Macroeconomic conditions, regulatory changes and noise: are managers effectively responsible of port's efficiency? A multi-step approach to test European ports' relative efficiency.

Angela Stefania Bergantino, Department of Economics, Faculty of Economics, University of Bari, Via Camillo Rosalba, 53, Bari - 70124 (Italy)
Enrico Musso, Department of Economics, Faculty of Economics, University of Genoa, Via Vivaldi 5, Genova – 16124 (Italy)

Very provisional draft – do not quote without authors' approval

Abstract
This paper provides an estimation of the impact of exogenous factors – such as governance regimes and local socio-economic conditions – and managerial capacity, cleared of statistical noise, on the efficiency of ports. We implement a three stage DEA procedure following the approach of Fried et al. (2002), using a panel of European ports, observed over a ten year period. By using in the second stage of the analysis a stochastic framework model, we are able to identify the determinants of input-specific efficiency differentials across ports. The outcome shows that, in general, governance related factors and other external elements predominate on the managerial skills in determining efficiency conditions of ports: performances change significantly by controlling for factors considered outside direct ports' managers control. The procedure helps to gain further insights on the evolution of the port industry in the EU and to define strategies for improving operational performance of ports, passing through governance and regulatory framework.
Key words: ports, efficiency, regulation, multi-step DEA

1. INTRODUCTION

The port sector plays an important role in the economic development of a country and public sector involvement, although to a varying degree in the different EU countries, is still quite significant. Economic conditions, globalisation and technological innovations have augmented the competitive pressures on the overall industry. This situation has stimulated interests on the capacity of ports to respond effectively to the increasingly growing requirements of shipping lines, the hinterland, local authorities and, in general, final users. Information of ports' efficiency and its evolution is pivotal for the evaluation of both managerial strategies and port planning, at local and national level. This is the more so in the presence of policy changes that might influence the governance structure of ports. Many countries, especially in Europe, have, in the last decades, adapted their port-related legal framework in order to give ports more flexibility in all aspects related to management, commercial strategies and financing (De Monie, 1996; Suykens and Van de Voorde, 1998; Trujillo and Nombela, 2000; Noteboom and Winkelmans, 2001; Bergantino, 2002; Tovar et al., 2004; Castillo-Manzano et al., 2008; Musso, 2008) in a strive to increase ports' efficiency and performance. These are, in fact, the main drivers of port selection by shippers and shipping companies[1] and, thus, determine the ability of a port to contribute to a country's economy.

[1] For a review of the port selection criteria and their evolution the reader is referred to, for instance: Murphy and Daley (1994); Bergantino and Coppejans (2000); Cullinane et al. (2001) and Tongzon (2002).

The role played by non-discretionary characteristics in affecting performances, however, has been gaining momentum in the literature investigating the determinants of production inefficiency in sectors with relevant involvement of the public sector. Efficiency gaps, in fact, might be due to, besides managerial lack of capability, either the high degree (or the form) of government involvement (i.e. alternative governance regimes might give rise, *ceteris paribus*, to inefficiency differentials across operators) or the different operating conditions, that are not controlled by operators. These considerations fit well the transport sector in general and the port industry in particular.

Researchers have, thus, focussed increasing attention on the measurement of efficiency in the port industry[2]. Although a number of different approaches have been adopted, there is a general consensus on either DEA or SFA related measures[3]. They represent two alternative methods to measure efficiency based on frontier models. Both techniques allow derivation of relative efficiency within a group of units of analysis.

It is well known that DEA is a non-parametric mathematical programming technique used for estimating the relative efficiency and return to scale of decision making units that perform the same or similar tasks in a production system, through the construction of a best practice frontier. Since it was first developed by Charnes et al. (1978) and extended by Banker at al. (1984), various DEA approaches have been widely applied for the efficiency evaluation throughout different industries, including public and private sectors. SFA, on the other hand, is an econometric technique which involves imposing a particular functional form and specific distribution assumptions for the one-sided error term associated with technical efficiency. Both have advantages and disadvantages. In particular, DEA, contrary to SFA which allows to include the term explicitly in the model, seemed to be unable to give insights on the role played by the operating environment focussing on internal factor.

On the basis of these considerations, for a long time, the SFA has been favoured in the dedicated literature. Stochastic frontier models allow to analyse directly the impact of these factors on the absolute efficiency of the sample. The widespread result is that the predictions from incentive theory do, indeed, explain productive efficiency differentials. With reference to the maritime industry, Cullinane et al (2002) and Cullinane and Song (2006) estimated the efficiency of terminal

[2] In the recent past a number of papers have adopted either SFA or DEA methodology to test terminal or port authorities' efficiencies focussing, principally, on estimating traditional endogenous and time invariant sources of inefficiency at either single or multi-country level. Among the latter, see, for instance, Martinez- Kim and Sachish (1986), Budria et al (1999), Noteboom *et al* (2000), Cullinane and Song (2001), Tongzon (2001a, b), Valentine and Gray (2001), Wang et al (2002), Cullinane et al. (2002), Cullinane and Song (2003), Barros and Athanassious (2004), Bonilla et al, (2004), Cullinane et al. (2004), Park and De (2004), Turner et al (2004), Cullinane et al. (2005), Cullinane and Wang (2005), Tongzon and Heng (2005), Truijllo and Tovar (2005 and 2007), Barros (2006), Cullinane and Song (2006), Cullinane et al. (2006), Rios and Gastaud-Maçada (2006), Wang and Cullinane (2006), Rodriguez-Alvarez *et al* (2007), Herrera and Pang (2008), Al-Eraqi et al. (2008). For a detailed review of applications to the port sector, see: Gonzalez and Trujillo (2009).

[3] For a general overview of DEA approach the reader is referred to Charnes et al. (1978), Banker et al (1984) and Cooper et al. (2000). In addition, for a comparison of the two methods, see: Coelli et al. (2005) and Fried et al (2008).

operators dealing with the role played by different administrative and ownership structures in the industry as exogenous factors affecting inefficiency differentials. They also find a significance influence of external factors on the overall terminal's efficiency. Also Trujillo and Tovar (2007) results point in the same direction. Particularly rich is the analysis carried out in Barros (2003b) for specific national contexts.

These studies although shading light on the relevance of the operational and institutional environment of ports in influencing ports' efficiency outcome, show only "aggregated" efficiency results. In fact, while stochastic methods provide extremely valid insights in identifying the importance of the relationship between factors external to companies' control and their performance, they do not yield indications on how to narrow the efficiency-gaps nor on which inputs are majorly affected by the operating conditions. They fall short of distinguishing the impact of external factors and noise from the effects of managerial skills on efficiency, on an input-by-input base. As a matter of fact, inputs employed by ports can be rationalised to different extents. Hence, changes in regulation and/or non-discretionary characteristics may induce higher efficiency in the use of more controllable inputs compared to less controllable ones: capital and labour, for instance, might be influenced differently by different forms of regulation or different economic conditions. Their overall effect on the technical efficiency of the port might differ, independently of the managerial capacity of the authorities.

On this account, in recent years, there have been some developments in DEA-based models. In particular, starting from the work of Fried et al. (1999 and 2002), operating environment and statistical noise have been introduced explicitly in the DEA-framework through a multi-stage procedure combining DEA and SFA[4].

This current analysis presents a number of advantages and integrates well the existing studies. Building on previous literature it aims at verifying the extent to which both governance and other non-discretionary factors affect input inefficiencies in the port sector, across countries, using a combination of DEA and SFA as in Fried et al.. Differently from their study, however, and, to our knowledge, from other studies on the port industry, we have used panel data, adopting, in the second step of the analysis both random and fixed effect modelling.

Ports' relative efficiency has been calculated without imposing any ex-ante assumption on the functional form as, instead, it would have been necessary, should SFA have been adopted and it has been possible to quantify, input by input, the contribution to a port's efficiency level of three main factors: exogenous factor (outside the managers' control but modifiable by regulators and policy-makers), managers' abilities and statistical noise, exploiting the longitudinal characteristics of the dataset.

[4] One of the first application of multi step procedure was that of Timmer [1971] in an attempt to explain interstate variation in technical efficiency in US agriculture. A two-stage approach has been used also by McCarty and Yaisawarng [1993] to investigate efficiency in New Jersey public school districts. Worthington and Dollery [2002] compare different methods to account for the effect of EVs on the efficiency of 73 New South Wales local governments in Australia. More recently, multi step procedures have been used to estimate efficiency of the banking systems (…), education (..), health service provision (Porcelli, 2009)

The outcome of the study allows the assessment the efficiency enhancing effect of different forms of governance of the port authorities across countries and regions and complements the SFA in the capacity of identifying the source of inefficiencies input by input. The third stage reruns the DEA using inputs that are adjusted to reflect differences in the nature of ports' exogenous conditions. What is left is a set of rankings that more accurately reflects differences in ports' relative efficiency.

The rest of the paper is organised as follows. Section 2 briefly reviews the mixed DEA-SFA methodology used by Fried et al. (2002) to take account of input-by-input sources of slacks and adopts it to take account of the panel nature of the dataset. Section 3 details the implementation to our case study with the identification of the variables and the data description. The results of the three step procedure are presented in Section 4. Section 5 concludes the paper with a brief outline of the main implications of the analysis and some suggestions for future research.

2. ESTIMATION METHODOLOGY

The two main limitation of DEA, i.e. assumption that data is free of measurement errors and that it cannot take explicitly into account environmental factors, have lead to the flourishing of different solutions aiming to overcome these limits. There are at least two main approaches to incorporating uncontrollable or non-discretionary inputs in DEA. The first approaches were based on a single step procedure, where uncontrollable inputs were included in DEA as a constraint in linear programming (Banker and Morey, 1986). However, for all those case for which it is preferable to test the direction of the impact of discretionary factors on efficiency, this approach is not appropriate (Avkiran and Rowlands, 2008) and the multiple step approach comes in. This approach entails a number of methods. However, a common practice is to run DEA where all the inputs are treated as controllable and then, in stage two, regress the emerging efficiency scores on non-discretionary inputs and run the DEA using the adjusted inputs.

The purpose of this section is to detail the estimation approach used in identifying the true managerial performance of ports once the playing field has been levelled by taking account of input-by-input sources of slacks. As stated in the introduction, our approach is based on Fried et al. (2002)'s three step methodology, however, it is extended to take account of the longitudinal characteristics of the dataset. We use, in fact, panel data approach adopting both variable and fixed effect modelling[5].

2.1 Three step procedure

Fried et al (2002)'s procedure to clear producers' performance evaluation of environmental effects and statistical noise consists of a three stage analysis that starts with DEA. The second stage is a SFA. It serves to explain the variation in organisational performance measured in the first stage in terms of operating environment, statistical noise and managerial efficiency. Global input inefficiencies determined in stage one are regressed on a set of regressors relating to regulatory and to other exogenous factors. The third stage concludes with a new DEA of

[5] On the advantages of modifying existing frontiers models to allow the use of panel data and for a presentation of the different alternative estimators the reader is referred to the seminal work of Schmidt and Sickles (1984).

organisational performance. The analysis is carried out using adjusted data from the second stage that have been purged of the influence of the operating environment and statistical noise. The re-evaluation of performance allows for a better assessment of the role played by managerial skills as the evaluation emerging from stage three DEA represents managerial efficiency only.

2.1.1 First step

Consider *I* Decision Making Units (DMUs), with i = 1, . . ., I, each of them employing N inputs (n = 1, . . ., N) to produce M outputs (m = 1, . . ., M) at year T (t=1,...,T). Using data on observed inputs and outputs, a standard input-oriented variable returns to scale envelopment problem is solved for each i_{th} DMU in the sample (Banker et al. 1984). The Linear programming problem outlined by the authors is:

$$\min_{\theta,\lambda} \theta \qquad [1]$$

$$\text{s.t. } \theta x_i \geq X\lambda$$
$$\lambda Y \geq y_i$$
$$\lambda \geq 0$$
$$e^T \lambda = 1$$

where x_i is a DMUs N×1 non-negative input vector; y_i is a DMUs M×1 non-negative vector of outputs; $\lambda = [\lambda_1, \ldots, \lambda_I]$ is an I×1 vector of intensity variables; $X = [x_1, \ldots, x_I]$ is an N×I matrix of input vectors in the comparison set; $Y = [y_1, \ldots, y_I]$ is an M×I matrix of output vectors in the comparison set; e = [1, . . ., I] is an I×1 vector.

The optimal solution to emerge from equation [1] are the preliminary performance evaluation scores. The total slacks - radial plus non radial -, for each input are calculated as the following non-negative scalars[6]:

$$s_{nit} = x_{nit} - X_n\lambda \qquad [2]$$

These measures, however, based on the DEA methodology, neglect two possible sources of inefficiency: external and operation factors which, together with input and output data, might have a significant role in affecting overall efficiency levels of the various DMUs and, potentially, given the deterministic approach, omitted variables, which might, instead play a role in determining overall efficiency.

Not accounting for either of these non-discretionary differentials across firms belonging to the sample might lead to over or under evaluation of performances and misleading rankings. As Fried et al (2002) suggest, using SFA to decompose DEA input slack into its three potential components – exogenous effects, managerial inefficiency and statistical noise – should overcome the problem.

[6] The input slack represents the overall input excess with respect to the optimal use under best practice conditions. The slacks include both the distance from the isoquant (the Debreu-Farrell measure of efficiency) and the difference between the definition of efficiency by Koopmans and that by Debreu-Farrell. These difference tends to zero with the increase in the number of DMUs and it is not present in the econometric approach.

2.1.2 Second step

Using SFA, in the second stage input slacks are regressed on observable non-discretionary regulatory and environmental variables with the objective of clearing slacks of external effects. Furthermore, a composite error term, made up of two parts, allows to capture and distinguish also statistical noise due to measurement errors and to managerial inefficiency. The SFA regressions for each slack take the following form:

$$s_{nit} = f_n(z_{it}, \beta_{nt}) + (\upsilon_{nit} + u_{ni}) \qquad [3]$$

where $s_{nit} \in (0,1)$, is the slack obtained in step 1 for the n^{th} input and the i_{th} DMU at the t^{th} year, $z_i = [z_{1i}, \ldots, z_{Ki}]$ is a vector of K exogenous variables, β_{nt} are unknown parameters to be estimated and $(\upsilon_{ni} + u_{ni})$ is the composite error term. The symmetric component $\upsilon_{nit} \sim (0, \sigma^2_{\upsilon nt})$ represents statistical noise, while u_{ni} reflects pure managerial inefficiency.

In [3], in fact, the term $f_n(z_{it}, \beta_{nt})$ captures the impact of observable external factors (regulation and environment) on the stage one slacks (i.e. deterministic feasible slack frontier), while the expression $f_n(z_{it},\beta_{nt})+\upsilon_{nit}$ (stochastic feasible slack frontiers) indicates the minimum achievable slack in a noisy context, at year t, given that $u_{ni} \geq 0$. The latter, since the effect of non-discretionary variables and statistical noise have been netted out, is the managerial inefficiency component of the slacks. It reflects, thus, in [3], the variability of managerial inefficiency across both DMUs and inputs. With the random effect model, it reflects also variability through time, see [4].

Depending on the hypothesis on the distribution of pure managerial inefficiency and on the relevance of time in determining managerial efficiency, [3] can be estimated with Maximim Likelihood (ML) estimation or with Fixed Effect (FE) *within* estimator[7].

In the first case, the error term u_{ni} is assumed one-sided half-normal distributed (i.e., the distribution is derived from a normal distribution $N(0, \sigma^2_{un})$ truncated from below at zero) and the managerial inefficiency terms can be modelled according to the time-varying inefficiency model defined by Battese and Coelli (1992)[8]:

$$u_{nit} = u_{nT} * e^{-\eta(t-T)} \qquad [4]$$

where T indicates the final year of the time series for each port; t = 1,...N, denotes the time, η is a parameter to be estimated which indicates the direction and the magnitude of the trend of the u-term over time, and the inefficiency term, u_{nT}, is assumed have an i.i.d. half-normal random variable distribution $N^{+}(0, \sigma_u^2)$.

---

7 Most of the empirical works that uses multi stage approach usually account for the fractional nature of the dependent variable using a Tobit model in the second-stage regression. However, following the work of the recent paper of Papke and Woolridge (2008), given that our dependent variable although bounded from below to zero is never equal to zero, we consider the Tobit model not suitable. For greater details the reader is referred to the demonstration in Papke and Woolridge (2008) in journal of econometrics.

8 See also Coelli et al (1998; 2005) for greater details.

A positive value of η implies a downward trend in the managerial efficiency term over time while a negative value implies an upward trend. Thus, the trend of the managerial inefficiency for each input, along with its statistical significance, is directly derived from the data, once both environmental factors and noise have been removed. This model might be associated to a random effects model and ML estimator can be used.

For each regression, the parameters to be estimated are β_{nt}, $\sigma^2_{\upsilon nt}$, σ^2_{un}. In obtaining ML estimates the variance of the composite error term is parameterised as: $\sigma^2_n = \sigma^2_{\upsilon n} + \sigma^2_{un}$. The proportion of the total error variance attributable to managerial inefficiency on the overall inefficiency can be calculated as: $\gamma = \sigma^2_{un}/\sigma^2_n$. A likelihood ratio test for this structural parameter provides an insight on whether pure managerial inefficiency may be neglected from the analysis. With ML, all parameters are allowed to vary across the N input slack regressions, which allows all of the three elements (the non-discretionary variables, statistical noise and managerial inefficiency) to exert, each, a different impact across inputs.

The ML estimator is, however, subject to the potential criticism of having arbitrary assumptions about the distribution of the random terms and the restrictive assumption that the two random components are uncorrelated with each one of the explanatory variables. This implies that the firm's inefficiency is uncorrelated with its observed characteristics included in the regression. In the real world, however, many of these factors may affect the firm's inefficiency.

Following the approach of Schmidt and Sickles (1984)[9], it is possible to verify the robustness of the ML results. In their model the one-sided fixed component u_{ni} that represents managerial inefficiency, is identified by a fixed effects (FE) specification with no assumption on its distribution, and [3] can be estimated through OLS or within estimator. Inefficiency scores are estimated as the distance to the firm with the minimum fixed effect, that is: $u_{ni} - \min\{u_{ni}\}$. The resulting model is a fixed-effects model and is labeled as the FE model in the rest of the paper.

As the ML, the FE approach controls for unobservable firm-specific effects, such as inefficiency, that are not captured by control variables. The main advantage of the fixed-effects specification is that the estimations are unbiased even if explanatory variables are correlated with firm-specific dummies. However, the inefficiency measures may be confounded with time-invariant factors, which cannot not be included in the model. The time invariant variables, in fact, are captured by the fixed effects and this implies that the inefficiency estimators include the variations in time-invariant firm characteristics. Moreover, inefficiency is assumed to be constant over time.

The choice between random effects and fixed effects models also depends on whether or not firms belong to the same population[10]. The random effects model is a legitimate specification to the extent that the heterogeneity among companies is limited to a single population. For our study, we believe that it is credible to use fixed effect modeling as the units of analysis belong to different populations.

[9] For a presentation of this method see also Simar (1992).
[10] See Baltagi (2001) and Hsiao and Sun (2000) for detailed discussions on fixed vs random effects.

Neither of the SFA regression models presented above require specification of the direction of the impact of the non-discretionary variables: it can be read by the sign of the estimated coefficients.

2.1.3 Third step

In the third step, parameter estimates obtained from SFA regressions estimated using both ML and FE, are used to predict input slacks attributable to the operating environment and to statistical noise. Inputs are adjusted netting out exogenous effects and statistical noise. A new DEA is ran with the adjusted inputs. The efficiency ranking is then compared with the previous results to verify the impact of these factors on efficiency scores. The ex-ante efficiency results are defined as gross efficiency, the new efficiency results can be considered net efficiency levels.

2.1.3.1 Adjusting inputs

In order to asses true performance of each port observed at each year it is necessary to take account of environment and to distinguish between i) statistical noise (υ_{nit}) due to the inputs used from ii) managerial inefficiency (u_{ni}) in the composed error term of the SFA regression[11].

As a first stage of the third step of the analysis, observed inputs are adjusted, thus, for the impact of the environment and statistical noise using the resulting estimates for β_{nt} and υ_{nit}, respectively:

$$x_{nti}^{Adj} = x_{nit} + [\max_i(z_{it}\hat{\beta}_{nt}) - z_{it}\hat{\beta}_{nt}] + [\max_i(\hat{\upsilon}_{nit}) - \hat{\upsilon}_{nit}] \qquad [5]$$

where (x_{nit}^{Adj}) is the adjusted quantity of the n*th* input in the i*th* DMU at the t[th] year.

The terms in brackets represent the adjustments and are used to create, “artificially”, a level playing field for the DMUs in the sample: the first term in square brackets places all firms in the least favourable environment observed in the sample, while the second term in square brackets forces all firms to operate in the worst situation observed in the sample. By doing so, distortions from the efficient usage of each input due to external factors and random noise, which are not under the control of DMUs, are removed[12].

2.1.3.2 Rerunning-DEA

In the third step DEA is repeated replacing the observed input data with adjusted input data. The outcome represent DMUs performance due to managerial efficiency only. The comparison between initial and final DEA efficiency measures yields, *ceteris paribus*, a measure of the impact of non-discretionary variables on efficiency differentials. Before comparing ex-ante and ex-post efficiency outcomes to test the

---

[11] The method used to separate the composed error term into its components has been developed by Jondrow et al. (1982).

[12] The statistical noise attached to an input usage, which is conditional on the composite error structure, is estimated by subtracting from the input slack calculated in step 1, the estimate of the input slack for a given DMU attributed to non-discretionary factors and the conditional estimate of managerial inefficiency for the same input and DMU.

robustness of the two approaches used, ML and FE, a correlation analysis is carried out on the resulting ranking of the efficiency scores.

3. THE SPECIFICATION OF THE MODEL

The current section describes the implementation of this methodology to our case study, focusing on the specification of nonparametric deterministic reference technology and on the modelling of regulatory schemes and other environmental variables involved in the subsequent SFA. One might, in principle, try to estimate the efficiency conditions in either a demand or a supply-related framework. However, as Cullinane and Wang (2006) point out, supply-related output indicators of port services might be considered under greater managerial control than demand. Although regulatory constrains (both institutional and financial) influence strongly the service level provision and supply in general, it is reasonable to think that such constraints are the outcome of some negotiation process with the regulatory authorities. Thus, the analysis is carried out adopting an input-oriented DEA framework.

3.1 Variables selection

Port activity is complex and involves a number of functions and stakeholders. Ports are "factories designed to receive and dispatch cargo that arrives in many different forms" (Jara-Diaz et al. 2006, p. 68) and, depending on which feature of the port operations are being valued, there are a number of different measures of port output. The movement of cargo is one of the most widely used ones and can take many different forms. Since the scope of the current analysis is to test efficiency of ports across various EU countries, notwithstanding their specific vocation, port output is identified as "port throughput expressed in total tonnes of cargo handled per annum". Although the selected measure has been subject to some criticism when the analysis was focussed on container terminal[13], its use in this framework might be justified in the light of the wider scope of the present study. In this case, in fact, the more commonly used measure of the number of containers handled reported in terms of twenty-feet equivalent unit (TEU), although it would improve the precision of the estimates by considering a more homogeneous product, it would limit the extent of the analysis to only one of the port activities[14]. As stated earlier, we considered each port with all its transport related activities, a single unit of analysis.

The services produced by the port require a large variety of inputs. Based on the production framework, port inputs can be generalised as: land, labour and capital, which can be grossly redefined as space, employees, facilities and equipment, respectively. In the light of the difficulties in obtaining reliable direct data and information on labour inputs, this variable is generally considered pre-determined and it is excluded from the estimation[15].

[13] For a detailed analysis of the variable selection the reader is referred to Cullinane and Song (2006).

[14] A number of authors consider that port activities should be specified in a multiple output form, however, the aggregate output approach, on account of data availability, has been favoured in many studies. For a detailed review of the issue, see, for instance, Jara-Diaz et al., 2006.

[15] A number of authors point out that labour information can be determined as a function of the facilities of a port and that, thus, they can be excluded from the estimation (see for instance: Tongzon, 1995; Notteboom et al., 2000; Turner et al, 2004; Trujillo and Tovar, 2005; Gonzales and Trujillo, 2008). In particular, Notteboom et al (2000), report no statistical significance for this input and attribute the result to the co-linearity of the variable with that related to equipments. As

Following the literature flourished in this field, thus, the choice of inputs has fallen on those related to physical factors: dimension of quay, number of terminals, area of the port used for handling freight, cargo handling equipment (cranes, lifters, link-belt).

As previously illustrated, in order to take account the external conditions that might influence ports' efficiency scores, a number of exogenous variables, beyond management control, have been considered. The exogenous variables used in the second stage are of two types: environmental, non-discretionary, variables and policy related variables. The former, take account of the impact of the different characteristics of the area where the port is located, thus control for heterogeneity among ports. The latter, relates to the governance set-up and, more specifically, it aims to pin-point the potential changes in the economic environment that occurs after the introduction of new regulatory framework. This variable, vary across country and time, but is not differentiated for ports belonging to the same country, since, in general, port regulation is determined at national level.

This set of variables have been selected with a twofold objective: on the one side to capture additional sources of inefficiency not accountable by managerial efforts; on the other side, to identify their specific effects on each of the inputs considered in the analysis and thus highlight possible specific policy intervention measures.

Non-discretionary characteristics include variables linked to the operating context of each port and to other external factors outside management control. Considering the need to identify variables that would be able to account differentials both among ports of different countries and ports of the same country, the choice has fallen on: regional gross domestic product, employment rate, population density, accessibility. Gross domestic product (*gdp*) to capture the derived nature of the port service and maritime transport demands from economic activity. It is expected that as *gdp* grows the throughput of a port increases. Also regional employment rate (*empl*) and population density per square kilometre (*popdens*) is considered a proxy for local demand. All these values are reported as a ratio to EU average values in order to signal the differences to the other areas involved in the analysis.

Accessibility, to the mind of the authors, should have been included as the effective level of surface accessibility (rail/road) to the origin/destination market of the freight, considering the country import/export flows. Difficulties in gathering data sufficiently homogeneous among the different areas involved, has induced us to define the variable as the presence of a direct link to the national rail arteries from within the port. The variable (*access*) takes the value of 0 and 1, with 0 for the ports which do not have a direct link to the main rail network. This data has been collected from published data and also through direct interviews.

Cullinane et al (2004) point out, however, it should be emphasised that there are a number of caveats linked to this assumption which should be clearly stated. For instance, they refer to technological progress, which might induce dramatic changes in any pre-determined relationship between terminal facilities and the absolute number of workers or to the differences in the use of labour in ports of different sizes, with different clients, or, and this is particularly relevant for this study, for different governance regimes. For greater details, Cullinane et al. (2002).

In relation to port legislation and ports' governance framework, the last twenty years have been characterised by significant changes. A number of measures were implemented aiming at increasing the autonomy of individual ports in the management, financing and organisation of its activities. Most ports in the sample experienced a change in the regulation during the period under investigation. Since identifying the extent of the implementation of each subsequent measure at port level is an extremely complex task, the regulatory context has been approximated by a dummy (*reg*), taking the value of one after the introduction of a relevant policy measure aiming at increasing the autonomy of the port with respect to the central government in all aspects related to management, commercial strategies and financing. In the footsteps of previous studies related to terminal operations and to other transport sectors, especially public transport, it is expected that the introduction of greater autonomy will increase the level of efficiency and reduce the slacks in the use of the resources, at least for those inputs that are more suitable for rationalisation.

The expectation is that all these exogenous variables should have a positive effect on technical efficiency through a reduction of the slacks for the selected capital and space related inputs.

A time trend (*trend*) has also been included to account for any technological changes. Given the structure of the second stage estimation, the time trend variable captures only technological shifts, and not, instead, changes in managerial performances which are embodied in the one-sided distributed error component[16]. Although technical progress is a usual hypothesis, there are no *a priori* forecasts on its impact, especially within an input-by-input framework. However, it wouldn't be surprising if technological progress was encouraged by the increasingly competitive situation of the European port industry.

Finally, two dummies have been defined to verify if results generally observed can be confirmed by our exercise: a dummy segmenting ports by size (*ddim*) and a dummy separating ports accordingly to their involvement in container traffic (*dcont_rate*). In the first case the dummy takes the value of 1 if the port is within the top 25% of the ports in the database ordered by total throughput, in the second case, ports for which more than 60% of throughput is derived from container traffic are classified as specialised ports and the dummy takes the value of 1. Although the ranking of ports exhibits some variation through time (changes in relative positions), the classification of ports does not change within the time span considered (all ports have the belong to the same classification throughout the ten-year period) nor with reference to dimension nor to size, and, therefore, these are classified as time-invariant variables.

Descriptive statistics for the variables used in the study are reported in Table 1.

Table 1 – descriptive statistics
- INSERT HERE -

[16] Changes in managerial performance due to experience are embodied in the one-sided distributed inefficiency component as specified in the Battese and Coelli (1992) SFA approach.

3.2 Data description

The dataset used in the following analysis consists of a balanced panel of 32 European ports. Observations cover the ten year period 1995-2005. The database is assembled with data referring to 1995, 1997, 2000, 2002, 2005 for a total of 160 pooled observations.

Although the database is rather small, our sample is fairly representative of the European port system: about 40% of the sampled ports are specialised in the container service while the remaining 60% mostly operate in the international, long distance, traffic and can be defined as multi-service ports. Fourteen operators are located in the Northern Range and eighteen provide services in Central and Southern Mediterranean basin.

The information for the construction of the database was gathered from different sources, although the bulk of information were extracted from Lloyds Port of the world, Containerisation International Yearbook and Port Authority Reports and websites. Disaggregated information concerning specific aspects have been obtained thought direct telephone interviews with port authority representatives. The environmental, non discretionary variables, related mainly to macro-economic indicators, used in the second stage of the estimation, are taken from the Eurostat database, integrated, when necessary, with national statistical office information. The information on the governance practice for the European port industry was gathered from both indirect sources (mainly ministries websites) and direct interviews aiming at classifying the governance mechanism adopted by the competent authority and its recent evolution.

4. ESTIMATION RESULTS

4.1 Step 1

The unadjusted DEA has been run using the 160 observations. Table 2 reports average DEA efficiency scores. By ordering the scores on the basis of port dimension and traffic specialisation, it is possible to infer that, on average, larger ports and multiservice ones reach higher efficiency levels than the average level of the entire sample. Furthermore, larger ports show slightly lower efficiency levels compared to the highly specialised ones. Also, the lower value of the variance of the efficiency scores for the ports specialised in container traffic implies that, in general, they are closer to their own efficiency frontier than the other ports and that differences among ports in this category are less marked. This can be expected as the activity carried out within the port is more homogeneous and, thus, more easily comparable. The variance of average efficiency outcomes is greater for larger ports, implying a higher variability in their behaviour, although average efficiency scores are relatively close.

TABLE 2 – DEA efficiency scores (step 1)

- INSERT HERE -

Although these scores might give interesting insights on the distribution of efficiency among sampled ports, they do not provide evidence on the source of the inefficiency and thus, they might lead to erroneous conclusions on the capacity of the management to govern ports. In order to explore the contribution of different factors to each input inefficiency, we run a SFA on each input slack, adopting the two estimators presented in section 2.1.2.

4.2 Step 2

Table 3 reports the results from second stage SFA input-by-input regressions. Two models have been estimated: the maximum likelihood-random effect specification (model I) and the fixed effect specification (model II). The regressions have been carried out on the whole database, stacking, for each slack, the 32 ports observed over the ten-year period. Each regression has been run, thus, on 160 observations. Exogenous regulatory and environmental factors are included as exogenous determinants of input slacks.

TABLE 3 – Results of SFA – parameter estimates of slack equations

- INSERT HERE -

Table 3 reports the estimated parameters for the two models run on the four input slacks. All the time varying variables have been used in both models. The FE estimation obviously does not include time-invariant variables. As it can be seen, the order of magnitude of the coefficients of the input slack regressions between the two models are, in general, comparable.

The coefficients of the policy variable *reg* are, as expected, significant and negative, for all the slacks, for both models, thus indicating a reduction in the slack as a consequence of the introduction of greater autonomy of port authorities in determining investments and in their financing. The underlying mechanism of the port sector reforms seems to have been successful in most countries. It has induced port authorities to increase the use of the facilities.

However, the magnitude of the coefficient for *area* and for *equip* implies that for these inputs the effect is, in general, greater: the rationalisation of the area destined to freight handling and of equipment is easier to carry out than that of other inputs, characterised by greater indivisibilities. This result confirms previous evidence on the effectiveness of new regulatory framework in reducing production inefficiency[17], while, at the same time, extending the latter by letting regulatory practice changes provide a differentiated impact on the different types of input.

The coefficients for the *gdp* variable appear to be highly significant for all the inputs and show the expected negative sign. This implies that an increase in the gdp of the area would reduce the input slacks. The dimension of the impact, however, is quite limited. The same is true for both specifications. The impact of the *empl* variable is generally not statistically significant and shows alternations in signs. It implies, thus, that a higher employment rate does not necessarily stimulate demand for port services and a better usage of fixed inputs – and, thus, a reduction in input slacks - as it had been assumed *a priori*. Also the coefficient of the *popdens* have the expected negative sign, but it is significantly different from zero only for the slack regression for *quay* for model I. In the model II specification, it is not significantly different from zero for all inputs.

[17] For instance: Cullinane and Wang (2005, 2006); Cullinane et al. (2005); Gonzales and Trujillo (2005, 2008); Castillo-Manzano et al.(2008).

The coefficient relating to *access* is in line with expectations in both magnitude and significance. Indeed, greater accessibility promotes a more efficient use of port infrastructure and equipment which, in turn, leads to an improved performance for those inputs which are more linked to capital utilisation. The coefficients are significant, although to a varying degree, for all the regressions of the two models.

The ML estimation reports also additional information. For all the regressions, the parameter η is positive and significantly different from zero: the trend of the input-specific technical inefficiency is negative, which implies that managers' ability to reduce overuse of inputs improved over time. This might be due to the capacity of ports to adapt, especially with respect to more flexible inputs, to the new organisational models required by the reforms. It is worthwhile underlining that this trend of managerial efficiency during the observed years is distinguished from technological change, which is, instead, captured by the time variable *trend.*

The estimated coefficient for the trend variable is significant but it alternates signs among regressions. It is positive for *quay* and *term* and negative for *area* and *equip*. The managerial efficiency for infrastructure related inputs does not show a progressive improvement, as, instead, it is the case for equipment and area of operations.

As expected, the dummy associated with the dimension of the port *ddim* had a negative and generally significant impact on the input slacks. This means that if the port grows, the efficiency conditions improve. Consistently with previous studies[18] the result seems to confirm that a large scale of production is more likely to be associated with high efficiency scores and that thus, the efficiency of a terminal is significantly influenced by its production scale. As Cullinane and Wang (2006) point out, this is not surprising considering the fact that large terminals are more likely to utilise more state-of-the-art equipment and sophisticated management than their smaller counterparts. This result has relevant policy implications. For instance, conspicuous investment in port infrastructure should be carried out at ports where traffic flows concentrate in order to exploit economies of scale and scope within the port notwithstanding other logics which often prevail in funding allocation.

Also the coefficient related to the containerisation rate, *dcont_rate*, is negative and rather significant, thus implying, according to our interpretation, that diversified ports are, in general, more affected by a higher variability in efficiency conditions than ports operating mainly with container traffics. This higher variability means, in turn, higher input slacks. The result of the estimation seems to support the idea, already drafted by the results of the simple comparison of average efficiency ranking between specialised ports and the entire sample, that ports with a more homogeneous output tend to be more efficient and, looking at the magnitude and significance of the coefficients across input slacks, that quay length, terminal and equipment seem to be more influenced than the slack relating to the *area* variable.

[18] For instance, Cullinane and Wang, 2006 and De Neufville and Tsunokawa (1981).

4.3 Step 3

The third stage of the process was carried out using algorithm [4] for adjusting the input data. Parameter estimates obtained from SFA regressions, estimated using both ML and FE, are used to net out exogenous effects and statistical noise from inputs. DEA was re-runned with the new dataset. The estimation yielded new adjusted scores, no longer affected by exogenous, non discretionary and controllable factors nor by random noise. The adjusted results are reported in table 4.

Table 4 –Adjusted DEA efficiency scores (step 3)

- INSERT HERE –

The two versions of the new DEA, ran using the adjusted parameters, yield comparable result: the average outcomes of the two models are relatively similar. On average, Model II outcomes tend to be slightly greater that the ones obtained using Model I outcomes. In both cases, average comparative efficiencies are higher than the ones obtained with the unadjusted DEA. Although, it should be careful, when interpreting the results, in remembering that the relative values are obtained on different efficiency frontiers and are, thus, not directly comparable in absolute terms. What can be said, however, is that, in general, the values of the average adjusted efficiency have a significantly reduced dispersion around the average value, implying that, once exogenous factors and noise are taken account of, there seems to be a greater similarity in managers' performances. Also highly containerised ports improved, on average, their performance: in general, the dispersion around the average can be interpreted as a sign that a large part of the inefficiency is due to exogenous factors rather than to the capacity or the effort of managers.

A more sound analysis can be carried out comparing relative rankings among the three outcomes: unadjusted efficiencies; model I adjusted efficiencies and Model II adjusted efficiencies. A correlation test is carried out calculating Spearman's correlation test among the different rankings and results are reported in Table 5. The results confirm the need to carry out more detailed analysis of efficiency and, thus, the use of multistep approach. Being able to "clean" the efficiency scores from exogenous factors allows to verify the actual role of port management strategies. As it would be expected, in fact, being demand for transport services a derived demand, ports performance depend heavily on macro-economic factors. The presence of this "noise" could lead to a misrepresentation of ports performance as the ranking reported in table 5 highlights.

Table 5 – relative efficiency rankings according to average technical efficiency indices, 1995-2005.

- INSERT HERE –

Table 5 compares the ranking of the ports ordered in terms of their relative efficiency: the first column (A) reports the ranking on the basis of the ordinary DEA analysis (step 1), the second (B) and third (C) columns report the relative performance when regulation and other non-discretionary factors are taken account of, when either the ML or the FE models are used to estimate the adjustment coefficients. The Spearman's rank correlation coefficient calculated on the unadjusted relative ranking and the adjusted rankings has an absolute value of 0,20 and 0,27, respectively and both are not statistically significantly different from zero. This implies an extremely limited relationship among the rankings, and, thus, supports the adoption of the multi-step procedure to take account of external factors influencing ports' performance, besides managerial capacities. The rankings of ports based on efficiency levels without taking account of exogenous conditions and of statistical noise risks to yield misleading results. The rankings of the ports' efficiency levels calculated on the basis of the adjusted values have, instead, a very high correlation value (0,93), statistically significant at 1%. This last evidence as well as the stability of the results across the rankings obtained with the two different models, corroborate the choice of the multiple-stage procedure, and at the same time, show that most of the deviation from the frontier is not due to inefficiency but, rather, to socio-economic and regulatory factors and statistical noise. Both approach seem to take account of this properly.

5. CONCLUSIONS AND FURTHER RESEARCH

In this paper we extend previous work on port efficiency to take account of a number of issues connected to operating environment which, as we show through the analysis, play a significant role in determining efficiency scores (Bergantino and Musso, 2009). The main results are encouraging. We provided evidence supporting that greater autonomy granted to ports though governance reforms, has had beneficial effects for the EU port system as a whole. In particular, the effect has been more relevant for *area* and *equip*: it seems, thus, that space utilisation and capital investment in equipment, variables that can be varied in a shorter time frame, respond more to exogenous shocks caused by policy changes. We find, also, that environmental factors in general do play a role on ports efficiency and that, depending on the specific characteristics of the port, inputs are influenced differently by different factors. In particular, general economic conditions do have a significant, positive effect on ports' efficiency, although the impact is relatively limited and uniform with respect to input factors' utilisation. Employment level is, instead, not relevant for all the inputs as it is the population density of the region with respect to number of terminal, equipment, area of the port used for handling freight. For the remaining input the coefficient, although significantly different from zero, is extremely small. Accessibility does, instead, play a relevant role in determining efficient input utilisation: its coefficient is significant and negative, implying that greater accessibility favour the utilisation of the ports' production factors. On account of the magnitude of the relevant coefficients, the impact is larger for those inputs directly linked to capital utilisation. We also find that, in relation to the sampled ports, the inefficiency in the use of infrastructure related inputs does not show progressive improvements as, instead, do the ones related to the other inputs. Furthermore, as expected on the basis of the results of previous studies, both ports' dimension and containerisation rate play a relevant role in determining input efficiency. Bigger ports seem to lead to greater efficiency in input usage so as ports with a more homogeneous production. These results seem to confirm, also at input by input level, the presence of significant economies of scale within a port. No significant support, instead, can be found for economies of scope within sampled ports. Finally, we show how, once operational environment and regulatory effects have been eliminated, pure managerial efficiency could be elicited, giving a more precise assessment of the change of managers' incentives over time. The policy implications are relevant. Ports reform that go in the direction of greater managerial autonomy seem to support the drive toward efficiency, especially with respect to inputs under the direct control of ports' managers and that can respond in the short-medium period to external impulses. Also, the analysis seems to offer renovated support for the idea that larger ports can exploit greater economies of scale and that port specialisation can lead to more efficient utilisation of inputs. The results, however, are based on the sample of ports included in the exercise. There is still a lot to be done in terms of both empirical (enlarging the database, cleaning up the data, ecc.) and methodological research. For the former aspect, the authors are working on developing a larger database with a more refined definition of variables. For the latter aspect, a number of extremely recent integrations to the Fried et al. (2002) approach are developing (for instance, bootstrapping on the basis of the work of Simar and Wilson (2007) or alternative adjustment methods (Tone and Tsutsui (2006)), whose effects would be interesting to test on the same database in order to verify the robustness of both the model and the empirical output.

ACKNOWLEDGEMENTS
The authors would like to thank Francesco Porcelli for very helpful comments and suggestions. The usual disclaimer applies.

TABLES

Table 1 – Descriptive statistics

Variable	Average	St. Deviation	Between	Within
Total movements (tons)	57.206,50	86.921,86	73.861,76	54.884,65
Dimension of quay (sqm)	153.587,64	205.879,00	389.784,43	66.005,75
Number of terminals (units)	17	20,069	16,562	6,461
Area of the port for handling (sqm)	1.636.037,393	1.580.033,952	2.046.787,786	675.865,97
Handling equipment (units)	315,928	359,697	254,986	156,839
GDP per person in PPS (EU27=100)	92,38	26,14005	19,0471	10,6732
Population density (Inhabitants/km^2) (EU27=100)	93,72	34,23016	27,9829	9,7621
Employment rate (employed/active population) (EU27=100)	93,65	43,32257	32,8972	10,2328
Accessibility	0,5625	0,50565	0,2139	0,18118
Port size	0,25	0,43994	0,3828	Nd
Involvement in container traffic	0,40625	0,498991	0,47986	Nd

TABLE 2 – DEA efficiency scores (step 1)

	All	Large	Specialised
Mean efficiency	76,56	89,86	91,33
Minimum	38,37	67,29	67,29
St. Dev.	19,3	12,12	9,64

Number of efficient units	26	13	22
Number of units	160	40	65

Table 4 –Adjusted DEA efficiency scores (step 3)

	Model I			Model II		
	All	**Large**	**Specialised**	**All**	**Large**	**Specialised**
Mean efficiency	92,23	94,77	96,89	93,75	96,38	97,54
Minimum	67,97	78,43	68,59	68,57	80,02	77,93
St. Dev.	9,09	9,16	6,55	9,07	6,78	4,17
Number of efficient units	48	19	37	54	27	38
Number of units	160	40	65	160	40	65

Table 5 – relative efficiency rankings according to average technical efficiency indices, 1995-2005.

Original DEA ranking (avrg)	**Original DEA ranking (avrg)**	**Adjusted DEA ranking - Model I (avrg)**	**Adjusted DEA ranking - Model II (avrg)**
	A	**B**	**C**
Algeciras	1	8	5
Rotterdam	2	4	3
Antwerp	3	3	1
Valencia	4	5	8
Gioia Tauro	5	12	15
Marseilles	6	27	22
La Valletta	7	21	24
La Spezia	8	19	25
Bremen-haven	9	1	2
Hamburg	10	2	6
Le Havre	11	14	11
Amsterdam	12	12	10
Bilbao	13	32	29
Liverpool	14	23	21
Goteborg	15	30	30
Dublin	16	31	31
Helsinki	17	28	17
Trieste	18	11	12
Cagliari	19	18	18
Piraeus	20	29	27
Felixstowe	21	15	13
Thamesport	22	16	16
Bari	23	20	20

Salerno	24	10	14
Barcelona	25	6	4
Taranto	26	7	7
Thessaloniki	27	22	19
Genoa	28	8	8
Limassol	29	17	32
Terragona	30	25	28
Santander	31	24	26
Toulon	32	26	23
Spearman's rank correlation A-B; A-C		*0,2033 (1,1373)*	*0,2752 (1,5979)*
Spearman's rank correlation B-C			*0,9279*** (13,6318)*

REFERENCES

Al-Eraqi, A. S., Mustafa, A., Khader, A. T. & Pestana Barros, C. (2008), 'Efficiency of Middle Eastern and East African Seaports: Application of DEA Using Window Analysis', *European Journal of Scientific Research*, **23** (4), 597 – 612.

Avkiran, N. K. & Rowlands, T. (2006), 'How to better identify the true managerial performance: State of the art using DEA', *Omega*, **36**, 317 – 324.

Banker, R. D., Charnes, A. & Cooper, W.W. (1984), 'Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis', *Management Science*, **30**, 1078 - 1092.

Banker, R.D. & Morey, R.C. (1986), 'Efficiency analysis for exogenously fixed inputs and outputs', *Operations Research*, **34**, 513 – 21.

Barros, C.P. (2003a), 'Measurement of efficiency of portuguese sea port authority with DEA', *International Journal of Transport Economics*, **30** (3), 335-354.

Barros, C.P. (2003b), 'Incentive regulation and efficiency of Portuguese sea port authorities', *Maritime Economics & Logistics*, **5**, 55-69.

Barros, C.P. and Athanassious, M. (2004), 'Efficiency in European seaports with DEA: Evidence from Greece and Portugal, *Maritime Economics & Logistics*, **6** (2), 122-140.

Barros C.P. (2006), 'A Benchmark Analysis of Italian Seaports Using Data Envelopment Analysis', *Maritime Economics & Logistics*, **8**, 347–365.

Battese, G.E. and Coelli, T.J. (1992), 'Frontier production functions, technical efficiency and panel data: With application to paddy farmers in India', *Journal of Productivity Analysis*, **3**, 153-169.

Bergantino, A.S. (2002), 'The European Commission's approach to port policy: some open issues', *International Journal of Transport Economics*, **XXIX**(3), 337 - 379.

Bergantino, A.S. and Coppejans, L. (2000), 'Shipowner Preferences and User Charges: allocating port infrastructure costs', *Transportation Research - Part E*, **36** (2), 97 - 113.

Bergantino, A.S. and Musso E. (2009), "A multi-step approach to model the relative efficiency of European ports: the role of regulation and other non discretionary factors”, in *Federalismo, integrazione europea e crescita regionale*, Atti della XXX Conferenza AISRE, Firenze, settembre 2009

Bonilla, M., Casasus, T., Medal, A. and Sala, R. (2004), ‘An efficiency analysis with tolerances of the Spanish ports system’, *International Journal of Transport Economics*, **XXXII** (3), 380-400.
Coelli, T. J., Rao, D. S. P., O’Donnell, C. J., & Battese, G. E. (2005), *An Introduction to Efficiency and Productivity Analysis*. Springer, second edition.
Coelli, T. J., Rao, D. S. P. and Battese, G. E. (1998), *An Introduction to Efficiency and Productivity Analysis*. Springer, first edition.
Castillo-Manzano, J.I., Lopez-Valpuesta, L. and Perez, J.J. (2008), ‘Economic analysis of the Spanish port sector reform during the 1990s’, *Transportation Research Part A: Policy and Practice*, **42** (8), 1056-1063.
Charnes, A., Cooper, W.W. and Rhodes, E. (1978), ‘Measuring the efficiency of Decision Making Units’, *European Journal of Operational Research*, **2**, 429-444.
Cooper, W. W., Seiford, L. M. & Tone, K. (2000). *Data Envelopment Analysis: A Comprehensive Text with Models, Applications, References and DEA-Solver Software*. Boston: Kluwer Academic Publishers.
Cullinane, K.P.B. and Song, D-W. (2001), ‘The administrative and ownership structure of Asian container ports’, *International Journal of Maritime Economics*, **3** (2), 175-197.
Cullinane, K.P.B., Song, D-W. and Gray, R. (2002), ‘A stochastic frontier model of the efficiency of major container terminals in Asia: Assessing the influence of administrative and ownership structures’, *Transportation Research A,* **36** (8), 743-762.
Cullinane, K.P.B. and Song, D-W. (2003), ‘A stochastic frontier model of the productive efficiency of Korean container terminals’, *Applied Economics,* **35** (3), 251-267.
Cullinane, K.P.B; Song, D-W; Ji, P. and Wang, T-F. (2004), ‘An application of DEA windows analysis to container port production efficiency’, *Review of Network Economics*, **3** (2), 186-208.
Cullinane, K.P.B; Ji, P. and Wang, T-F. (2005a), ‘The relationship between privatization and DEA estimates of efficiency in the container port industry’, *Journal of Economics and Business*, **57** (5), 433-462.
Cullinane, K.P.B; Song, D-W. and Wang, T-F. (2005b), ‘The application of mathematical programming approaches to estimating container port production’, *Journal of Productivity Analysis*, **24** (1), 73-92.
Cullinane, K.P.B; Wang, T-F; Song, D-W. and Ji, P. (2005c), ‘A comparative analysis of DEA and SFA approaches to estimating the technical efficiency of container ports’, *Transportation Research A: Policy and Practice*, **40** (4), 354-374.
Cullinane, K.P.B. and Wang, T-F. (2006), ‘The efficiency of European container terminals: A cross-sectional Data Envelopment Analysis’, *International Journal of Logistics: Research and Applications*, **9** (1), 19-31.

Cullinane, K.P.B. and Song, D-W. (2006), 'Estimating the relative efficiency of European container ports: A stochastic frontier analysis', in K.P.B. Cullinane and W.K. Talley (eds), *Port Economics,* Research in Transportation Economics, Vol. XVI, Elsevier, Amsterdam, pp. 85-115.
De Monie, G., 1996. Privatisation of port structures. In: Bekemans, L., Beckwith, S. (Eds.), *Ports for Europe: Europe's Maritime Future in a Changing Environment*, European Interuniversity Press, Brussels, pp. 267–298.
De Neufville, R. and Tsunokawa, K. (1981), 'Productivity and returns to scale of container ports', *Maritime Policy and Management*, **8**(2), 121-129.
Fried, A. O., Lovell, A. K., & Schmidt, S. S. (2008), *The Measurement of Productive Efficiency. Oxford University Press, second edition.*
Fried, H.O., Lovell, C.A.K., Schmidt, S.S. and Yaisawarng, S. (2002), 'Accounting for environmental effects and statistical noise in Data Envelopment Analysis', *Journal of Productivity Analysis*, **17** (1/2) 157-174.
Gonzalez, M.M. and Trujillo, L. (2009), 'Efficiency measurement in the port industry: A survey of the empirical evidence', *Journal of Transport Economics and Policy*, **43** (2), 157-192.
Gonzalez, M.M. & Trujillo L. (2008), 'Reforms and infrastructure efficiency in Spain's container ports', *Transportation Research - Part A*, **42**, 243 – 257.
Herrera, S. & Pang G. (2008), 'Efficiency of Infrastructure: The Case of Container Ports', *Revista EconomiA*, **9** (1), 165 - 194.
Jara-Díaz, S.R., Martínez-Budría. E. and Díaz-Hernández, J.J. (2006), 'Multiple outputs in port cost functions', in K.P.B. Cullinane and W.K. Talley (eds), *Port Economics*, Research in Transportation Economics, Vol. 16, Amsterdam: Elsevier, pp. 67-84.
Jondrow, J., Lovell, C., Materov, I. and Schmidt, P. (1982), 'On the estimation of technical efficiency in the stochastic frontier production model', *Journal of Econometrics*, **19**, 233-238.
Kalirajan K. P. and Shand R. T. (2002), Frontier Production Functions and Technical Efficiency Measures, Journal of Economic Surveys, 13 (2), 149 – 172.
Kim, M. and Sachish, A. (1986), 'The structure of production, technical change and productivity in a port', *Journal of Industrial Economics*, **35**(2), 209-223.
McCarty, T. A. and Yaisawarng, S. (1993). Technical Efficiency in New Jersy School Districts. In Fried, A. O., Lovell, A. K., and Schmidt, S. S., editors, The Measurement of Productive Efficiency, chapter 10, pages 271 – 287. Oxford University Press.
Murphy, P. R. & Daley, J. M. (1994), A Comparative Analysis of Port Selection Factors, *Transportation Journal*, **34** (1), 15 - 21.
Musso, E. (2008). *Future developments in ports*, unpublished report, Genova.
Martinez-Budria, E., Diaz-Armas, R., Navarro-Ibanez, M. and Ravelo-Mesa, T. (1999), 'A study of the efficiency of Spanish port authorities using Data Envelopment Analysis', *International Journal of Transport Economics*, **XXVI** (2), 237-253.
Notteboom, T., Coeck, C. and van den Broeck, J. (2000), 'Measuring and explaining the relative efficiency of container terminals by means of bayesian stochastic frontier models', *International Journal of Maritime Economics*, **2** (2), 83-106.
Notteboom, T. E. & Winkelmans, W. (2001), 'Reassessing Public Sector Involvement in European Seaports', *International Journal of Maritime Economics*, **3**, 242 - 259.

Papke, L. E. and Wooldridge, J. M. (2008). Panel data methods for fractional response variables with an application to test pass rates. Journal of Econometrics, 145:121–133.
Park, R.K. and De, P. (2004), 'An alternative approach to efficiency measurement of seaports',*Maritime Economics & Logistics*, **6**, 53-69.
Rodriguez-Alvarez, A., Tovar, B. and Trujillo, L. (2007), 'Firm and time varying technical and allocative efficiency: An application to port cargo handling firms', *International Journal of Production Economics*, **109** (1-2), 149-161.
Rios, L.R. & Gastaud-Maçada, A. C. (2006), 'Analysing the Relative Efficiency of Container Terminals of Mercosur using DEA', *Maritime Economics & Logistics*, **8** (4), 331 - 346.
Simar, L. and Wilson, P.W. (2007), 'Estimation and inference in two-stage, semi-parametric models of production processes', *Journal of Econometrics*, **136** (1), 31-64.
Schmidt P and Sickles R.C. (1984). Production Frontiers and Panel Data, Journal of Business & Economic Statistics, 2 (4), 367-374.
Suykens, F. & Van de Voorde, E. (1998). A quarter of a century of port management in Europe: Objectives and tools. *Maritime Policy and Management*, **25** (3), 251 – 261.
Timmer, C. P. (1971). Using a probabilistic frontier production function to measure technical efficiency, Journal of Political Economy, 79(4):776–794.
Tone, K. & Tsutsui M. (2006), *Tuning SFA Results for Use in DEA*, GRIPS Policy Information Center Research Report: I-2006-0013.
Tongzon, J. (1995), 'Determinants of port performance and efficiency', *Transportation Research*, **29** (3), 245-252.
Tongzon, J.L. (2001a), 'Efficiency measurement of selected Australian and other international ports using Data Envelopment Analysis', *Transportation Research A: Policy and Practice*, **35**, 113-128.
Tongzon, J. (2001b), 'Efficiency measurement of selected Australian and other international ports using Data Envelopment Analysis', *Transportation Research*, **35** (2), 107-122.
Tongzon, J. (2002). *Port Choice Determinants in a Competitive Environment*, *Proceedings of the International Association of Maritime Economists Conference*, 13-15 November, Panama.
Tongzon, J.L. and Heng, W. (2005), 'Port privatization, efficiency and competitiveness: Some empirical evidence from container ports (terminals)', *Transportation Research A: Policy and Practice*, **39**, 405-424.
Tovar, B., Trujillo, L. & Jara-Diaz, S. (2004). Organisation and regulation of the port industry: Europe and Spain. In P. Coto-Millan (ed.). *Essays on Microeconomics and Industrial organisation, second edition. Physica-Verlag*, 189 - 205.
Trujillo, L. & Nombela, G. (2000). Seaport. In A. Estache & G. de Rus (eds.), *Privatisation and regulation of transport infrastructure. Guidelines for policymakers and regulators*. The World Bank, Washington, D.C., 113 - 170.
Trujillo, L. and Tovar, B. (2005), *The European Port Industry: An Analysis of its Economic Efficiency*, City University Economics Discussion Paper 07/05, London: City University.
Trujillo, L. & Tovar, B. (2007), 'The European Port Industry: An Analysis of its Economic Efficiency', *Maritime Economics & Logistics*, **9** (2), 148 – 171.

Turner, H., Windle, R. and Dresner, M. (2004), 'North American containerport productivity: 1984–1997', *Transportation Research Part E: Logistics and Transportation Review*, **40** (4), 339-356.

Valentine, V.F. and Gray, R. (2001), 'The measurement of port efficiency using Data Envelopment Analysis', *Proceedings of the 9th World Conference on Transport Research*, 22-27 July, Seoul, South Korea.

Wang, T., Song, D. W. & Cullinane, K. (2002), 'The Applicability of Data Envelopment Analysis to Efficiency Measurement of Container Ports?, *Proceedings of the International Association of Maritime Economists Conference*, 13-15 November, Panama.

Wang, T-F. and Cullinane, K.P.B. (2006), 'The efficiency of European container terminals and implications for supply chain management, *Maritime Economics & Logistics*, **8** (1), 82-99.

Worthington, A. C. and Dollery, B. (2002). Incorporating contextual information in public sector efficiency analaysis: A comprative study of nsw local government. Applied Eonomics, 34:453–464.