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Systematic Review and Meta-Analysis of Efficiency in Maritime Industry

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Abstract

The purpose of this paper is to complement and extend previous literature reviews on technical efficiency (TE) in Maritime Industry, analysing the effects of different methodologies and study-specific characteristics on Mean Technical Efficiency (MTE). The researchers independently conducted a systematic review of more than 171 full text papers from four key electronic databases and the results from meta-regression analysis of 35 published papers in maritime industry worldwide are discussed. The variation in the mean indexes in the literature can be explained by the methodology of estimations (parametric, non-parametric), the data collecting scheme and sample size. This study makes two important contributions: first, it updates and compares previous works on frontier estimation efficiency in maritime industry; and second, it has brought in 'sector' as another dimension for analysis.

Keywords
Maritime Industry; Meta-Analysis; Operational Efficiency; Frontier Models.

1. INTRODUCTION

The role of maritime industry is a crucial in global trade and economic activities. The United Nations Conference on Development and Trade (UNCTAD) statistics has indicated a rapidly increasing trend in the annual demand and supply for all types of cargoes transported (Asariotis et al., 2015). Around 80% of world merchandise depends on seaborne transportation. For the year 2014, in the most developing economies and also in the economies in transition, the gross domestic product has expanded at slower rates between 4.5% and 0.9%, respectively (Asariotis et al., 2015).

There have been perennial concerns concerning the expansion of the world 's seaborne trade and derived profits and the argument have centered around actions for improving efficiency. Several studies have highlighted that scope exists for maritime industry to boost profits and performance (Gutiérrez, Lozano, & Furió, 2014; Chang & Liao, 2012; Kim, Lee, Bae, & Park, 2011; Odeck, 2008; Managi, 2007). In such light, understanding the factors affecting efficiency is imperative to improve performance and efficiency. Effectiveness was defined by Farrell (1957) in 2 ways: first, the ability of firms to create the maximum feasible output with a given bundle of inputs (output oriented); or even second, the ability of firms to make use of minimum inputs to produce a given level of outputs (input oriented).

Corrective actions based on efficiency measurements as also identifying the potential sources of inefficiency can result in substantial resource savings. These resource savings have important implications for both policy formulation and shipping management. Therefore, a firm may be considered to be technically efficient if it is able to achieve maximum output from its set of inputs (Talas, et al., 2013), or perhaps minimise its consumption of inputs to produce a given level of output (Kuwahara et al., 2013).

Different methodologies and tactics to measure TE have produced a wide range of results. Timmer (1971) used linear programming techniques to estimate the efficiency frontier and generated both probabilistic and deterministic frontiers. Nevertheless, both the methods have been compared with the ordinary least squares (OLS) technique. But the outcome from OLS technique application appears to have a management bias and lacks identifiable statistical properties (Greene, 1980).

Management bias occurs when efficiency correlates to the efficiency factors. When such a condition persists, the estimation becomes useless and can only be used to justify the hypotheses. Many authors have discussed the advantages and limitations of different methodological approaches (Coelli, Rao, O'Donnell & Battes, 2005; Banker, Charnes & Cooper, 1984; Charnes, Cooper, & Rhodes, 1978; Schmidt, 1976).

Many alternate techniques may be proposed to evaluate comparative efficiencies such as the least squares econometric production model and total factor productivity index etc. It is to be observed that these models fundamentally presume that all firms are technically efficient, and are applied to defined scenarios and not widely used.

To choose an effective tool for such measurements, efficiency can be defined as the relative overall performance of a set of firms that make use of a variety of identical inputs to produce a variety of identical outputs (Afzal & Lawrey, 2012). This is also referred to as economic efficiency or technical efficiency and the price (TE) of the industry, as interpreted by Farrell (1957). In this context, TE measures the shortfall of the output (Danquah, Barimah, & Ohemeng, 2013) with an approach towards the industrial frontier (Deng, Wong, Wooi, & Xiong, 2011).

Within this scope of this context, this paper complements and extends the previous literature reviews on efficiency in maritime industry. This was achieved by compiling all the newly published empirical evidences and analysing the effects of different methodologies. In order to achieve this goal, a meta-regression analysis of 35 published papers in maritime industry has been applied. This study makes two important contributions to the literature, firstly it has updated and compared the previous works on frontier estimation of efficiencies in maritime industry and secondly it has added two maritime industry related dimensions to the known differentials of efficiency measurements (viz., economic development and size).

2. LITERATURE REVIEW

The preliminary works comparing the productivity levels amongst different nations commenced in the mid-20th century (Broadberry & Fremdling, 1990). During that period, productivity was measured as the ratio of output to the variety of workers. For instance, Rostas (1943) measured productivity as the ratio of physical output per value and per person.

Farrell (1957) provided a new definition for productive efficiency, as the connection between the set and the output pair of inputs. Furthermore, Farrell interpreted that technical efficiency reflects the quality of the inputs, while the price efficiency is actually the manifestation of the firm 's adaptability to the price factor.

Similarly, Farrell and Fieldhouse (1962) validated the findings of Farrell (1957) in a study of productivity and efficiency measurements in situations where there are several outputs and many inputs. They recommended two techniques to measure productivity when such a condition is experienced and the condition persists. One set of results measured each output over the set of inputs while the other measured the set of outputs over each input.

Schmidt (1976) studied the appropriateness of the parametric frontier estimation techniques of OLS and maximum likelihood estimation (MLE). Schmidt (1976) argued that OLS is the appropriate method for testing a hypothesis concerning the constant returns to scale. But for estimating the frontier only, OLS may not appropriate. Likewise, where the regularity conditions (independent of a parameter) are uncertain, application of MLE could be only on a case-by-case basis.

Charnes, Rhodes and Cooper (1978) developed a model to estimate the efficiency of firms with common outputs and inputs. This model employs OLS and will be appropriate for aggregated time series only, but the new model is adaptable while measuring multiple firms at one point of time. The latest development referred to as CCR (constant returns to scale model) measures the effectiveness of the ratio of weighted outputs over weighted inputs. This particular design is primarily used to assess the programme/product and the management of a firm (Banker et al., 1984). Later, Banker et al. (1984) developed another model to measure technical and price inefficiency, known as the BCC model. Based on these initial ideas, data envelopment analysis (DEA) and stochastic frontier analysis (SFA) analysis methods have been designed and used to estimate the relative efficiency amongst firms (Coelli et al., 2005).

2.1 Data Envelopment Analysis

Data envelopment analysis (DEA) is a very useful support tool (Leal Jr., Garcia, & D'Agosto, 2012; Liang, Jiang, & Lai, 2008) for measuring reputation (Brønn & Brønn, 2005) and determining the position of an enterprise (Talas et al., 2013) by benchmarking amongst the companies or amongst the decision-making units (DMUs) (Das & Patel, 2014). DEA helps managers to understand performance as a full, or perhaps the performance of individual units (Borenstein, Becker, & Prado, 2004). Additionally, DEA is able to form a part of a systematic evaluation (Lang & Golden, 1989) for multi-criteria vendor evaluations (Gregoriou, 2006), judiciously approached performance assessment (Gerard & Roderick, 2003) and resource efficiency measurement (Boles, Donthu, & Lohtia, 1995).

In a powerful environment, DEA is easily modified to deal with the changing needs of the management (Golany & Storbeck, 1999) by ascertaining the inputs and outputs for programme improvement and decision making (Banker, Charnes, Cooper, & Schinnar, 1981). DEA has proved to be a useful methodology (Helmig & Lapsley, 2001) utilising a strong analytical technique (Santos, Amado, & Santos, 2012). In summary, it may be argued that DEA is a powerful, efficient and comprehensive mechanism to determine the most effective and probably the least efficient DMUs (Husain, Abdullah, & Kuman, 2000; Min & Joo, 2006).

2.2 Stochastic Frontier Analysis

Similar to DEA, stochastic frontier analysis (SFA) is another tool used to measure efficiency (Baten, Kamil, & Haque, 2010). SFA measures the differences between the inefficiency of units as well as the frontier through the residuals (Barros, 2005) by isolating the purely random error term, which reflects the efficiency (Taktak & Triki, 2012). SFA is actually useful on extremely rare occasions where the situation, such as the theoretical restrictions for cost frontier/production, can't be easily tested due to the difficulty in estimation, affected by noise due to uncontrollable and unpredictable factors (Martín, Román, & Voltes-Dorta, 2009). Since SFA uses MLE, the final estimators will include desirable statistical properties like unbiasedness, efficiency, and consistency in small samples (Radam, Yacob, & Muslim, 2010).

2.3 Hypothesis Formulation

Previous studies have shown that the DEA and SFA models do not yield similar results, and always differed slightly (Rowena, 2001). Hence, there is some debate in the literature on the preference of models. Sav (2012) explains that the DEA model provides greater efficiencies compared to SFA, while Radam et al., (2010) argue that the SFA model provides some statistical inference in the functional form of the frontier relative to the DEA model.

Based on such arguments, the following hypotheses are put forward:

H1. Efficiency varies according to the method of estimation (parametric, non-parametric).
H2. Efficiency varies according to the data collection scheme (panel vs cross-sectional).
H3. Efficiency varies according to the geolocation of the sample.

3. METHODOLOGY

This research was conducted on systematic approach. Figure 1 shows the selection of studies included in the systematic review.

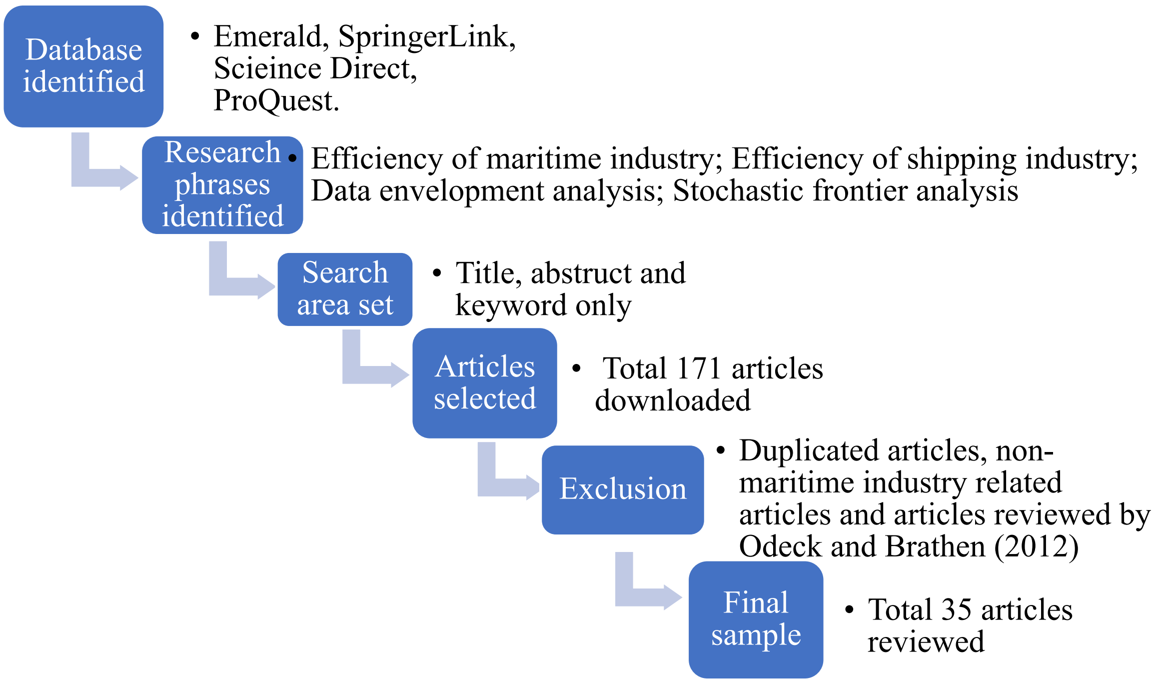

Figure 1: Search Strategy and Article Review Process.

First, the database was selected, which included the large majority of scientific journals of interest from sources such as Emerald, SpringerLink, Science Direct, and ProQuest. Second, the keywords for search were identified and inserted at appropriate search phrases such as 'Efficiency of maritime industry', 'Efficiency of shipping industry', 'Data envelopment analysis', 'Stochastic frontier analysis' and so forth. The search phrases were restricted to the title, abstract and keywords, which resulted in a collection of 171 papers.

The following criteria were used for exclusion of papers from the final full text review: duplicated papers; non-maritime industry related papers; papers already anaysed by Odeck and Brathen (2012) and inadequate information in relation to the methodology etc. A manual review of the abstracts (of the chosen 171 papers) was undertaken while applying the exclusion criteria. The filtering process resulted in 35 papers, which were included for a full text review.

A regression analysis was applied to the distributions from this carefully selected sample of 35 papers. This was exclusive of the data from Odeck and Brathen's (2012) studies. As explained in earlier second section, the hypotheses of this study are based on the assumption that the variation in the efficiencies reported in the literature can be explained by the attributes considered in the selected studies. This includes the estimation techniques, data collection methods and sample sizes.

Three regression models were estimated. Model I included the estimation technique and data collection method. Model II introduced two dummies to account for the effect of sector on efficiency. Model III included a variable to capture the potential sample size effects.

Model I

$$EFF = f\,(SFA, DEA, CS, P) \tag{1}$$

where EFF is the mean efficiency, as reported in the studies; SFA included a dummy variable equal to 1 if the model is a stochastic frontier analysis and 0, otherwise; DEA included a dummy variable equal to 1 if the estimation was performed using data envelopment analysis and 0, otherwise; CS included a dummy variable equal to 1 if the data is cross-sectional and 0, otherwise; P is a dummy variable equal to 1 if a panel data is used and 0, otherwise; and SZ is the number of observations included in the study.

Model II

$$Eff = f\,(SFA, DEA, CS, P, PORT, SHIP)$$

Where PORT is a dummy variable equal to 1 for studies at ports/terminals and 0, otherwise; SHIP is a dummy variable equal to 1 if the conducted studies were for shipping sector and 0, otherwise. All other variables are as defined in (1) above.

Model III

$$Eff = f\,(SFA, DEA, CS, P, PORT, SHIP, INT, AME, EUR, ASI, OCE)$$

Where INT is a dummy variable equal to 1 for international studies and 0, otherwise; AME is a dummy variable equal to 1 if the studies have been conducted in America and 0, otherwise; EUR is a dummy variable equal to 1 for studies conducted in Europe and 0, otherwise; ASI is a dummy variable equal to 1 if the studies have been conducted in Asia and 0, otherwise; OCE is a dummy variable equal to 1 for studies conducted in Oceania and 0, otherwise. All other variables are as defined in (1) above.

The models were estimated using the least square dummy variable (LSDM) analysis, given that the efficiency scores are within 0 and 1. LSDM is easy to estimate and interpret (Ali, Er, Ahmad, Lyndon, & Ahmad, 2013). At the same time, LSDM is also capable of providing control to omitted variables between cases (Venkadasalam, 2014).

4. RESULTS

A list of all the new papers included in this review is shown in Table 1 including the authors' names, year of publication, country, sample size, sector of search and mean efficiency values. Amongst the tabulated 35 papers, DEA methods have been applied in 29 cases and SFA methods in 6 cases.

While employing data collecting schemes, 14 studies have used panel data and remaining 21 studies have used cross-sectional data. Notably, most of the studies are related to the shipping sector, with 17 studies conducted on ports and 18 being on shipping. It may be inferred from these observations that the recent research in maritime field are more inclined towards shipping, non-parametric methods and cross-sectional data sampling.

Table 1. List of New Papers Included In This Review

No	References	Country	Sector	No. of observation	Mean efficiency
1	Schøyen & Odeck, 2013	Europe	Port	168 (P)	0.82 (DEA)
2	Navarro-Chávez & Zamora-Torres, 2014	International	Port	32 (CS)	0.455(DEA)
3	Díaz-Hernández, Martínez-Budría, & Salazar-González, 2014	Spain	Port	216 (P)	0.985 (DEA)
4	Odeck, 2008	Norway	Shipping	246 (P)	0.797 (SFA)
5	Kompas & Che, 2005	Australia	Shipping	131 (P)	0.917 (SFA)
6	Kim et al., 2011	Korea	Shipping	17 (CS)	0.587 (SFA)
7	Gutiérrez et al., 2014	International	Shipping	18 (CS)	0.865 (DEA)
8	Haralambides & Gujar, 2012	India	Port	16 (CS)	0.957 (DEA)
9	Bergantino & Musso, 2011	Southern European	Port	108 (P)	0.837 (DEA)
10	Low, 2010	East Asian	Port	23 (CS)	0.782 (DEA)
11	García-Alonso & Martín-Bofarull, 2007	Spain	Port	22 (P)	0.902 (DEA)
12	Chang & Liao, 2012	International	Shipping	64 (P)	0.522 (DEA)
13	Koster, Balk, & Nus, 2009	International	Port	38 (CS)	0.728 (DEA)
14	Førsund, 1992	Norway	Shipping	138 (CS)	0.971 (DEA)
15	Kirkley, Squires, & Strand, 1995	Mid Atlantic	Shipping	10 (CS)	0.672 (SFA)
16	Sharma & Leung, 1998	Hawaii	Shipping	91 (CS)	0.86 (SFA)
17	Pascoe et al., 2013	Torres Strait	Shipping	47 (P)	0.56 (DEA)
18	Pinello, Liontakis, Sintori, Tzouramani, & Polymeros, 2016	Greece	Shipping	283 (CS)	0.54 (DEA)
19	Pérez, Trujillo, & González, 2016	Caribbean	Port	378 (P)	0.843 (SFA)
20	Pjevčević, Vladisavljević, Vukadinović, & Teodorović, 2011	Serbia	Port	12 (CS)	0.953 (DEA)
21	Jiang & Li, 2009	Northeast Asia	Port	12 (CS)	0.778 (DEA)
22	Almawsheki & Shah, 2015	Middle eastern	Port	19 (CS)	0.669 (DEA)
23	Bang, Kang, Martin, & Woo, 2012	International	Shipping	14 (CS)	0.751 (DEA)
24	Birgun & Akten, 2005	Sea of Marmara and the Mediterranean	Port	10 (CS)	0.582 (DEA)
25	Dias, Azevedo, Ferreira, & Palma, 2009	Iberia	Port	10 (CS)	0.84 (DEA)
26	Huang, Chao, & Chang, 2017	International	Shipping	204 (P)	0.799 (DEA)
27	Itoh, 2002	Japan	Port	80 (P)	0.702 (DEA)
28	Kang & Kim, 2017	International	Shipping	350 (P)	0.269 (DEA)
29	Kutin, Nguyen, & Vallée, 2017	ASEAN	Port	141 (CS)	0.816 (DEA)
30	Hilmola, 2013	Baltic sea	Shipping	12 (CS)	0.915 (DEA)
31	Omrani & Keshavarz, 2015	Iran	Shipping	36 (P)	0.800 (DEA)
32	Panayides & Lambertides, 2011	International	Shipping	18 (CS)	0.824 (DEA)
33	Pantouvakis, Vlachos, & Zervopoulos, 2017	Greek	Shipping	397 (CS)	0.528 (DEA)
34	Park & Lee, 2015	Korea	Shipping	70 (P)	0.440 (DEA)
35	Zheng & Park, 2016	Korea and China	Port	30 (CS)	0.816 (DEA)

Notes: P: Panel studies; CS: Cross-sectional Studies; SFA: Stochastic Frontier Analysis; DEA: Data Envelopment Analysis.

Table 2 presents a quantitative survey of the 35 studies. With respect to the type of data used, the majority of studies (60%) used cross-sectional data whereas 40% used panel data. Of the 60% that used cross-sectional data, 51.43% were from DEA applications while only 8.57% were from SFA studies. The same trend is also observed for studies that were either port or shipping sector related, where 51.43% were shipping related and the rest 48.57% were port related. Of these, specifically 45.71% were from port studies with DEA, while only 2.86% were from port studies with SFA.

The regions where the studies were conducted are of interest as they may influence efficiency scores. The studies considered were from the following regions: International, America, Europe, Asia and Oceania. From Table 2 it may be seen that the studies under the group Europe have the highest representation at 34.28% followed by Asia (28.57%), International (22.86%), America (8.57%) and Oceania (5.72%).

Table 2: Quantitative Survey of The Literature.

	SFA	DEA	Total
No of studies	6	29	35
Cross sectional	8.57%	51.43%	60%
Panel	8.57%	31.43%	40%
Port	2.86%	45.71%	48.57%
Shipping	14.29%	37.14%	51.43%
International	0%	22.86%	22.86%
America	8.57%	0%	8.57%
Europe	2.86%	31.42%	34.28%
Asia	2.86%	25.71%	28.57%
Oceania	2.86%	2.86%	5.72%

It is of interest to provide an overview of how the different part of the studies differ with respect to the MTE scores and these analytical scores are projected in Table 3. Considering the total samples, panel data has the higher MTE scores than the cross-sectional data, whereas port studies have higher MTE than the shipping studies. Further, for cross sectional data analysis, the DEA has a higher count of MTE than its SFA counterpart; while for the panel studies, the DEA depicts higher scores than the SFA. Regarding the sector of study, port shows higher MTE than shipping. These are nonetheless, observations of the group level averages. The statistical analysis to validate the significance of these findings follows.

Table 3: Average MTE Scores By Different Study Characteristics.

	SFA	DEA	Total
Overall	0.788	0.730	0.759
Cross sectional	0.706	0.765	0.736
Panel	0.87	0.694	0.782
Port	0.843	0.784	0.807
Shipping	0.733	0.676	0.705
International	N/A	0.652	0.652

America	0.792	N/A	0.792
Europe	0.797	0.957	0.877
Asia	0.587	0.751	0.735
Oceania	0.917	0.56	0.739

Table 4 presents the results of regression analysis for all 3 models. Model 2 is very significant at the 1% level. The parameter estimate for the DEA is actually positive and statistically significant. The end result suggests that the reported MTE scores appear to be much better on non-parametric techniques and data methods. MTE scores on non-parametric techniques are approximately 28% higher compared to the parametric techniques.

The parameter estimates of the panel is also positive and statistically significant. In this data set, 60% of the observations are cross sectional data. The results indicate that the MTE scores are approximately 30% higher on panel analysis. Studies focusing non-ports appear to produce higher MTE scores than studies that were conducted on ports. This is significant at the 1% significance level.

Table 4: Regression Results

	Model 1**	Model 2***	Model 3*
Constant	0.619*	0.636*	0.189
DEA	0.286**	0.282**	0.446***
PANEL	0.310**	0.307**	-0.043
PORT		- 0.037***	-0.548
International			0.324
America			0.271
Europe			0.035
Asia			-0.163
Oceania			0.629
R sq	0.195	0.198	0.587
Adj. R sq	0.145	0.120	0.460

Note: Table 4 includes 315 observations from the 35 selected groups.

***significance at 1% confidence level

** significance at 5% confidence level

* significance at 10% confidence level

5. CONCLUSION

By analysing the effects of various techniques in the MTE, this document supplemented and extended the review of earlier work on TE in the marine industry. Meta-regression models that included the methodological characteristics of geographic location and studies were used to explain the MTE estimations given in 35 published articles. This study added to the existing literature in two ways: first, it updated and contrasted earlier work on border estimation of TE in the maritime business; and second, it introduced a dimension of the maritime industry, sector (port and shipping), to the known TE measurement differentials.

A metaregression model was used to analyse and test several topics found in the literature on efficiency. The econometric results reveal that when the estimate is made from non-parametric boundaries rather than parametric models, the TE level is actually larger. The DEA's coefficients were positive, indicating that the DEA creates more MTE than the SFA. Furthermore, when research employed the panel's dataset, the parameter for panel data reveals a higher MTE. These findings can be used to guide the selection of appropriate methodologies for measuring and modelling MTE.

This study provides evidence to support the H1 (efficiency varies according to the technique of estimation) and H2 (efficiency varies according to the data collection scheme). Only H3 (efficiency varies according to the geolocation of the sample) is not confirmed in this specific study. Analysing the level of TE by geographical location shows non-significant in all locations. This study recommends further studies on the H3. In future, the analysis is only able to focus on top 3 locations.

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