COMPARATIVE ANALYSIS OF SEAPORTS PERFORMANCE USING DATA ENVELOPMENT ANALYSIS

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Abstract:

Measures of seaport efficiency or performance indicators use a diverse range of techniques for assessment and analysis, but although many analytical tools and instruments exist, problems arise when one tries to apply them to a range of different seaports. Data envelopment analysis (DEA) is a technique for comparing the efficiency of organizations which have a number of different inputs and outputs. DEA enables relative efficiency ratings to be derived within a set of analyzed units. Thus it does not require the development of 'standards' against which efficiency is measured, although such standards can be incorporated in the DEA analysis. The efficiency of units is compared with an 'efficiency envelope' that contains the most efficient units in the group.

In this paper it is demonstrated that data envelopment analysis (DEA) can augment the traditional ratio analysis of seaports combining operational and financial variables. DEA can provide a consistent and reliable measure of managerial or operational efficiency of a seaport. The paper also evaluates how close the Omani seaports are to the frontier of best practice. The DEA efficiency ratings can be useful tool for port managers and for researchers, providing a deeper insight into port performance. Weaknesses can be detected, leading the way to potential improvements.

Key words: Data envelopment analysis, seaports, efficiency, best practice.

1. Introduction:

In order to support trade oriented economic development, port authorities have increasingly been under pressure to improve port efficiency by ensuring that port services are provided on an internationally competitive basis. Ports form a vital link in the overall trading chain and, consequently, port efficiency is an important contributor to a nation's international competitiveness (Tongzon, 1989; Chin and Tongzon, 1998). Thus, monitoring and comparing one's port with other ports in terms of overall efficiency has become an essential part of many countries' microeconomic reform programs.

This study hopes to contribute to this important task by applying an innovative approach to port efficiency ratings covering a selected sample of ports. Relying on mathematical programming techniques, this approach, called data envelopment analysis (DEA), has been applied to a wide number of different situations where efficiency comparisons are required due to its inherent advantages compared with conventional approaches. 1 Firstly, the characteristics of DEA, such as its ability to analyze several outputs and inputs simultaneously and to derive efficiency rating within a set of analyzed units, are particularly suitable for measuring port efficiency. Port output can be multi-dimensional depending on the objective that ports want to achieve. Secondly, DEA does not require the development of ``standards'' against which efficiency is measured, although such standards can be incorporated in the DEA analysis. Roll and Hayuth (1993) have advocated the use of this approach to the measurement of port efficiency, and demonstrated, based on hypothetical port data, how the relative efficiency ratings of ports could be obtained. This paper builds on their work by applying the DEA analysis to actual performance data for selected ports. Given the multiplicity of ports and cargoes handled, it is necessary to restrict the scope of analysis to a limited number of ports and a specific type of cargo. This study examines efficiency with respect to containerized cargoes across ports recognized for their high level performance (in terms of throughput) in Asia and Europe for which data are available. 2 Data availability is particularly important since many of the ports surveyed for data via questionnaires refused to reveal information on some aspects of their port operations due to confidentiality. Thus, apart from the data obtained from the survey, the study has to depend on secondary sources. The following are the secondary sources of data for this study: the Australian Bureau of Transport and Communications Economics (1996) survey data on four Australian ports and selected Asian and European ports for data on reliability and speed; Containerization International Yearbook (1998) and Lloyd's Ports of the World (1998) for data on port infrastructure. The Australian Bureau of Transport and Communications Economics data on reliability and speed should be quite reliable and unbiased since these were obtained from the same shipping lines calling at the selected ports, rather than from their various port authorities or terminal operators. These data and the sampled ports are shown in Appendix A.

2. Port output and port input measures

Various studies have compared ports using selected performance and efficiency criteria or measures, for example, the Australian Bureau of Industry Economics (1993, 1995), Australian Transport Advisory Council (1992), and Tongzon and Ganesalingam (1994). However, these measures partially reflect different aspects of port operation and fail to provide us with an overall measure of port efficiency. DEA analysis can combine all these partial measures without the setting of a priori weights for the various parameters to produce an overall efficiency measure. Further, in contrast to conventional econometric techniques such as the regression analysis used to estimate a production function, in DEA more than one output measure can be specified. A number of different measures of port output are available, depending on which features of port operation are being evaluated.

This study uses two output and six input measures of port performance for the year 1996, the year for which the latest data on port throughputs are available. The output measures are cargo throughput and ship working rate. The first output measure is the total number of containers loaded and unloaded in 20-foot equivalent units (TEUs). This output relates to the need for cargo-related facilities and services. Further, since ships are major port users, the second output is the ship working rate. Ship working rate measures the number of containers moved per working hour per ship and thus is an indicator of the speed with which ships are worked. This measure can represent the level and quality of port service. Since the container handling aspect of port operation is the largest component of total ship turnaround time, the speed of moving cargoes off and onto ships at berth has considerable implications for the port users. Moreover, improving efficiency in this area is consistent with port authority intentions of maximizing berth utilization, a factor which will influence both port charges imposed on ship owners and the actual throughput handled.

To produce the above outputs and to facilitate port operations, a variety of inputs are required.

Based on the production framework, port inputs can be generalized as land, labor and capital.

The major capital inputs in port operations are the number of berths, cranes and tugs. The most fundamental labor input is the number of stevedoring labor. However, due to a lack of information on this particular variable, a proxy variable is used represented by the number of port authority employees for the respective ports. 4 This proxy variable is less difficult to obtain because it is usually published in the annual reports of some ports. 5 With respect to the land input, the study uses the terminal area of the ports. 6 Another important factor influencing port outputs is the amount of delay time which is the difference between total berth time plus time waiting to berth and the time between the start and finish of ship working, and is an indicator of how well working time is being used. These delays could be due to labor disputes, work practices such as meal breaks, equipment breakdown, port congestion, perceived ship problems or bad weather. These output and input variables are also defined in Appendix A.

3. Data envelopment analysis

DEA is an efficiency evaluation model based on mathematical programming theory. DEA

offers an alternative to classical statistics in extracting information from sample observations. In contrast to parametric approaches such as regression analysis which ®t the data through a single regression plane, DEA optimizes each individual observation with the objective of calculating a discrete piece-wise frontier determined by the set of Pareto efficient decision management units (DMUs) In other words, the focal point of DEA is on individual observations as opposed to single optimization statistical approaches which focus on averages of parameters. In the present application, DEA refers to each port as a DMU, in the sense that each is responsible for converting inputs into outputs. DEA analysis can involve multiple inputs as well as multiple outputs in its efficiency valuation. This makes DEA analysis more suitable for port efficiency measurement because ports produce a number of different outputs. Among these outputs are the quantities and the variety of cargoes handled, the types of ships serviced, the interchange with land transport modes, the additional services rendered such as warehousing and so on (Roll and Hayuth, 1993, p. 153). Furthermore, DEA calculations are non-parametric and do not require an explicit a priori determination of relationships between inputs and outputs, or the setting of rigid importance weights for the various factors. Benchmarking has also become a part of normal commercial culture of the port industry. DEA makes benchmarking easier and more realistic because it enables derivation of an efficiency envelope, which contains the most efficient ports of the group analyzed, against which all other ports are compared, rather than just choosing the most efficient port. The choice of one port representing the best international practice may be unfair due to differences in contexts. For many applications, these features make DEA a more flexible tool as compared to other conventional efficiency measures derived from stochastic production frontier or economic value added (EVA), which are based on production function estimation involving many inputs but only one output.

Since its introduction by Charnes et al. (1978), there have been many applications of DEA. Some applications have involved efficiency evaluation of organizations with characteristics similar to ports, such as hospitals (Banker et al., 1986), schools (Ray, 1991), courts (Lewin et al., 1982), post o�ces (Deprins et al., 1984), and air force maintenance units (Charnes et al., 1985). DEA provides the flexibility to permit ``unconventional'' variables such as the number of students graduated, number of patients served, even journal ranking (Burton and Phimister, 1995) to be used for efficiency evaluation. DEA has also been applied in the transportation sector to airlines (Banker and Johnston, 1994; Charnes et al., 1996), and railways (Oum and Yu, 1994). A detailed bibliography related to DEA (1978±1992) can be found in Charnes et al. (1995, ch. 22). Since the early work of Charnes, Cooper and Rhodes (CCR), there have been a number of extensions to the DEA model. For example, Charnes et al. (1985) introduced window analysis to handle panel data sets involving pooled cross section and time series observations.

The concept of DEA is developed around the basic idea that the efficiency of a DMU is determined by its ability to transform inputs into desired outputs. This concept of efficiency was adopted from engineering which defines the efficiency of a machine/process as Output/Input≤1. In this approach, efficiency is always less than or equal to unity as some energy loss will always occur during the transformation process. DEA generalizes this single output/input technical efficiency measure to multiple outputs/inputs by constructing a relative efficiency measure based on a single ``virtual'' output and a single virtual input. The efficient frontier is then determined by selecting DMUs which are most efficient in producing the virtual output from the virtual input. Because DMUs on the efficient frontier have an efficiency score equal to 1, inefficient DMUs are measured relative to the efficient DMUs. The efficiency measure is relative to other DMUs. It is not possible to determine if DMUs judged to be efficient are optimizing the use of inputs to produce outputs.

More formally, assume that there are n DMUs to be evaluated. Each DMU consumes varying amounts of m different inputs to produces different outputs. Specifically, DMUj consumes amounts {Xj . xij} of inputs (i = 1, ... ,m) and produces amounts Yj = {fyrj} of outputs (r = 1. . . . . , s) The s x n matrix of output measures is denoted by Y, and the m x n matrix of input measures is denoted by X. Also, assume that xij > 0 and yrj > 0. Consider the problem of evaluating the relative efficiency for any one of the n DMUs, which will be identified as DMU0. Relative efficiency for DMU0 is calculated by forming the ratio of a weighted sum of outputs to a weighted sum of inputs, subject to the constraint that no DMU can have a relative efficiency score greater than unity. Symbolically:

$$\max_{u,v} \frac{\sum_r u_r y_{r0}}{\sum_i v_i x_{i0}} = \frac{u^{\mathrm{T}} Y_0}{v^{\mathrm{T}} X_0}, \quad \text{where } u = (u_1, \ldots, u_s)^{\mathrm{T}}, \quad v = (v_1, \ldots, v_m)^{\mathrm{T}}$$

subject to

$$\frac{u^{\mathrm{T}} Y_j}{v^{\mathrm{T}} X_j} = \frac{\sum_r u_r y_{rj}}{\sum_i v_i x_{ij}} \leqslant 1$$

$$\text{for } j = 1, 2, \ldots, n; \quad u_r, v_i \geqslant 0 \quad \text{for } r = 1, 2, \ldots, s \quad \text{and} \quad i = 1, 2, \ldots, n,$$

where ur and vi are weights assigned to output r and input i, respectively.

For this fractional programming problem with a potentially in®nite number of optimal solutions, Charnes et al. (1978) were able to specify an equivalent linear programming problem (LP).

This requires the introduction of a scalar quantity (h) to adjust the input and output weights:

$$\theta = \frac{1}{v^{\mathrm{T}} X_0}, \quad \mu^{\mathrm{T}} = \theta u^{\mathrm{T}}, \quad \omega = \theta v^{\mathrm{T}}.$$

Appropriate substitutions produce the CCR LP problem:

$$\max_{\mu, v} \quad \Lambda_0 = \sum_r \mu_r y_{r0} = \mu^{\mathrm{T}} Y_0$$

subject to

$$\omega^{\mathrm{T}} X_0 = \sum_i \omega_i x_{i0} = 1, \quad \sum_r \mu_r y_{rj} - \sum_i \omega_i x_{ij} \leqslant 0, \qquad \mu_r, \omega_i \geqslant \epsilon,$$

where the value of Λ0 is the relative efficiency of DMU0 and € is a positive constant, called the non-Archimedian infinitesimal, which is introduced to facilitate solving of the LP problem. In DEA, this LP is known as the CCR model, as it was developed by Charnes, Cooper and Rhodes.

In addition to the CCR DEA model, two other DEA models are also often associated with the DEA methodology (e.g., Ali et al., 1995): the BCC model and the Additive model. The models differ mainly in their envelopment surface orientation and projection path to the e�cient frontier for an inefficient DMU. The CCR model results in a constant returns to scale, piece-wise linear envelopment surface with both input and output orientations for projection paths. The BCC model provides a variable returns to scale, piece-wise linear envelopment surface, which is similar to the Additive model. However, its projection path has both input and output orientations, which differ from the Additive model. The Additive model was introduced by Charnes et al. (1985). The envelopment surface derived from the Additive model has a piece-wise linear, variable returns to scale property. The model is based on the concept of a Pareto efficient (minimum) function. For any particular one of the n DMUs, again denoted by DMU0, the LP for the Additive model is:

$$\max_{\mu, v, u_0} \quad \Omega_0 = \mu^{\mathrm{T}} Y_0 - \omega^{\mathrm{T}} X_0 + \gamma_0$$

subject to

$$\mu^{\mathrm{T}} Y - \omega^{\mathrm{T}} X + \gamma_0 \tau \leqslant 0,$$
$$-\mu^{\mathrm{T}}, \ -\omega^{\mathrm{T}} \leqslant -\tau$$

where τ is a column vector of 1.