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PRODUCTIVITY DRIVERS IN JAPANESE SEAPORTS

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Abstract

This paper analyses efficiency drivers of a representative sample of Japanese seaports by means of the two-stage procedure proposed by Simar and Wilson (2007). In the first stage, the technical efficiency of seaports is estimated using several models of data envelopment analysis (DEA) that might be employed in order to establish which of them are most efficient. In the second stage, the Simar and Wilson (2007) procedure is used to bootstrap the DEA scores with a truncated bootstrapped regression to identify efficiency drivers. The policy implications of our findings are considered.

Keywords: Seaports; Japan; Data Envelopment Analysis; Truncated Bootstrapped Regression.

1. Introduction

Efficiency is a main concern in contemporary port economics, on grounds of port's strategic position in connecting different countries in a globalised world, as well as connecting different locations inside the country (Cullinane *et al*., 2002). Based On its strategic role, efficiency is of major importance and has been the focus of intense research in recent years including Martinez *et al*. (1999), Tongzon (2001, 2005), Estache, Gonzalez and Trujillo (2001), Cullinane, Song and Gray (2002), Cullinane and Song (2003), Park and De (2004).

This study analyzes seaport industry in Japan. In fact, increased modal competition in Asia and Europe has placed Japanese seaports in a much more competitive environment where they are now under greater pressure to find out the performance of their competitors through benchmarking (Haralambides *et al*., 2001). Ideally, evaluation of the seaport in Japan needs to deal with a variety of aspects such as wharf improvement for cargo and passengers, to breakwater, waste disposal by reclamation, open space construction, and water and seabed cleanup among others (Morisugi, 2000). However, key factors to evaluate the efficiency in seaport are increasing capacity utilization of cargo handling and reduction of marine transportation cost. Therefore, this study intends to analyze how seaport in Japan is able to increase the efficiency of shipping, and bulk and container handling. In so doing, it enlarges previous research in these seaports, adopting an innovative methodology and focusing in Japanese seaports, which were not previous analysed.

In this paper, the technical efficiency of a representative sample of Japanese seaports from 2003 to 2005 is analyzed with a simultaneous two-stage procedure: in the first stage, Data Envelopment Analysis (DEA) is used to estimate the relative efficiency scores ranking seaports according to their efficiency (Charnes, Cooper and

Rhodes, 1978).[1] Four DEA models are adopted for comparative purpose, the DEA-CCR model, Charnes, Cooper and Rhodes, (1978); the DEA-BCC model, Banker, Charnes and Cooper (1984); the Cross-Efficiency DEA model, Sexton, Silkman and Hogan (1986), Doyle and Green (1994) and the Super-Efficiency DEA Model, Andersen and Petersen (1993).

In the second stage, the Simar and Wilson (2007) procedure is applied to bootstrap the DEA scores with a truncated regression. Using this approach enables us to obtain more reliable evidence compared to previous studies analysing the efficiency of seaports. This is because the Simar and Wilson (2007) procedure ensures the efficient estimation of the second-stage estimators, which is not a property of alternative methods. First, the true efficiency score θ is not observed directly but is empirically estimated. Thus, the usual estimation procedures that assume independently-distributed error terms are not valid. Second, the empirical estimates of the efficiency frontier are obtained based on the chosen sample of seaports, thereby ruling out some efficiency production possibilities not observed in the sample. This implies that the empirical estimates of efficiency are upwardly biased (Simar and Wilson, 2007). Thirdly, the two-stage procedure also depends upon other explanatory variables, which are not taken into account in the first-stage efficiency estimation. This implies that the error term must be correlated with the second-stage explanatory variables. The method introduced by Simar and Wilson (2007) overcomes these difficulties by adopting a procedure based on a double bootstrap that enables consistent inference within models, explaining efficiency scores while simultaneously producing standard errors and their confidence intervals. As shown by these authors,

[1] DEA was first introduced by Farrell (1957) and then developed by Charnes, Cooper and Rhodes (1978) as a non-parametric procedure that compares a decision unit with an efficient frontier, using performance indicators.

the alternative bootstrap procedure adopted by Xue and Harker (1999) is inconsistent. Moreover**,** **t**he truncated bootstrapped second-stage regression proposed by Simar and Wilson (2007) accounts for the efficiency scores better than a Tobit model.

Readers who are not familiar with the technique are referred to Fare et al. (1994), Charnes et al. (1995), Coelli, Rao and Battese (1998), Cooper et al. (2000), Thanassoulis (2001) and Zhu (2002).

The layout of the paper is the following. Section 2 briefly discusses the theoretical literature motivating our empirical analysis. Section 3 outlines the two-stage procedure of Simar and Wilson (2007). Section 4 presents the empirical results. Section 5 draws some policy implications and concludes.

2. Literature Survey

2.1. Empirical Literature in Seaport

Whilst there is extensive literature on benchmarking, applied to a wide diversity of economic areas, the Japanese seaport sector is relatively under-researched. Review of the literature of seaport showed that all three scientific methods of quantitative efficiency analysis, namely, ratio analysis; the econometric frontier; and DEA have been applied.

Song and Cullinane (2001) apply ratio analysis to Asian container ports with regard to DEA, Roll and Hayuth (1993) present a theoretical exposition and propose the use of cross-section data from financial reports in order to render the DEA approach operational. Tongzon (2001) uses cross-section data from 1996 covering 4 Australian and 12 other ports from around the world. Martinez *et al*. (1999) estimate the efficiency of Spanish ports. Barros (2003a) analyses the technical and allocative efficiency of Portuguese seaports. Barros (2003b) analyses the total productivity change in the Portuguese seaports in two stages: In the first stage, a Malmquist index is estimated, followed by Tobit regression in the second stage. Barros and Athanassiou (2004) compare the efficiency of Portuguese and Greek seaports. finally, Park and De (2004) analyse the efficiency of 11 Korean seaports.

Papers using the econometric frontier analysis include Baños Pino, Coto Millan and Rodriguez Alvarez (1999), who apply a translog function to Spanish ports. Liu (1995) compares the efficiency of public and private ownership in Britain with a translog function. Coto Millan, Baños Pino and Rodriguez Alvarez (2000) estimate a translog cost frontier for Spanish ports. Estache, Gonzalez and Trujillo (2001) estimate a Cobb-Douglas and a translog production frontier for Mexican ports. Cullinane, Song and Gray (2002) estimate a Cobb-Douglas production function for major Asian container terminals. Cullinane and Song (2003) estimate a production function for Korean container terminals. The variables used in the literature cited are listed in Table 1.

Table 1: Literature Review

Papers	Method	Units	Inputs	Outputs
Roll and Hayuth (1993)	DEA-CCR model	Hypothetical numerical example of 20 ports	Manpower, capital, cargo uniformity	Cargo throughput, level service, consumer satisfaction, ship calls
Martinez Budria, Diaz Armas, Navarro Ibáñez and Ravello Mesa (1999)	DEA-BCC model	26 Spanish ports, 1993 to 1997	Labour expenditure, depreciation charges, other expenditure	Total cargo moved through docks, revenue obtained from rent of port facilities
Tongzon (2001)	DEA-CCR additive model	4 Australian and 12 other international ports for 1996	Number of cranes, number of container berths, number of tugs, terminal area, delay time, labour,	Cargo throughput; ship working rate
Barros (2003a)	DEA-allocative and Technical Efficiency	5 Portuguese seaports, 1999-2000	Number of employees, book value of assets	Outputs: Ships, movement of freight, gross tonnage, market share, break-bulk cargo, containerised cargo, Ro-Ro traffic, dry bulk, liquid bulk, net income Prices: Price of labour measured by salaries and benefits. divided by the

				number of employees; price of capital measured by expenditure on equipment and premises divided by the book value of physical assets
Barros (2003b)	DEA-Malmquist index and a Tobit model	10 Portuguese seaports, 1990-2000	Number of employees and book value of assets	Ships, movement of freight, break-bulk cargo, containerised freight, solid bulk, liquid bulk
Park and De (2004)	DEA-CCR and BCC	11 Korean seaports for the year 1999	Berthing capacity (number of ships) and cargo handling (tons)	Cargo throughputs, number of ship calls, revenue and consumer satisfaction
Barros and Athanassiou (2004)	DEA-CCR and BCC	2 Greek and 4 Portuguese	Labour and capital	Nr. of ships, movement of freight , cargo handled, container handled
Liu (1995)	Translog production function	28 British port authorities, 1983 to 1990	Movement of freight (tons)	Turnover
Coto Millán, Baños Pino and Rodriguez Alvarez (2000)	Translog Cost model	27 Spanish Ports, 1985 to 1989	Cargo handled (tons)	Aggregate port output (includes total goods moved in the port in thousand tonnes, the passenger embarked and disembarked and the number of vehicles with passengers)
Estache, Gonzalez and Trujillo (2001)	Translog and Cobb-Douglas production frontier model	14 Mexican ports 1996 to 1999.	Containers handled (tons)	Volume of merchandise handled
Cullinane, Song and Gray (2002)	Stochastic Cobb-Douglas production frontier:half normal, exponential, truncated models	15 Asian container ports observed in 10 years, 1989 to 1998.	Number of employees	Annual container throughput in TEUs
Cullinane and Song (2003)	Stochastic Cobb-Douglas production frontier:half normal, exponential, truncated models	5 container terminals, Korean and UK, different year of observations (65 observations)	Fixed capital in euros (1998=100)	Turnover derived from the provision of container terminal services, but excluding property sales
Cullinane, Song and Wang (2005)	DEA-CCR, DEA-BCC and DEA-FHD models	57 international container seaports in 1999	Container throughput	Terminal length, terminal area, quayside gantry, yard gantry and straddle carries
Tongzon and Heng (2005)	Stochastic Cobb-Douglas model and a competitiveness regression. We restrict the analysis to the frontier equation.	25 international container seaports	Container throughput	Terminal quay length, number of quay cranes, port size measure by a dummy which is one for ports which exceed one million TEU and private participation in the port

Barros (2005)	Stochastic Translog cost frontier	10 Portuguese seaports, 1990-2000	Price of labour, price of capital, ships, cargo, trend.	Total cost
Cullinane, Wang, Song and Ji (2006)	Stochastic Cobb-Douglas and DEA model	28 International container seaports, observed from 1983-1990.	Container throughput	Terminal length, terminal area, quayside gantry, yard gantry and straddle carries

The general conclusions that emerge from this body of research are that dimensions are important. The location is important, while capital intensity has no significant impact and private ownership has no significant advantage (Liu, 1995). Moreover, small ports are more efficient than larger ones and autonomy does not make any difference (Coto Millan *et al*., 2000; Tongzon, 2001). There is overcapitalisation in Spanish ports (Baños Pino *et al*., 1999). In addition, action intended to improve the rate of total productivity growth is to be welcomed, as long as it is focused on capital accumulation and the rate of innovation to shift the frontier of technology, i.e. technical change (Barros, 2003b). Finally, scale economies and non-neutral progress contributed to decrease in costs, while pure technical change contributed to increase in costs.

Comparing the above-mentioned research with that undertaken in other fields, one sees that ports represent one of the main fields in economics where frontier models have been applied, with methods as diverse as DEA to econometrics. This shows openness to different approaches that we do not see in other fields. However, there are too many studies that replicate previous research yet making scant methodological improvements.

On the other hand, we observe a growing number of papers with international comparisons, which seems a sound step forward, reflecting globalisation. Finally, we have not yet seen papers applying Fourrier frontiers (Altunbas *et al*., 2001), input distance functions (Coelli and Perelman, 1999, 2000) or papers using non-traditional DEA models such as the Cone-ratio DEA model of Charnes *et al*. (1990) and the Assurance Region DEA model of Thompson *et al.* (1986,1990). In the light of the above observations, the present paper is a methodological improvement in this field, since it estimates the efficiency scores with alternative DEA models and then tests statistically several hypotheses.

2.2 Theoretical Framework

There are two main types of theoretical models providing an explanation for within-industry variation in efficiency. The first are based on strategic-group theory (Caves and Porter, 1977), which explains differences in efficiency scores as being due to differences in the structural characteristics of units within an industry, which in turn lead to differences in performance. In the case of Japanese seaports, units with similar asset configurations pursue similar strategies, with similar results in terms of performance (Porter, 1979). Although there are different strategic options in different sectors of an industry, owing to mobility impediments, not all options are available to each seaport, causing a spread in the efficiency scores of the seaport industry. The second type of model adopted is the resource-based one (Barney, 1991; Rumelt, 1991; Wernerfelt, 1984), which justifies different efficiency scores in terms of heterogeneity in resources and skills on which seaports base their strategies. These may not be perfectly mobile across the industry, resulting in a competitive advantage for the best-performing seaports.

Purchasable assets cannot be considered sources of sustainable profits. In this respect crucial resources are those not available in the market but rather built up and accumulated on the seaports' premises, their non-imitability and non-substitutability being dependent on the specific traits of their accumulation process. The difference in resources thus results in barriers to imitation (Rumelt, 1991) and in the seaports managers' inability to alter their accumulated stock of resources over time. Such unique assets account for inherently differentiated levels of efficiency, sustainable profits ultimately being a return on them (Teece et al., 1997).

3. Empirical Methodology

As mentioned above, we follow the two-stage approach of Simar and Wilson (2007). The DEA model used in the first stage of our empirical analysis is a non-parametric technique that allows the inclusion of multiple inputs and outputs in the production frontier. Following Farrell (1957), Charnes *et al*. (1978) first introduced the term "Data Envelopment Analysis" to describe a mathematical programming approach to estimating production frontiers and measuring efficiency relative to the frontier.

3.1. Estimation of Efficiency Scores

To estimate efficiency scores for each observation, we use a DEA estimator. The DEA approach usually (but not always) assumes that all seaports, or more broadly, decision-making units (DMUs) within a sample have access to the same technology for transforming a vector of N inputs, denoted by x, into a vector of M outputs, denoted by y. We assume that technology can be characterised by the technology set, T, defined as:

$$T = \{(x, y) \in \Re_+^N \times \Re_+^M \quad : \quad x \in \Re_+^N \quad can\ produce \quad y \in \Re_+^M\}. \tag{1}$$

Moreover, we assume that standard regularity conditions of the neo-classical production theory hold (for details, see Färe and Primont, 1995). Having access to the same technology, any of the DMUs may or may not be on the frontier; the distance of a particular DMU from it may depend on various factors, specific to the DMU. These factors may be endogenous to the DMU, such as internal economic incentives influenced by the ownership structure, management quality, and/or exogenous, such as different macroeconomic and demographic conditions, government regulation policies. The distance from the actual location of each DMU given its technology set *T* from the frontier of *T* is thought to represent the inefficiency of each DMU, caused by the DMU's specific endogenous or exogenous factors and some unexplained statistical noise. Our goal is to measure such inefficiency and investigate its dependency on efficiency drivers.

In the first stage of our analysis, we estimate efficiency scores for each DMU *j* (*j=1,…, n*), using the Farrell/Debreu-type output-oriented technical efficiency measure:

$$TE(x^j, y^j) = \max_{\theta}\{\theta \quad : \quad (x^j, \theta\, y^j) \in T\}. \qquad (2)$$

In practice, *T* is unobserved, thus we replace it with its DEA-estimate, $\hat{T}$:

$$\hat{T} = \{(x, y) \in \Re_+^N \times \Re_+^M \quad : \quad \sum_{k=1}^{n} z_k y_m^k \geq y_m, \;\; m = 1, \ldots, M, \;\; \sum_{k=1}^{n} z_k x_i^k \leq x_i, \;\; i = 1, \ldots, N, \;\; z_k \geq 0 \;, \;\; k = 1, \ldots, n \;\}. \qquad (3)$$

where $z_k \geq 0$ ($k = 1, \ldots, n$) are the intensity variables over which optimisation (2) is made. Geometrically, $\hat{T}$ is the smallest convex free-disposal cone (in the (x, y)-space) that contains (or 'envelopes') the input-output data. For more details on DEA, see Fare, Grosskopf and Lovell (1994), Charnes et al. (1995), Coelli, Prasada and Battese (1998), Copper et al. (2000) and Thanassoulis (2001).

This is a consistent estimator of the unobserved true technology set T, under the assumption of constant returns to scale (CRS). Alternatively, non-increasing returns to scale (NIRS) or variable returns to scale (VRS) can be considered by adding to (3) the constraint $\sum_{k=1}^{n} z_k \leq 1$ or $\sum_{k=1}^{n} z_k = 1$, respectively. In this paper, we assume CRS to be able to discriminate better between DMUs and then analyse the returns-to-scale component in the second stage. The proof of consistency also requires certain regularity conditions (see Kneip et al., 1998, 2003, for these conditions, the resulting rates of convergence and the limiting distribution of the DEA estimator).

We choose this particular efficiency measure over others for several reasons. First, it satisfies a set of desirable mathematical properties. These properties include various forms of *continuity*, (weak) monotonicity, commensurability, homogeneity and (weak) indication for all technologies satisfying certain regularity conditions (see Russell (1990, 1997) for details). Secondly, this measure is also relatively easy to compute and straightforward to interpret, and therefore the most widely adopted in practice.

The estimates of the efficiency scores, $\hat{TE}_j$ ($j=1,\ldots,n$), obtained by replacing T with $\hat{T}$ in (2) are consistent estimates of the corresponding true efficiency scores, TE_j ($j=1,\ldots,n$) given by (2). They are bounded between unity and infinity, with unity representing an estimated perfect (technical or technological) efficiency score of 100%. On the other hand, $(1/\hat{TE}_j)$ would represent the estimated relative *%-level* of the efficiency of the j^{th} DMU ($j= 1,\ldots, n$), relative to the estimated best-practice technology frontier, $\hat{T}$.

3.2 Regression Analysis of Determinants of Efficiency

Next, following Simar and Wilson (2007), we briefly outline regression analysis for studying dependency between the efficiency scores and hypothesised explanatory variables. We assume and test the following specification:

$$TE_j = a + Z_j\delta + \varepsilon_j, \qquad j = 1, \ldots, n \tag{4}$$

which can be interpreted as the first-order approximation of the unknown true relationship. In equation (4), a is the constant term, ε_j is statistical noise, and Z_j is a (row) vector of observation-specific variables for DMU_j that we expect to affect its efficiency score, TE_j, through the vector of parameters δ (common for all j) that we need to estimate.

A common practice in the DEA literature for estimating model (4) had previously been to employ the Tobit-estimator, until Simar and Wilson (2007) highlighted the limitations of such an approach. Instead, they introduced a method based on a truncated regression with a bootstrap and illustrated through Montecarlo experiments its satisfactory performance. Here, we will employ their approach. Specifically, noting that the distribution of ε_j is restricted by the condition $\varepsilon_j \geq 1 - a - Z_j\delta$ (since both sides of (4) are bounded by unity), we follow Simar and Wilson (2007) and assume that this distribution is truncated normal with zero mean (before truncation), unknown variance and a (left) truncation point determined by this very condition. Furthermore, we replace the true but unobserved regressand in (4), TE_j, by its DEA estimate $T\hat{E}_j$. Formally, our econometric model is given by:

$$T\hat{E}_j \approx a + Z_j\delta + \varepsilon_j, \qquad j = 1, \ldots, n, \tag{5}$$

where

$$\varepsilon_j \sim N(0,\sigma_\varepsilon^2)\text{, such that} \qquad \varepsilon_j \geq 1 - a - Z_j\delta\,,\;\; j = 1,\, \ldots,\, n, \qquad (6)$$

which we estimate by maximising the corresponding likelihood function, with respect to $(\delta, \sigma_\varepsilon^2)$, given our data. Relying on asymptotic theory, normal tables can be used to construct confidence intervals but more precision can be gained by using the bootstrap. This is particularly so because in our analysis the regressand is not an observed variable, but an estimate that is likely to be dependent on unobserved variables (see Simar and Wilson, 2007, for details). To construct the bootstrap confidence intervals for the estimates of the parameters $(\delta, \sigma_\varepsilon^2)$, we use a parametric bootstrap regression method, which incorporates information on the parametric structure and distributional assumption. Details of the estimation algorithm can be found in Simar and Wilson (2007).

4. Empirical Analysis

4.1. Data Description and Sources

To estimate the cost frontier, we used balanced panel data on Japanese seaport authorities in the years 2003 to 2005 (39 seaport authorities × 3 years = 117 observations). This small number of observations restricts the estimation of a stochastic frontier model, but enables the estimation of a DEA model. The data was obtained from the Transport Research and Statistics Division of the Ministry of Land, Infrastructure and Transport, Japan.

We measured the production of the seaport companies through a generalised Cobb-Douglas production function. Given the scant guidance provided by the literature review as to which variables to use in the analysis, we relied on microeconomics (Varian, 1987) for the choice of outputs and inputs and in he literature review.

Frontier models require the identification of inputs (resource) and outputs (transformation of resources). Several criteria can be used in their selection. The first empirical criterion is the availability of inputs and outputs. Second, the literature survey is a way to ensure the validity of the research and is thus another criterion to take into account (Cullinane, *et al.*, 2006). These are the criteria employed in the paper to select inputs and outputs.

Thus *output* is measured by 3 indicators: Number of ships, tons of bulk and container TEU (twenty foot equivalent unit). We measure *inputs* by 2 indicators: number of personnel and number of cranes.

The combination of indicators measured ensures respect to the DEA convention that the minimum number of DMU observations is greater than three times the number of inputs plus outputs [(117≥3(3+2)] (Raab and Lichty, 2002). Moreover, we also observe the convention that the minimum number of units is equal to or larger than the product of the number of outputs and inputs (Boussofiane and Dyson, 1991).

Output orientation can determine whether a seaport is capable of producing the same level of output with less input. The characteristics of the variables are shown in Table 2. One can see that Japanese seaports are relatively heterogeneous, with the standard deviation being higher than the mean for some variables.

Table 2: Characteristics of the Variables

Variables	Definition	Minimum	Maximum	Mean	Square deviation
Outputs					
Ships	Number of ship arrivals and departures	5301	771417	137561	156740
Bulk	Tons of liquid and dry bulk loaded and unloaded	3343968	374721891	102672404	96458515
Containers	Number of containers with TEU(twenty foot equivalent unit)	265	3840951	454998	869871
Inputs					
Personnel	Number of employees	11352	17211457	2988227	3904936
Cranes	Number of cranes in seaport	0	476312	44932	90391

4.2. DEA Results

The DEA index can be calculated in several ways. Here, we estimate an output-oriented, technically efficient (TE) DEA index, assuming that seaports aim to maximise the profits resulting from their activity. In this context, inputs are exogenous and outputs endogenous because of the competitive environment in which the units operate (Kumbhakar, 1987).

CCR efficient score model, is probably the most widely used and best known DEA model. It is the DEA model that assumes constant returns to scale relationship between inputs and outputs. It is named following their authors, Charnes, Cooper and Rhodes (1978) and measures the overall efficiency for each unit, namely aggregating pure technical efficiency and scale efficiency into one value, see Gollani and Roll (1989).

The BCC efficient score model is a DEA model that assumes variable returns to scale (VRS) between inputs and outputs. It is named following their authors, Banker, Charnes and Cooper (1984) and measure pure technical efficiency alone (Gollani and Roll, 1989). The efficiency score obtained with the BCC model gives a score which is at least equal to the score obtained using the CCR. The scale efficiency score is obtained dividing the aggregate CCR score by the technical efficient BCC score, (Fare et al, 1994). A unit is scale efficient when its size of operation is optimal. If its size is either reduced or increased, its efficiency will drop. Assuming that pure technical efficiency is attributed to managerial skills, the BCC scores are interpreted as managerial skills. All the DEA scores used in the paper are called ratio models, because they define efficiency as the ratio of weighted outputs divided by the weighted inputs. They use a radial or proportionate measure to determine the technical efficiency. A unit's technical efficiency is defined by the ratio of the distance from the origin to the inefficient unit, divided by the distance from the origin to the composite unit on the efficient frontier.

VRS were assumed to decompose technical efficiency into two different components: pure technical efficiency and scale efficiency (Fare et al, 1994). The VRS scores measure pure technical efficiency. However, the constant returns-to-scale (CRS) index is composed of a non-additive combination of pure technical and scale efficiencies. A ratio of overall efficiency scores to pure technical efficiency scores provides a measurement of scale efficiency. The relative efficiency of Japanese seaports is presented in Table 3, with the seaports aggregated by country, using a MATLAB program.

Table 3: Efficiency in Japanese seaports

Nobs	Seaport	DEA-CCR model	DEA-BCC Model	Scale Efficiency	
1	Hokkaido	0.199	1.000	0.199	Drs
2	Aomori	0.136	1.000	0.136	Drs
3	Iwate	1.000	1.000	1.000	Crs
4	Miyagi	0.182	1.000	0.182	Drs
5	Akita	0.210	1.000	0.210	Drs
6	Yamagata	1.000	1.000	1.000	Crs
7	Fukushima	0.306	1.000	0.306	Drs
8	Ibaraki	0.104	1.000	0.104	Drs
9	Chiba	0.068	1.000	0.068	Drs
10	Tokyo	0.042	1.000	0.042	Drs
11	Kanagawa	0.035	1.000	0.035	Drs
12	Niigata	0.059	1.000	0.059	Drs
13	Toyama	0.387	1.000	0.387	Drs
14	Ishikawa	1.000	1.000	1.000	Crs
15	Fukui	0.321	1.000	0.321	Drs
16	Shizuoka	0.152	1.000	0.152	Drs
17	Aichi	0.054	1.000	0.054	Drs
18	Mie	0.240	1.000	0.240	Drs
19	Kyoto	1.000	1.000	1.000	Crs
20	Osaka	0.045	1.000	0.045	Drs
21	Hyogo	0.093	1.000	0.093	Drs
22	Wakayama	0.414	1.000	0.414	Drs
23	Tottori	1.000	1.000	1.000	Crs
24	Shimane	1.000	1.000	1.000	Crs
25	Okayama	0.169	1.000	0.169	Drs
26	Hiroshima	0.416	1.000	0.416	Drs
27	Yamaguch	0.147	1.000	0.147	Drs
28	Tokushima	0.534	1.000	0.534	Drs
29	Kagawa	0.297	1.000	0.297	Drs
30	Ehime	0.260	1.000	0.260	Drs
31	Kochi	0.920	1.000	0.920	Drs
32	Fukuoka	0.085	1.000	0.085	Drs
33	Saga	1.000	1.000	1.000	Crs
34	Nagasaki	1.000	1.000	1.000	Crs
35	Kumamoto	1.000	1.000	1.000	Crs
36	Oita	0.245	1.000	0.245	Drs
37	Miyazaki	0.783	1.000	0.783	Drs
38	Kagoshima	0.144	1.000	0.144	Drs
39	Okinawa	0.189	1.000	0.189	Drs
	Mean	0.416	1.000	0.416	—
	Median	0.245	1.000	0.245	—
	Std. Dev.	0.372	0.000	0.372	—

A number of points emerge. Firstly, consistently with previous research on Asian seaports, there appear to be significant differences in efficiency among the seaports analysed measure by CCR-DEA model, (Tongzon, 2001, Park and De, 2004; Cullinane, Song and Gray, 2002). Note that the DEA score is between zero (0%) and 1 (100%). Units with DEA scores equal to 1 (100%) are efficient. A unit with a score of less than 100% is relatively inefficient, e.g. a unit with a score of 95% is only 95% as efficient as the best-performing seaports. Scores are relative to the other units, i.e., they are not absolute. Secondly, best-practice calculations indicate that almost all Japanese seaports operated at a high level of pure technical efficiency in the period under examination.

Finally, all technically efficient CRS seaports are also technically efficient in VRS, indicating that the dominant source of efficiency is scale (see Gollani and Roll, 1989). CRS is assumed if an increase in a unit's input leads to a proportionate increase in its outputs. This means that, regardless of the scale at which the unit operates, its efficiency will remain unchanged, assuming its current operating practices. VRS can be either increasing or decreasing returns to scale. In the former case an increase in a unit's inputs yields a greater than proportionate increase in its outputs; in the latter, a decrease in a unit's inputs yields a lower than proportionate increase in output. The above evidence suggests that variable returns to scale better characterize the technical efficiency of Japanese seaports.

It can be observed that BCC-DEA model rate all units in the frontier. To overcome this problem the Cross-efficiency and Super efficiency DEA models are adopted. Table 4 presents the results of cross-efficiency DEA model, Sexton, Silkman and Hogan (1986) and Doyle and Green (1984) and Super Efficiency DEA models, Anderson and Petersen (1993), which were applied to the Japanese seaports with two objectives: first, to cross-validate the DEA-CCR and DEA-BCC models; and second, to restrict the number of DMU's on the best practices frontier. The DEA-CCR and DEA-BCC often rate too many units as efficient.

Table 4: Cross-Efficiency DEA model and Super-Efficiency DEA model on Japanese seaports

Nobs	Seaports	Technical Efficiency, Cross –efficiency scores	Technical Efficiency, Super-Efficiency Scores
1	Hokkaido	0.951	0.963
2	Aomori	0.943	0.962
3	Iwate	0.998	1.000
4	Miyagi	0.960	0.965
5	Akita	0.970	0.968
6	Yamagata	1.000	1.000
7	Fukushima	0.962	0.971
8	Ibaraki	0.947	0.955
9	Chiba	0.938	0.943
10	Tokyo	0.957	0.982
11	Kanagawa	0.985	0.941
12	Niigata	0.939	0.940
13	Toyama	0.918	0.985
14	Ishikawa	0.997	1.000
15	Fukui	0.992	0.986
16	Shizuoka	0.957	0.961
17	Aichi	0.968	0.953
18	Mie	0.951	0.973
19	Kyoto	0.989	1.000
20	Osaka	0.967	0.938
21	Hyogo	0.953	0.937
22	Wakayama	0.945	0.987
23	Tottori	0.957	1.000
24	Shimane	0.985	1.000
25	Okayama	0.958	0.960
26	Hiroshima	0.991	0.989
27	Yamaguch	0.963	0.959
28	Tokushima	0.990	0.991
29	Kagawa	0.978	0.981
30	Ehime	0.966	0.978
31	Kochi	0.981	0.998
32	Fukuoka	0.957	0.941
33	Saga	0.983	1.000
34	Nagasaki	0.992	1.000
35	Kumamoto	0.995	1.000
36	Oita	0.983	0.975
37	Miyazaki	0.973	0.995
38	Kagoshima	0.821	0.957
39	Okinawa	0.968	0.958

	Mean	0.416	0.416
	Median	0.967	0.975
	Std. Dev.	0.031	0.021

4.3. Determinants of Efficiency

In order to examine the hypothesis that the efficiency of the Japanese seaports is determined by different variables, we followed the two-step approach, as suggested by Coelli *et al*. (1998), estimating the regression shown below. It is recognised in the DEA literature that the efficiency scores obtained in the first stage are correlated with the explanatory variables used in the second stage, and that the second-stage estimates will then be inconsistent and biased. A bootstrap procedure is needed to overcome this problem (Efron and Tibshirani, 1993). To this end, as explained earlier, we adopt the approach of Simar and Wilson (2007).

The estimated specification is as follows, Cullinane, Song and Wang (2005):

$$\theta_{i,t} = \beta_0 + \beta_1.Trend_{i,t} + \beta_2.Trend_{i,t}^2 + \beta_3.GDP_{i,t} + \beta_4 Hub_{i,t} + \beta_5 Population_{it} + \varepsilon_{i,t} \tag{7}$$

where θ represents the DEA-CCR model efficiency score, estimated in table 2. *Trend* is a yearly trend. *Square trend* is the square value of the trend. GDP is the *county gross domestic product* ; this aims to capture the local market effect related to each Japanese seaport. *hub* is a dichotomic variable identifying seaports hubs. Hubs are common in contemporary airports, Barros and Dieke (2007) and are appearing also in seaports. It identifies seaports that distribute international traffic towards other local seaports. *Population* is the county population aiming to capture the importance of the local market in attracting traffic. Finally, Following Simar and Wilson (2007), we employ a MATLAB program to bootstrap the confidence intervals, with 2000 replications. The results are presented in Table 5.

Several models were estimated for comparison purposes. The results are quite robust, since the variables that were significant in Model 1 remained significant after dropping the insignificant variables. Also, all variables have a positive and statistically significant coefficient.

Table 5: Truncated Bootstrapped Second-Stage Regression
(*dependent variable: CCR index)*

Variable	Model 1	Model 2	Tobit
Constant	1.16***	1.10***	1.16***
Trend	0.11***	0.09**	0.19*
Square trend	-0.03***	-0.07**	-0.07*
GDP	0.08***	0.07**	0.05*
Hub	0.12***	0.10***	0.15*
Population	0.02	—	0.04
Variance	0.03	0.03	0.10
Total number of observations	1000	1000	1000

***, **, * statistically significant at 1%, 5%, and 10% respectively. *The Tobit model variance is sigma.*

The truncated regression with a bootstrap model appears to fit the data well, with positive t-statistics, which are statistically significant for all parameters, with the exception of the population variable. The estimations generally conform to a priori expectations. It is observed that the efficiency scores increases over the observation period, according to the trend, but at a decreasing rate since square trend is negative. *GDP* is positive, signifying that local wealth contributes for the trade and therefore for the technical efficiency of the seaports. *Hub* status contributes to efficiency. This means that the discipline of the internationalization and the public scrutiny inherent in it contribute to the efficiency of seaports. International seaports function in some way as a hub for the adjacent region, and therefore the result supports previous research on seaports relative to hubs, Min and Guo (2004). The population variable while positive is statistical insignificant and therefore deleted from model 2. The Tobit model presented for comparative purpose, present similar results, but with larger variances.

5. Discussion

In this paper we have adopted the DEA two-stage model to analyse the performance of Japanese seaports between 2003 and 2005. The main innovation in our analysis is to apply the two-stage procedure proposed by Simar and Wilson (2007) to bootstrap the DEA scores. In the first stage four DEA models are use to obtain technical efficiency scores. In the second stage the Simar and Wilson (2007) procedure is adopted. This procedure improves both efficiency of estimation and inference. In particular, the adoption of the functional form (truncated functional form) in the second stage enables consistent inference with models explaining efficiency scores, while simultaneously producing standard errors and confidence intervals for these efficiency scores. Benchmarks can be obtained for improving the operations of seaports that perform poorly.

Our empirical findings suggest the following: First, the technical efficiency scores spread along the Japanese seaports analysed, signifying that in this context, unique assets are seen as exhibiting inherently differentiated levels of efficiency; sustainable production is ultimately a return on the unique assets owned and controlled by the seaports (Teece et al., 1997). In addition, the strategic-groups theory (Caves and Porter, 1977), which justifies different efficiency scores on the grounds of differences in the structural characteristics of units within an industry, explains the dispersion of the efficient scores along the different Japanese seaports. The seaports which have adopted strategic procedures, such as hub strategy, are on average more efficient than those which do not adopt this strategy. A rationale for this finding is found in the strategic-based theory (Caves and Porter, 1977). This theory refers to the differences in structural characteristics of units within an industry, which causes differences in performance. In the seaports, units with similar asset configurations tend to pursue similar strategies with similar performance results (Porter, 1979), and these differentiated strategies result in different efficiency scores.

Local governments control all seaport authorities. The financial sources come from the subsidies of central government, shares of the local government and various port charge revenues (Morisugi, 2000). What should the managers from the Japanese seaports do to improve efficiency? Firstly, they should adopt a benchmark management procedure in order to evaluate their relative position and to adopt managerial procedures for catching up with the frontier of "best practices". As the frontier is shifting over time, an effort is needed to catch up with it. Secondly, they should adopt a resource-based view of management in order to develop critical resources in strategic issues.

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REFERENCES

Altunbas, Y.; Gardener, E.P.M.; Molyneux, P. and Moore, B. (2001) ´Efficiency in European Banking`. *European Economic Review*, 45, 1931-1955.

Andersen, P. amd Perersen, N.C. (1993) A procedure for ranking efficiency units in Data Envelopment Analysis. Management Science, 39,10, 1261-1264.

Baños Pino, J.; Coto Millan, P. and Rodriguez Alvarez, A. (1999) Allocative efficiency and overcapitalisation: na application. International Journal of Transport Economcs, 2, 181-199.

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

Barney J. (1991). Firm resources and sustained competitive advantage. *Journal of Management,* Vol. 17, pp. 99-120.

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

Barros, C.P. (2003a) Incentive Regulation and Efficiency of Portuguese Port Authorities. Maritime Economics & Logistics 5(1): pp 55-69.

Barros, C.P. (2003b). The Measurement of Efficiency of Portuguese Seaport

Authorities with DEA. International Journal of Transport Economics 30(3): pp. 335 354.

Barros, C.P. (2005) Decomposing Growth in Portuguese Seaports: A Frontier Cost Approach. Maritime Economics & Logistics 7(4): pp. 315.

Boussofiane, A., Dyson, R. G., 1991.Applied Data Envelopment Analysis. European Journal of Operational Research. 52, 1-15.

Caves R. and Porter M.E. (1977). From entry barriers to mobility barriers: Conjectural decisions and contrived deterrence to new competition, *Quarterly Journal of Economics*, Vol. 91, pp. 241-261.

Charnes A, Cooper WW and Rhodes E. (1978). Measuring the efficiency of decision making units. European Journal of Operational Research, 2(6): pp. 429-444.

Charnes, A.; Cooper, W.W.and Huang, Z.M. (1990) Polyhedral cone-ratio DEA with an illustrative application to large commercial banks. Journal of Econometrics, 46, 73-91.

Charnes, A.; Cooper, W.W., Lewin, A.Y. and Seiford, L.M. (1995) *Data Envelopment Analysis: Theory, Methodology and Applications*, Boston, Kluwer.

Coelli, T.J., Rao, P. and Battese, G.E., 1998, *An Introduction to Efficiency and Productivity Analysis*. Kluwer Academic Press.

Coelli, T. J. and Perelman, S. (1999) A Comparison of Parametric and Nonparametric Distance Functions: With Application to European Railways, *European Journal of Operations Research*, 117 (2): 326-39.

Coelli, T. J. and Perelman, S. (2000) Technical Efficiency of European Railways: A Distance Function Approach, *Applied Economics*, 32 (15): 1967-76.

Cooper, W.W.; Seiford, L.M. and Tone, K., 2000, *Data Envelopment Analysis*. Boston, Kluwer.

Coto Millan, P.; Banos Pino, J. and Rodrigues Alvarez, A. (2000). Economic Efficiency in Spanish Ports: Some Empirical Evidence. Maritime Policy & Management 27(2): pp. 169-175.

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 Part A, (36): pp. 734-762.

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): pp. 251-267.

Cullinane Kevin, Dong-Wook Song, Tengfei Wang. (2005). The Application of Mathematical Programming Approaches to Estimating Container Port Production Efficiency. Journal of Productivity Analysis 24: pp. 73-92.

Cullinane, K.; Wang, T.F.; Song, D.W. and Ji, P. (2006). The technical efficiency of Container Ports: Comparing Data Envelopment Analysis and Stochastic Frontier Analysis. Transportation Research Part A 40: pp. 354-374.

Doyle, J. and Green, R. (1994) Efficiency and Cross-efficiency in DEA: Derivations, Meanings and Uses. Journal of Operational Research Society, 45,5, 567-578.

Estache, A.; Gonzalez, M. and Trujillo, L. (2001). Efficiency Gains from Port Reforms and the Potential for yardstick Competition: Lessons from Mexico. World Development 30(4): pp. 545-560.

Fare, R. Grosskopf, S., S. , Lovell, C. A. K. , 1994. Production Frontiers. Cambridge University Press.

Farrell, M.J. (1957) The Measurement of Productive Efficiency, *Journal of the Royal Statistical Society*, Series A, 120 (3), pp. 253-290.

Gollani, B., Roll, Y., 1989. An Application Procedure for DEA. Omega International Journal of Management Sciences, 17, 237-250.

Haralambides, HE, Verbeke, A, Musso, E. and Benacchio, M. 2001. Port Financing and pricing iin the European Union: Theory, politics and reality. International Journal of Maritime Economics 3; 368-386.

Kneip, A., Park, B., Simar, L., 1998. A note on the convergence of nonparametric DEA estimators for production efficiency scores. Economic Theory, 14, 783-793.

Kneip, A., Simar, L., Wilson, P.W., 2003. Asympotics for DEA estimation in non-parametric frontier models. Discussion paper of the Institut de Statistique, Université Catolique de Louvain, Belgium.

Liu, Z. (1995). The Comparative Performance of Public and Private Enterprises. Journal of Transport Economics and Policy, 29, 3: 263-274.

Martinez Budria, E.; Diaz Armas, R. and Navarro Ibafiez, M. and Ravelo Mesa, T. (1999). A Study of the Efficiency of Spanish Port Authorities Using Data

Envelopment Analysis. International Journal of Transport Economics 2: pp. 237-253

Min, H. and Guo, Z. (2004) The location of hub-seaports in the global supply chain network using cooperative competition strategy. International Journal of Integrated Supply Management, 1,1, 51-63.

Morisugi, M. (2000) Evaluation methodologies of transportation projects in Japan, Transport Policy , 7 (1):; 35-40.

Park, Ro Kyung and De, Prabir 2004: An Alternative Approach to Efficiency Measurement of Seaports. Maritime Economics & Logistics 6: pp. 53-69.

Porter, M.E. (1979). The structure within industries and companies performance. *The Review of Economics and Statistics,* 61, 214-227.

Raab R., Lichty, R., 2002. Identifying Sub-Areas That Comprise a Greater Metropolitan Area: The Criterion of County Relative Efficiency. Journal of Regional Science 42, 579-594.

Roll Y. and Hayuth, Y. (1993). Port Performance Comparison Applying Data Envelopment Analysis (DEA). Maritime Policy and Management 20(2). Pp. 153-161.

Rumelt, R. (1991). How much does industry matter? *Strategic Management Journal,* Vol. 12, No. 2, 167-185.

Russell, R.R., 1990. Continuity of measures of technical efficiency. Journal of Economic Theory., 51, 255-267.

Russell, R.R.. 1997. Distance functions in consumer and producer theory. In: Index Number Theory: Essays in Honor of Sten Malmquist. Kluwer Academic Publishers, Boston , pp.7-90.

Sexton, T.R.; Silkman, R.H. and Hogan, A. (1986) Data Envelopment Analysis: Critique and Extension, in R.H. Silkman (ed) Measuring Efficiency: An Assessment of Data Envelopment Analysis. San Francisco, Jossey Bass, pp. 73-105.

Simar, L. and Wilson, P.W. (2007) Estimation and inference in two stage, semi-parametric models of productive efficiency. Journal of Econometrics, 136, 31-64.

Song, D.W. and Cullinane, K. (2001). The administrative and ownership structure of Asian Container Ports. International Journal of Maritime Economics 3(2): pp. 175-197.

Thanassoulis, E., 2001. Introduction to the Theory and Application of Data Envelopment Analysis: A Foundation Text with Integrated Software. AH Dordrecht, Kluwer Academic Publishers, Boston.

Thompson R.G., L. N. Langemeier, C. Lee and R. M. Thrall (1990) 'The Role of Multiplier Bounds in Efficiency Analysis with Application to Kansas Farming', *Journal of Econometrics*, 46, 93-108.

Thompson R.G., F. D. Singleton, R. M. Thrall and B. A. Smith (1986) 'Comparative Site Evaluation for Locating a High-Energy Physics Lab in Texas', *Interfaces* 16, 35-49.

Tongzon, J. and Heng, W. (2005). Port privatization, efficiency and competitiveness: Some empirical evidence from container ports (terminals). Transportation Research Part A – Policy and Practice 39: pp. 405-424.

Tongzon Jose (2001). Efficiency Measurement of selected Australian and other international ports using data DEA. Transportation Research Part A, Policy and Practice, 35(2): pp. 113-128.

Valentine V.F. and Gray R. (2001). The measurement of port efficiency using data envelopment analysis. Proceeding of the Ninth World Conference on Transport Research, Seoul, 22-27 July.

Varian, H.R.,1987, Intermediate Microeconomics: A Modern Approach, N.Y.: Norton and Co.

Wernerfelt, B. (1984). A resource-based view of the firm. *Strategic Management Journal,* 5, 2, 171-180.

Xue, M., Harker, P.T., 1999. Extensions of Modified DEA. Financial Institution Center, Working Paper 99-07. The Wharton School, University of Pennsylvania.

Zhu, J. (2002) *Quantitative Models for Performance Evaluation and Benchmarking: Data Envelopment Analysis with Spreadsheets*, Kluwer Academic Publishers, Boston.