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Assessing the Efficiency of Small-Scale and Bottom Trawler Vessels in Greece

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Abstract: This study explores the technical and scale efficiency of two types of Greek fishing vessels, small-scale vessels and bottom trawlers, using a bias-corrected input-oriented Data Envelopment Analysis model. Moreover, the associations between efficiency scores and vessel's and skipper's characteristics are also explored. The results indicate that small-scale vessels achieve a very low average technical efficiency score (0.42) but a much higher scale efficiency score (0.81). Conversely, bottom trawlers achieve lower scale but higher technical efficiency scores (0.68 and 0.73, respectively). One important finding of this study is that the technical efficiency of small-scale vessels, in contrast to trawlers, is positively associated with the experience of the skipper. In a looser context, it can be said that small-scale fisheries mainly rely on skill, whereas bottom trawlers rely more on technology. This study concludes that there is space for improvement in efficiency, mainly for small-scale vessels, which could allow the achievement of the same level of output by using reduced inputs.

Keywords: technical efficiency; scale efficiency; artisanal fishing; bottom trawls; socioeconomic aspects

1. Introduction

In the last decade, many studies have explored efficiency in the European fishing fleets. According to Farrell's model [1], technical efficiency is defined as the measure of the ability of a firm to obtain the best production from a given set of inputs. In the fishing sector, efficiency is related to the ability of achieving the best possible catch subject to the available resources (fishing stock and inputs). Improvements in efficiency are desirable provided that a management structure exists that prevents biological and economic overexploitation. If not, increased efficiency or the ability to catch more fish for a given amount of fishing effort can be detrimental to sustainability [2]. Efficiency is closely related with the concept of overcapacity which is the difference between the maximum potential output that could be produced—given technology, desired resource conditions, and full and efficient utilization of capital stock, other fixed and variable input—and a desired optimum level of output (e.g., the maximum sustainable yield, or maximum economic yield) [3].

In this study, efficiency is explored in terms of the optimal combination of inputs to achieve a given level of output using Data Envelopment Analysis (DEA). DEA is a non-parametric approach of estimating efficiency. It was originally proposed by Charnes et al. [4] and is based on Farrell's model [1]. By solving a linear programming problem, it allows the estimation of efficiency without assuming an a priori functional form for frontier production [5].

DEA has been used in several fisheries economic studies across Europe (e.g., [3,6,7]). In the Mediterranean region, Tsitsika et al. [8] investigated efficiency of the purse seiners in Greece using data envelopment analysis (DEA). Results indicate similar excess capacity for target species. Purse seiners could increase their catch by approximately 23% by increasing variable inputs such as days fished. Conversely, a fleet of smaller size could achieve the reported catch. Moreover, under the condition that the remaining vessels can be fully utilized, a proportional decrease in the fleet size might seem a rational management measure towards reducing overexploitation and attaining sustainable fisheries in the eastern Mediterranean Sea. Fousekis and Klonaris [9] studied efficiency in netters. Their results suggest that there is potential for short-run output increases without additional fishing effort. They also suggest that vessel and (to a lesser extent) skipper-specific characteristics do influence TE levels. Finally, in Sardinia, Idda and Madau [10] focused their study on the fishing capacity, technical efficiency, scale efficiency and capacity utilization in a particular fishing segment in the Mediterranean, i.e., the Northwest Sardinian fleet in Italy. They suggest that fishermen can appreciably reduce overcapacity and increase revenues by using their technical resources more efficiently. Therefore, rational distribution of the small-scale fleet through regional coastal waters may improve fishing efficiency, increase profits and reduce overexploitation in some critical areas.

In Greece, fisheries is an important economic activity. According to the 2012 Fleet Register, the Greek fleet consisted of 16,063 fishing vessels, with a combined gross tonnage of 79,678 tons and a total engine power of 462,429 kW. In particular, there were 13,918 fishing enterprises operating in Greece offering employment to 27,558 people. An important and unique characteristic of the Greek fishing fleet is that it consists mainly of small-scale fishing vessels that exploit the extensive Greek coastline. Thus, the fisheries sector can be separated into two main types, namely small-scale fisheries (coastal fisheries) and medium-scale fisheries (bottom trawlers and purse-seiners). From a socioeconomic point of view, these two categories have distinct characteristics. Small-scale fishing vessels use polyvalent passive fishing gears and rely mainly on the work of the vessel owners. On the other hand, bottom trawlers and purse seiners are characterized by high operating costs, especially personnel costs. It is also important to emphasize that medium-scale fisheries and in particular bottom trawlers appear to have high productivity and profitability.

The present study explores efficiency of the Greek fishing fleet. It focuses on both small-scale vessels and bottom trawlers, and therefore it allows for comparisons among these fleet segments. Additionally, the study associates efficiency with specific segment characteristics. Following similar studies (e.g., [6,11]), we consider efficiency using a nonparametric analysis and more specifically, a Data Envelopment Analysis model (DEA). Both the concepts of technical and scale efficiency were considered.

2. Materials and Methods

According to Kumbhakar and Lovell [12], technical efficiency is defined as the ability of a decision-making unit (DMU) to obtain the maximum output from a given set of inputs (output orientation) or to produce an output using the lowest possible quantity of inputs (input orientation). One mean to estimate TE is to measure a DMU's position relative to an efficient frontier, resulting in an efficiency score for this particular DMU.

In the fisheries context, there is a growing interest in the measurement of technical efficiency of different fishing fleets. This interest is twofold: to establish the underlying factors (e.g., [13,14]), and to assess the effects of several socioeconomic variables. In the fisheries economics literature, output-oriented technical efficiency is usually applied, as the main aim is the estimation of capacity utilization, a concept which is basically output-oriented (e.g., [11,13,15,16]). This study, on the other hand, focuses on input-oriented technical efficiency (TE) and scale efficiency (SE). Usually, fishing vessels are not technically efficient because they present too high running costs, or they are overcapitalized in the sense that a lower capital level could be used to achieve the same harvest. Technical inefficiency may surface for many reasons, but a major cause is inputs control that fails to prevent effort creep due to input substitution ([2,17]). Input oriented technical and scale efficiency are particularly meaningful in the case of the Greek small-scale and trawler fleets since the managerial strategy is mainly based on inputs control, especially in the recent years of financial crisis that dramatically affects cash flows.

Data envelopment analysis is a non-parametric method to estimate efficiency, developed by Charnes et al. [4]. The production frontier constructed by DEA is deterministic, so each deviation from the frontier is reported as inefficiency. Consider n DMUs producing m different output using h different inputs. $\mathbf{Y}$, is an $m \times n$ matrix of outputs and $\mathbf{X}$ is an $h \times n$ matrix of inputs. Both matrices contain data for all n DMUs. The technical efficiency (TE) measure can be formulated as follows:

$$\begin{aligned} &\min \theta, \\ &\text{subject to:} \\ -\mathbf{y}_i + \mathbf{Y}\lambda &\geqslant 0 \\ \theta \mathbf{x}_i - \mathbf{X}\lambda &\geqslant 0 \\ \lambda &\geqslant 0 \end{aligned} \tag{1}$$

and solved for each DMU in the sample. θ, is the DMU's index of technical efficiency, $\mathbf{y}_i$, and $\mathbf{x}_i$, represent the output and input of DMU i respectively and $\mathbf{Y}\lambda$ and $\mathbf{X}\lambda$ are the efficient projections on the frontier. A measure of $\theta_i = 1$ indicates that the DMU is technically efficient. Thus, $1 - \theta$, measures how much the DMU i's inputs can be proportionally reduced without any loss in output.

Model (1) implies that all DMUs operate under constant returns to scale (CRS). However, the CRS assumption is only appropriate when all DMUs are operating at an optimal scale (i.e., one corresponding to the flat portion of the LRAC curve) [18]. Several factors like imperfect competition and constraints on finance may cause a DMU not to operate at optimal scale. The use of the CRS specification when not all DMUs are operating at the optimal scale results in measures of TE which are confounded by scale inefficiencies.

The application of the Variable Returns to Scale (VRS) specification that permits the calculation of pure TE devoid of these scale inefficiencies, is as follows:

$$\begin{aligned} &\min \theta, \\ &\text{Subject to:} \\ -\mathbf{y}_i + \mathbf{Y}\lambda &\geqslant 0 \\ \theta \mathbf{x}_i - \mathbf{X}\lambda &\geqslant 0 \\ \mathbf{NI}'\lambda &= 1 \\ \lambda &\geqslant 0 \end{aligned} \tag{2}$$

The new constraint is $\mathbf{NI}'\lambda = 1$ where $\mathbf{NI}$ is a $n \times 1$ vector of ones. This constraint allows only the comparison of firms of similar size, by forming a convex hull of intersecting planes, so that the data is enveloped more tightly. Scale efficiency can be calculated by conducting both a CRS and a VRS DEA upon the same data. If there is a difference in the two TE scores for a particular DMU, then this indicates scale inefficiency, and the SE score is equal to the ratio of the CRS TE score to the VRS TE score.

A major criticism of the traditional DEA approach is that it produces point estimates of efficiency that are upward biased and lack statistical properties [19]. The upward bias is the outcome of the fact that DEA constructs an inner approximation of the underlying actual production possibility set. Assuming no measurement errors, all of the observations in the sample are from the technology set $\hat{T} \subset$ where T is the true but unknown technology. Then: $\hat{E}^k \geqslant E^k$, where E^k is the estimation of the true but unknown efficiency θ^k of the k DMU. This is the outcome of the minimization over a smaller technology set and thus the estimated efficiency may be larger than the real efficiency. The size of $\hat{T}$ depends on the sample, and therefore, E^k is sensitive to sampling variations in the obtained frontier.

This bias is particularly large in those parts of the production space where there are few observations, and can be estimated as [20]:

$$bias^k = EV\left(\hat{\theta}^k\right) - \theta^k \tag{3}$$

As the distribution of θ^k is unkown, there is no direct way to calculate $EV\left(\hat{\theta}^k\right)$, and a bootstrapping method can be used. Bootstrapping allows the assessment of whether the distribution has been influenced by stochastic effects and can be used to build confidence intervals for point estimates. Random samples are obtained by sampling with replacement from the original data set, which provides an estimator of the parameter of interest [21].

When θ^{kb} is a bootstrap replica estimate of θ^k, the bootstrap estimate of the bias is:

$$bias^{*k} = \frac{1}{B}\sum_{b=1}^{B}\theta^{kb} - \hat{\theta}^k = \overline{\theta}^{*k} - \hat{\theta}^k \tag{4}$$

where $\overline{\theta}^{*k}$ is the mean over the replications of θ^{kb}. The bias-corrected estimator of θ^k, $\widetilde{\theta}^k$ is then:

$$\widetilde{\theta}^k = \hat{\theta}^k - bias^{*k} = \hat{\theta}^k - \overline{\theta}^{*k} + \hat{\theta}^k = 2\hat{\theta}^k - \overline{\theta}^{*k} \tag{5}$$

To estimate $\widetilde{\theta}^k$, we applied the bootstrap algorithm proposed by Wilson and Simar ([19,22]). The approach replicates sampling uncertainty by creating repeated samples of the original sample. After the estimation of the above efficiency measures, a second-stage statistical analysis is performed to associate efficiency scores with several socio-economic variables. This set of variables includes education and age of the skipper, owner contribution to the labour, size of the vessel and gross cash flow. This analysis is performed using spearman correlation and Wilcoxon rank-sum test (Mann-Whitney two-sample statistic).

Data used in the analysis was collected through a sample survey using a structured socio-economic questionnaire. Face-to-face interviews with 263 fishermen were conducted, 229 of which were engaged in costal, small-scale vessels with total length between 5 and 12 m and 34 in bottom trawlers, with vessel length over 18 m. This data is part of a larger data set collected in the framework of the Greek National Fisheries Data Collection Program 2013 in application of the EC decision 93/2010. The variables used for the DEA analysis consist of four inputs, namely annual personnel cost, fuel cost, running cost and repair and maintenance cost. The output is the annual revenues of the vessels (see Table 1). It is noteworthy that, in the case of small-scale vessels, the standard deviation is too high. This could be explained by the fact that these vessels use polyvalent passive fishing gears which correspond to different levels of input use and a variety of catches.

Table 1. Descriptive statistics of the input and output variables used in the analysis.

Variable	Small-Scale Vessels		Bottom Trawlers	
	Mean Value (€)	**St. Deviation**	**Mean Value (€)**	**St. Deviation**
	Input variables			
Personnel cost	9400	6594	81,243	44,842
Fuel cost	4861	5905	118,825	57,005
Running cost	3377	5354	70,983	46,019
Repair and maintenance cost	2178	2265	20,229	12,854
	Output variable			
Revenues	19,655	16,602	359,080	277,570

Energy costs refer to the annual fuel costs for the engine while personnel costs refer to the total cost of paid labour plus any unpaid labour of the owner. Maintenance and repair costs refer to the annual costs of repairs for the vessel, the engine as well as the fishing gear. Finally, running costs refer to all other operation costs (e.g., bait and hooks) including the cost of lubricants and the commercial costs (e.g., ice, boxes and packages). Other annual expenses of the vessels like dock expenses and book keeping costs, were also included in the running costs. Annual revenues of the vessels were determined through the annual value of landings. Table 1 contains some descriptive statistics of the main variables used in the DEA analysis for both the small-scale vessels and for trawlers.

As far as the output variable is concerned, the use of revenue as the output measure is not ideal, as revenue is a function of price as well as quantity [23]. Consequently, price changes that affect the output measure independent of input use may be interpreted as changes in technical efficiency. Furthermore, assuming that fishermen seek to maximize profit, a change in relative prices may result in a change in their fishing strategy. As a result, the efficiency scores may represent a combination of allocative as well as technical efficiency. However, the potential biases introduced into the analysis from using revenues as the output measure are not likely to be significant. Squires [24] and Sharma and Leung [14] note that fishermen base their fishing strategies on the expected prices, the level of technology and the resource abundance. However, price expectations are not always accurate, information on the variation of the stock across fishermen is generally not available, and catch composition is governed largely by fishing gear that is not perfectly species selective.

Changing gears type is time consuming and usually needs to be done on shore rather than at sea. Hence, the ability of fishers to respond to changes in relative prices by varying their fishing activity is limited. Several recent studies (e.g., [25]) have suggested that the fishing activity is largely influenced by habit, with only relatively minor changes in effort allocations in response to price, in the short term. Additionally, we consider that the Greek small-scale and bottom trawlers fisheries are operating in a situation of unbalanced ratio between demand and supply, where cultural and economic factors generate a high demand for seafood products leading to constantly high prices, not significantly affected by either the landing volume or the season.

Finally, the use of inputs (and outputs) values rather than quantities is very common in efficiency studies. As Färe et al. [26] and Banker et al. [27] suggest, when the assumption that DMUs face equal input prices holds, then values can be used instead of quantities. This suggestion has been recently proved by Portela [28].

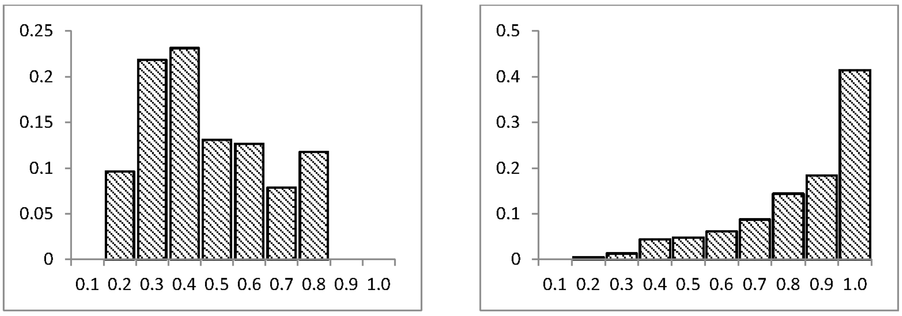
3. Results

3.1. Small-Scale Vessels

On average, small-scale vessels have a very low efficiency level, equal to 0.42 and therefore, they could proportionally decrease their inputs by 58% and still produce the same amount of output. Moreover, the standard deviation and the range of TE scores reveal that the results are characterized by high variation. Table 2 provides the descriptive statistics of TE and SE scores for the small-scale vessels in Greece (see also Figure 1a,b). It also reports the number of vessels that operate under constant, increasing and decreasing returns to scale.

Table 2. Descriptive statistics of Technical Efficiency (TE), Scale Efficiency (SE) and scale of operation for small-scale vessels.

Variable	Mean	Standard Deviation	CV	Min	Max
TE	0.42	0.18	43.9%	0.15	0.79
SE	0.81	0.20	24.9%	0.17	1 (51 vessels)
Scale of operation			**DMUs**		
IRS			43 vessels (63%)		
CRS			51 vessels (22%)		
DRS			35 vessels (15%)		



(a) **(b)**

Figure 1. Histograms of (**a**) Technical Efficiency (TE) and (**b**) Scale Efficiency (SE) scores of the small-scale vessels

On the other hand, the average scale efficiency score is much higher (0.81) and hence, small-scale vessels operate close to the optimal scale of production. According to Table 2, the majority of the vessels (63%) operates under increasing returns to scale, while 15% operates under decreasing returns to scale. This is a common finding in the relevant literature (e.g., [9,29,30]) and indicates that the majority of vessels can be more productive if they increase their input usage (to optimally operate under constant returns to scale).

Tables 3–5 provide the results of the Spearman correlation and Mann-Whitney tests between the efficiency scores and several socio-economic variables. The results suggest that the vessels with length between five and six meters are more technically efficient. Fousekis and Klonaris [9] report similar results in their study. Specifically, they found that larger Greek trammel netters tend to be less technically efficient than smaller vessels. They also point out that the crew size plays an important role, since larger vessels need more crew. Thus, a large crew size may reduce the ability of a skipper to adjust the level of other inputs [9].

Table 3. Variables that define groups with different Technical Efficiency (TE) scores in the small-scale fishing segment.

Variable that Define Groups		Average TE	Z Score	Result
Length class	5–6 m 6–12 m	0.50 0.40	2.65 **	Small vessels have higher TE
Level of education	basic advanced	0.44 0.38	2.89 **	Skippers with basic education perform better
Vessels registered in "Thessaly" region	Yes No	0.42 0.38	1.79 *	Vessels in this region have higher TE
Vessels registered in "South Aegean" and "Crete"	Yes No	0.50 0.41	−1.67 *	Vessels in these regions have higher TE
Young skipper (less than 40)	Yes No	0.43 0.37	2.11 **	Vessels whose skipper is very young have less TE

* 0.10 level of significance; ** 0.05 level of significance.

Table 4. Variables that define groups with different Scale Efficiency (SE) scores in the small-scale fishing segment.

Variable that Define Groups		Average SE	Z Score	Result
Fishing activity is the main source of income	Yes No	0.82 0.71	−2.81 **	Vessels whose skippers' main income is fishing present higher SE
Old skipper (more than 65)	Yes No	0.71 0.82	1.67 **	Vessels whose skipper is old, have less SE

** 0.05 level of significance.

Table 5. Spearman correlations of Technical Efficiency (TE) and Scale Efficiency (SE) scores of the small-scale vessels with technical and socioeconomic variables.

	TE	SE
Length	−0.23 **	0.19 **
Gt	−0.20 **	0.21 **
Revenues	0.02	0.24 **
Days at sea	−0.13 **	0.15 **
Unpaid labour to total labour	−0.22 **	−0.05

** 0.10 level of significance.

The results also reveal that TE is lower when the vessel is managed by a skipper younger than 40 years of age. Moreover, the literacy level appears to have a weak negative effect on TE. One possible explanation may lie in the fact that in small-scale vessels, the outcome of the fishing activity relies on the experience of the skipper rather than on his formal education or on the use of new technologies (commonly associated with younger skippers). Furthermore, the experience of the skipper plays a key role in the selection of the fishing gear, the fishing ground and the fishing day. These results are not always supported by similar studies. For example, Ali et al. [31] mention that formal education is generally associated with increased efficiency as it broadens the producers' minds and enables them to acquire and process relevant information. Moreover, according to Esmaeili [30] younger skippers are more efficient than others. Finally, Fousekis and Klonaris [9], explore the efficiency of Greek netters, and report that the "good skipper" is aged about 50, has a literacy level higher than the primary, and comes from a fishermen family.

The analysis also detects regional differences in the TE levels. Specifically, vessels operating in the region of Thessaly as well as in the South Aegean and Crete regions have higher TE scores. These regional differences can be explained by differences in the composition of the catch or differences in the extent of competition with the large scale vessels for the same fishing ground and/or the same markets. For example, in the case of the Thessaly and the South Aegean and Crete regions, the fishing grounds are characterized by rocky bottoms. Additionally, few large-scale vessels operate in South Aegean and Crete and therefore the competition between them and small-scale vessels is low.

As far as the scale efficiency is concerned, the analysis indicates that vessels between five and six meters are less scale efficient. These results are in line with the fact that scale inefficiencies are attributed mainly to increasing returns to scale (sub-optimum vessel's size). Moreover, when the fishing activity is the main source of income, the scale efficiency level is higher. This is an indication that the owners are trying to fully exploit returns to scale and thus, to operate very close to constant returns to scale. Moreover, bigger vessels, that have higher scale efficiency, belong to owners whose main income source is the fishing activity. Finally, the result that vessels with older skippers are less scale efficient, could be explained by the fact that older skippers are not interested in capital investments, like the purchase of a new bigger vessel.

The Spearman correlation analysis shows, as expected, that the vessels with smaller technical characteristics (LOA and GT) have higher TE. These vessels are capable of producing the same unit of output (revenues) with less input. The number of days that the vessel spends at sea is negatively correlated with TE. This could be explained by a more rational fishing strategy (i.e., operation only under optimal conditions). Moreover, a negative correlation is detected between TE and the presence of the owner on board the vessel, expressed as the ratio of unpaid labour to total labour costs. This is somehow contradictory with the results of previous studies (e.g., [14,30]) where owner-operated vessels are considered more efficient than others.

The correlation analysis also reveals that the scale efficiency scores are positively correlated with the length and the capacity of the vessels, which was expected, as the majority of the vessels operates under increasing returns to scale. Moreover, scale efficiency is positively correlated with days at sea. This was also expected, since bigger vessels, that are characterized by higher scale efficiencies, are usually able to fish more days than small vessels. Finally, no correlation between scale efficiency and percentage of unpaid labour was detected.

3.2. Bottom Trawlers

Table 6 provides the descriptive statistics of TE and SE scores for the Greek bottom trawlers (see also Figure 2a,b). The table also reports the number of the vessels that operate under constant, increasing and decreasing returns to scale. On average, the TE scores of bottom trawlers are higher than the scores of small-scale vessels. Specifically, the average technical efficiency score is 0.68, which indicates that fishermen can reduce their inputs by 32% and still produce the same amount of output. The descriptive statistics and the histogram (Figure 2a,b) reveal that TE scores in the case of bottom trawlers are more tightly clustered around the average, than in the case of the small-scale vessels. As far as scale efficiency is concerned, it is on average equal to 0.76. As expected, 91% of the vessels operates under increasing returns to scale, which means that the main reason for scale inefficiencies is the sub-optimal size of vessels.

Table 6. Descriptive statistics of Technical Efficiency (TE), Scale Efficiency (SE) and scale of operation of the bottom-trawlers.

Variable	Mean	Standard Deviation	CV	Min	Max
TE	0.68	0.14	20.0%	0.42	0.86
SE	0.73	0.21	28.7%	0.30	1 (3 vessels)
Scale of operation			**DMUs**		
IRS			31 vessels (91%)		
CRS			3 vessels (9%)		
DRS			0 vessels		

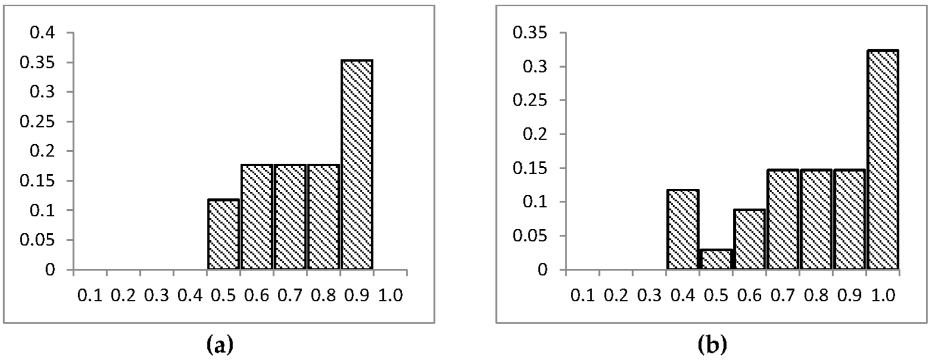


Figure 2. Histograms of (**a**) Technical Efficiency (TE) and (**b**) Scale Efficiency (SE) scores of bottom trawlers.

Unlike small-scale fisheries, the Mann-Whitney test and Spearman correlation (Table 7) indicate that the TE of bottom trawlers is not associated with any technical (LOA and GT) as well as social factor (age and literacy level of the skipper). This was expected since the majority of trawlers operate at a similar TE level. Furthermore, from a technical point of view, this segment is more homogenous, as the vessels use similar fishing gear and exhibit similar fishing behaviour. It is noteworthy that the gross cash flow per vessel is positively correlated with TE. This could be explained by the higher cash availability which is associated with higher investments in fishing equipment and technology.

Finally, the scale efficiency of trawlers, as in the case of small-scale vessels, is positively correlated with the technical characteristics of the vessels (LOA and GT). SE is also positively correlated with the gross cash flow. This correlation can be explained by the higher cash availability which allows for investments in better fishing equipment (gear and vessel).

Table 7. Spearman correlations of Technical Efficiency (TE) and Scale Efficiency (SE) scores of the bottom-trawlers with technical and socioeconomic variables.

	TE	SE
Length	0.06	0.34 **
Gt	0.07	0.30 *
Revenues	0.11	0.58 **
Days at sea	−0.25	0.12
Gross cash flow	0.59 **	0.65 **

** 0.05 level of significance; * 0.10 level of significance.

4. Discussion

In this analysis the technical and scale efficiency of the Greek fishing fleet is explored. The analysis focuses on small-scale, coastal fisheries as well as bottom trawlers and identifies similarities and differences between the two fleet segments. The issue of efficiency is explored using an input-oriented data envelopment analysis model. Additional information regarding the characteristics of the vessel (length and capacity) as well as characteristics of the skipper (age and education level) are also tested for correlation with technical and scale efficiency.

The results of the analysis indicate that small-scale vessels achieve a low average technical efficiency score of 0.42 but much higher scale efficiency score (0.81). The results of the analysis also indicate that in coastal fisheries, smaller vessels (5–6 m) achieve higher technical and scale efficiency scores than larger vessels. To some extent this can be explained by the high level of flexibility that characterizes small vessels. These vessels can easily adjust their cost determinants according to the seasonal or regional variations of the harvest. This can be done by several means like using alternative fishing gear, shifting to a different fishing ground, targeting different species or simply decreasing the level of the activity and operating only during the (potentially) more productive days.

On the other hand, the results of the analysis indicate that bottom trawlers achieve high technical but lower scale efficiency scores. The bottom trawlers fleet segment is more homogenous, in terms of technical efficiency, regardless of the size of the vessel, though size is positively correlated with scale efficiency scores.

One important finding of the analysis is that the technical efficiency of small-scale vessels is positively associated with the age and therefore the experience of the skipper. Conversely, the characteristics of the skipper have no effect on technical or scale efficiency in the case of bottom trawlers.

Overall, the results of the analysis suggest that in small-scale fisheries, efficiency relies mainly on qualitative factors, like the experience of the skipper. On the other hand, the higher efficiency scores of the bottom trawlers are the result of the improved technology these vessels utilize. For trawlers, qualitative factors, like the experience of the skipper, have no significant impact on efficiency. In a looser context, it can be said that small-scale coastal fisheries rely on skills, while bottom trawlers rely on technology.

To conclude, the results of the analysis, suggest that there is room for improvement in the technical efficiency of mainly small-scale vessels, which would allow for the production of the same level of output, using reduced inputs, provided that fishermen become technically efficient by improving their fishing ability. This can be facilitated by several policy measures, like the organization of educational programs, the exchange of knowledge among fishermen and the adoption of innovations. The efficiency of these actions has been largely recognized by the European Union and hopefully they will be promoted via the Multi-annual programs and the measures of the new Common Fishery Policy.

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Author Contributions: Dario Pinello, Angelos Liontakis and Alexandra Sintori prepared and analyzed the data and applied the methodology. Irene Tzouramani supervised the research as she was responsible for the socioeconomic fisheries data collection scheme of the Greek National Fisheries Data Collection Program 2013. She also assisted in the introduction and discussion sections. Konstantinos Polymeros assisted in the general description of the fishery sector and the discussion section.

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References

1. Farrell, M.J. The measurement of productive efficiency. *J. R. Stat. Soc. Ser. A* **1957**, *120*, 253–290. [CrossRef]
2. Grafton, R.Q.; Kirkley, J.; Kompas, T.; Squires, D. *Economics for Fisheries Management*; Ashgate Publishing, Ltd.: Aldershot, UK, 2006.
3. Pascoe, S.; Kirkley, J.E.; Greboval, D.F.; Morrison, C.J. *Measuring and Assessing Capacity in Fisheries: Issues and Methods*; Food & Agriculture Org.: Rome, Italy, 2003.
4. Charnes, A.; Cooper, W.W.; Rhodes, E. Measuring the efficiency of decision making units. *Eur. J. Oper. Res.* **1978**, *2*, 429–444. [CrossRef]
5. Coelli, T.J. *A Guide to DEAP Version 2.1: A Data Envelopment Analysis (Computer) Program*; CEPA Working Paper; University of New England: Armidale, Australia, 1996.
6. Lindebo, E.; Hoff, A.; Vestergaard, N. Revenue-based capacity utilisation measures and decomposition: The case of Danish North Sea trawlers. *Eur. J. Oper. Res.* **2007**, *180*, 215–227. [CrossRef]
7. Pascoe, S.; Coglan, L. The contribution of unmeasurable inputs to fisheries production: An analysis of technical efficiency of fishing vessels in the English Channel. *Am. J. Agric. Econ.* **2002**, *84*, 585–597. [CrossRef]
8. Tsitsika, E.V.; Maravelias, C.D.; Wattage, P.; Haralabous, J. Fishing capacity and capacity utilization of purse seiners using data envelopment analysis. *Fish. Sci.* **2008**, *74*, 730–735. [CrossRef]
9. Fousekis, P.; Klonaris, S. Technical efficiency determinants for fisheries: A study of trammel netters in Greece. *Fish. Res.* **2003**, *63*, 85–95. [CrossRef]
10. Idda, L.; Madau, F.A.; Pulina, P. Capacity and economic efficiency in small-scale fisheries: Evidence from the Mediterranean Sea. *Mar. Policy* **2009**, *33*, 860–867. [CrossRef]
11. Reid, C.; Squires, D.; Jeon, Y.; Rodwell, L.; Clarke, R. An analysis of fishing capacity in the western and central Pacific Ocean tuna fishery and management implications. *Mar. Policy* **2003**, *27*, 449–469. [CrossRef]
12. Kumbhakar, S.C.; Lovell, C.A.K. *Stochastic Frontier Analysis*; Cambridge University Press: Cambridge, UK, 2000.
13. Kirkley, J.; Paul, C.J.M.; Squires, D. Capacity and capacity utilization in common-pool resource industries. *Environ. Resour. Econ.* **2002**, *22*, 71–97. [CrossRef]
14. Sharma, K.R.; Leung, P. Technical efficiency of the longline fishery in Hawaii: An application of a stochastic production frontier. *Mar. Resour. Econ.* **1998**, *13*, 259–274. [CrossRef]
15. Vestergaard, N.; Squires, D.; Kirkley, J. Measuring capacity and capacity utilization in fisheries: The case of the Danish Gill-net fleet. *Fish. Res.* **2003**, *60*, 357–368. [CrossRef]
16. Pascoe, S.; Mardle, S.; Tingley, D. Capacity appraisal in the English Channel fisheries. Available online: http://www.faoadriamed.org/pdf/publications/td13/PMT-td-13.pdf (accessed on 14 July 2016).
17. Lee, S.-G.; Rahimi Midani, A. Productivity change under the vessel buyback program in Korean fisheries. *Fish. Sci.* **2015**, *81*, 21–28. [CrossRef]
18. Coelli, T.; Grifell-Tatje, E.; Perelman, S. Capacity utilisation and profitability: A decomposition of short-run profit efficiency. *Int. J. Prod. Econ.* **2002**, *79*, 261–278. [CrossRef]
19. Simar, L.; Wilson, P.W. Sensitivity Analysis of Efficiency Scores: How to Bootstrap in Nonparametric Frontier Models. *Manag. Sci.* **1998**, *44*, 49–61. [CrossRef]
20. Bogetoft, P.; Otto, L. *Benchmarking with DEA, SFA, and R*; International Series in Operations Research & Management Science; Springer: New York, NY, USA, 2011; Volume 157.
21. Gocht, A.; Balcombe, K. Ranking efficiency units in DEA using bootstrapping an applied analysis for Slovenian farm data. *Agric. Econ.* **2006**, *35*, 223–229. [CrossRef]
22. Simar, L.; Wilson, P.W. Statistical Inference in Nonparametric Frontier Models: The State of the Art. *J. Product. Anal.* **2000**, *13*, 49–78. [CrossRef]
23. Tingley, D.; Pascoe, S.; Coglan, L. Factors affecting technical efficiency in fisheries: Stochastic production frontier versus data envelopment analysis approaches. *Fish. Res.* **2005**, *73*, 363–376. [CrossRef]

24. Squires, D. Public regulation and the structure of production in multiproduct industries: an application to the New England otter trawl industry. *Rand J. Econ.* **1987**, *18*, 232–247. [CrossRef]
25. Holland, D.S.; Sutinen, J.G. Location choice in New England trawl fisheries: Old habits die hard. *Land Econ.* **2000**, *76*, 133–149. [CrossRef]
26. Färe, R.; Grosskopf, S.; Lee, H. A nonparametric approach to expenditure-constrained profit maximization. *Am. J. Agric. Econ.* **1990**, *72*, 574–581. [CrossRef]
27. Banker, R.D.; Chang, H.; Natarajan, R. Estimating DEA technical and allocative inefficiency using aggregate cost or revenue data. *J. Product. Anal.* **2007**, *27*, 115–121. [CrossRef]
28. Portela, M.C.A.S. Value and quantity data in economic and technical efficiency measurement. *Econ. Lett.* **2014**, *124*, 108–112. [CrossRef]
29. Del Hoyo, J.J.G.; Espino, D.C.; Toribio, R.J. Determination of technical efficiency of fisheries by stochastic frontier models: A case on the Gulf of Cadiz (Spain). *ICES J. Mar. Sci. J. Cons.* **2004**, *61*, 416–421.
30. Esmaeili, A. Technical efficiency analysis for the Iranian fishery in the Persian Gulf. *ICES J. Mar. Sci. J. Cons.* **2006**, *63*, 1759–1764. [CrossRef]
31. Ali, F.; Parikh, A.; Shah, M.K. Measurement of economic efficiency using the behavioral and stochastic cost frontier approach. *J. Policy Model.* **1996**, *18*, 271–287. [CrossRef]