as negative values cannot be logged, observations with negative boat cash income or full equity profits had to be excluded from the analysis.

The panel data models were estimated as both fixed and random effects models, and the results for the vessel level analysis are given in Table 1. Robust and clustered standard errors were estimated to correct for the potential bias in the standard error due to heteroskedasticity across "clusters" of observations (Colin and Miller, 2015; Abadie *et al.*, 2023), clustered at the vessel-year level. The Hausman (1978) tests suggested that there are no significant differences between the fixed and random effects specifications, with the parameter estimates being similar (and not statistically significant) in both also.

Goodness of fit was generally low, but increased as the economic measure was simplified from full equity profits to gross margins. Full equity profits and boat cash profits include fixed costs, which may be affected by factors other than those related to productivity. For example, expenditure on gear or repairs and maintenance may have a substantial impact on economic measures, but less directly related to the level of fishing activity. Similarly, other fixed costs, such as, for example, accountancy fees or other administrative fees, may vary between vessels for reasons not related to their fishing activity, but instead the business structure of the firm. Removing fixed costs (as in the case of gross margins) provides an economic measure most closely related to catch and effort, and best captured by technical performance measures.

Both technical efficiency and unbiased capacity utilization were found to be significant factors affecting economic performance. As the data in the regression models are logged, the parameter estimates represent the estimated economic performance elasticities (i.e. the responsiveness of the economic performance measure to a 1% change in technical efficiency and capacity utilization). From Table 1, a 1% increase in capacity utilization may result in a 0.5–0.6% increase in gross margins and boat cash profits, and a 0.8% increase in full equity. Similarly, a 1% increase in technical efficiency may result in a 0.9% increase in gross margins, and a 1.2–1.3% increase in full equity profits and boat cash profits. For all models, the coefficients relating to technical efficiency were not statistically significantly different to 1.

Discussion

Technical efficiency is a necessary but not sufficient condition for profit maximization. While market failure (particularly the

Table 1. Regression of vessel-level economic measures against key technical performance measures for the NPF.

	Full equity profits						Boat cash profits						Gross margins					
	Random effects			Fixed effects			Random effects			Fixed effects			Random effects			Fixed effects		
	Estimate	Std. Err.		Estimate	Std. Err.		Estimate	Std. Err.		Estimate	Std. Err.		Estimate	Std. Err.		Estimate	Std. Err.	
Intercept	13.437	0.171	***				13.425	0.173	***				14.157	0.106	***			
ln (TE)	1.192	0.174	***	1.194	0.183	***	1.301	0.201	***	1.338	0.217	***	0.897	0.099	***	0.912	0.103	***
ln (UCU)	0.795	0.220	***	0.782	0.221	***	0.514	0.359		0.485	0.361		0.597	0.112	***	0.590	0.112	***
$\overline{\theta}$	0.746						0.699						0.761					
R^2	0.360			0.109			0.455			0.082			0.497			0.154		
$\overline{R}^2$	0.357			0.075			0.453			0.042			0.496			0.127		
Hausman χ^2				0.052						1.109						0.911		

Significance: "***" 0.1% "**" 1% "*" 5%.

lack of succinct property rights) may result in a fleet overall not achieving the maximum profits, the assumption that individual fishers would aim to achieve their individual profits (subject to the constraints imposed by management) is reasonable (van Putten *et al*., 2012). Hence, it can be expected, *a priori*, that changes in this measure would reflect to some extent changes in economic performance. O'Donnell (2022) notes that productivity in an industry is a function of technical progress, environmental change, technical efficiency, scale, and mix efficiency. Our measure of "technical efficiency", estimated over the whole period of the data, implicitly captures the first three of these components, as a change in the output-per-unit-input ratio implicit in DEA between time periods can be due to "luck" (i.e. random variation), changes in relative stock abundance (such as catch per unit effort changes), technological change onboard the vessels (i.e. improved gear or search technologies), or efficiency of the operation (e.g. improved skipper skill). All of these factors (including "luck") will influence the level of realized output (revenue) given the inputs employed (costs), and hence the economic performance of the vessel. While decomposition into their different components may be of interest, it is not necessary in order to estimate the likely effect on economic performance. However, decomposition into efficiency change and technical change (including stock levels) through the use of Malmquist indexes, for example, may provide additional insights into changes in economic performance over time.

Productivity is not the only factor that affects economic performance; change in economic performance is also affected by changes in output prices and costs, such that profitability may change independently of the technical efficiency of the producer. Fortunately, changes in capacity utilization reflect changes in the underlying marginal costs and revenues to a large degree, again assuming profit maximization. Combined, the two measures, noting that the technical efficiency measure also captures the impact of changes in stock abundance over time, should capture most aspects of changes in economic performance.

The results of the analysis suggest that there is a relationship between the combined technical performance measures and measures of economic performance, as expected. Improvements in technical efficiency, as measured in the study, reflects both technological improvement as well as resource improvements, resulting in higher catch per unit of effort and higher levels of profitability. The measure of unbiased capacity utilization is a net measure of these improvements, and reflects changes in the economic environment (i.e. changes in prices or costs). An improvement in unbiased capacity utilization reflects the behavioural response to these changes, consistent with profit-maximizing behaviour.

The analysis used DEA to estimate both technical efficiency and capacity utilization. DEA is often considered inappropriate in fisheries analyses as it does not account for random variations in output (e.g. luck, influence of weather, etc.) (Holland and Lee, 2002). However, these random variations will also affect the economic performance of the vessels in a similar direction. For example, an unexpected or "random" increase or decrease in catch given the level of inputs used will also have a corresponding impact on vessel revenue, so in this regard, the measures are appropriate when acting as an indicator of economic performance.

Productivity analysis has most commonly been applied to estimate the impacts of fisheries management and other external drivers (e.g. changes in technology) on efficiency and capacity utilization (Pascoe and Tingley, 2007). This has not been the focus of this study, but the process of estimating technical efficiency and capacity utilization can provide other useful indicators as to the impacts of fisheries management. For example, from Figure 3, the effects of the buyback programme in 2006/07 on both measures can be clearly seen. The estimated increase in technical efficiency is consistent with other previous studies (Pascoe *et al.*, 2012), while the associated assumed increase in economic performance is supported also by other studies (Vieira *et al.*, 2010).

The analysis was based on one case study fishery, and its broader applicability is uncertain. Further case studies may need to be undertaken to develop a more general "rule-of-thumb" for translating technical performance measures into an index of economic performance. However, the results of the study suggest that these technical performance measures can be used as a proxy indicator of changes in economic performance of a fishery in the absence of specific cost and earnings information, at least in fisheries where input and output prices faced by fishers are likely to be similar. For lower-valued fisheries for which no economic surveys are undertaken, monitoring changes in technical efficiency and capacity utilization can provide a useful means to understand economic pressures facing the industry, and their potential causes (e.g. changes in stocks or the broader economic environment in which they operate). Even in fisheries where routine economic surveys are undertaken, there is usually a lag, often of several years, between the year of the survey information being collected and when these are made available to fisheries managers. In contrast, catch-and-effort information is usually collected in a more continuous and timely manner, often lagging only by a few months. As a result, the potential exists for almost-real-time indicators of performance to be derived to provide a more timely indication of economic performance of the fleet.

In our study, the catch-and-effort data we used was for the entire fleet, treating vessels in different time periods as effectively different decision-making units (DMUs). As a result, all DMUs (vessels) were assessed relative to those DMUs on the frontier at some point in time. This enables changes in underlying stock and other conditions to be captured in the efficiency scores. If a sample of vessels, however, had been used rather than the full fleet, then the composition of this sample (if changing) may also impact these productivity measures, with apparent efficiency changes reflecting sample change rather than true productivity change. Where possible, a consistent panel should be used if data for the entire fleet are not available. In our case, changes in fleet structure may result in an apparent change in the average efficiency, but the assumption (supported by the results) is that this should also correspond to a change in average economic performance as the least efficient and correspondingly least profitable vessels are likely to be the first to leave (Pascoe *et al.*, 2012).

Conclusions

The aim of this study was to determine the extent to which technical performance measures could provide proxy information on changes in fisheries economic performance over time, and the data-rich Northern Prawn Fishery provided such an opportunity.

We find that, at a minimum, the estimation of technical efficiency and capacity utilization can provide an indication of the direction and key drivers of changes in economic performance in the absence of fishery-specific economic information. As noted above, an increase in technical efficiency suggests that output per unit of input is increasing (and vice versa), and hence, economic performance of the fleet is likely to have improved. Similarly, changes in capacity utilization reflect fisher behavioural responses to price and cost changes, with improvements in capacity utilization suggesting improvements in economic conditions, while decreases suggested deterioration of economic conditions. As a result, these measures provide some information to managers on the economic pressures in the fishery, either in the complete absence of economic data in low-value fisheries or in providing preliminary updates to compensate for lags in economic data collection programmes.

For the case study fishery, at least, we have demonstrated that these measures can be useful indicators of economic performance and could form part of a more routine monitoring and reporting programme. We do not suggest, however, that these measures replace economic surveys, as these also provide information useful for other purposes (e.g. bioeconomic modelling) as well as providing a more definitive measure of economic performance.

Supplementary data

Supplementary material is available at the *ICESJMS* online version of the manuscript.

Conflicts of interest

The authors have no conflicts of interest to declare.

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Data availability

The data underlying this article were provided by AFMA and ABARES by permission. Data will be shared on request to the corresponding author with permission of both AFMA and ABARES.

Author contributions

Conceptualization: SP and SMcW; Data Curation: SP and RC; Formal Analysis: SP, RC, and EH; Funding: SMcW and SP; Investigation: SP, RC, and EH; Methodology: SP, SMcW, and PS; Software: SP, EH, and PS; Validation: SP and RC; Writing—original draft: SP; Writing—review and editing: SP, RC, EH, PS, and SMcW.

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