Efficiency Measurement of US Ports Using Data Envelopment Analysis

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ABSTRACT

Container transportation plays a key role in the process largely because of the numerous technical and economic advantages it provides over traditional methods of water transportation. Compared with traditional port operations, containerization has greatly improved performance of port production. Many container ports no longer enjoy the freedom yielded by a monopoly over the handling of cargo from within their vicinity. Instead, not only they are concerned with whether they can physically handle cargo, but also whether they can compete for that cargo. This paper aims to analyze port productivity using Data Envelopment Analysis technique. Two main results are presented. First, an efficient frontier or a set of the best practice ports is identified, which inefficient ports may want to emulate. Second, the sources and extent of inefficiency on which an inefficient port should focus in order to improve their operations are determined.

KEYWORDS: Port Productivity, Container Transportation, Data Envelopment Analysis

INTRODUCTION

The globalization of the world economy has ever increased the importance of the role for transportation. In the transportation arena container transportation plays a key role in the process because of its technological advantages as compared with the traditional methods of transportation. In order to support the global trade development, U.S. port authorities have increasingly been under pressure to improve port efficiency by ensuring that port services are provided on an internationally competitive basis. Compared with traditional port operation, containerization has improved port production. Port productivity and efficiency is an important contributor to the United State's international competitiveness.

Under such a competitive environment port performance measurement is not only a good management practice for port operators, but also an important input for regional and national port planning and operations. Port efficiency has been evaluated by calculating the cargo handling relation at the berth (Tabernacle, 1995, Ashar, 1997), or by comparing actual with optimum throughput over a specific time period (Talley, 1998). Jara-Diaz et. al. (2002) estimate a multi output cost function using a flexible form from a sample of 26 Spanish seaports over an 11-year period. Outputs are containerized general cargo, break bulk general cargo, liquid bulk, dry bulk, and total rent received for leases of port space. The results support the presence of economies of scale and scope.

Turner et al. (2003) study productivity of ports in the North America using a panel data during 1984 – 1997. To measure the efficiency of ports, they employed the Data Envelopment Analysis (DEA) technique. In this study, we will adopt the same technique and update their results based on a more recent panel data during 1998 – 2003. The study will provide new information on efficiency estimation that should be useful for planners and decision makers.

PORT PRODUCTION MEASUREMENT

Performance measurements play a significant role in the development of port terminals or other forms of organizational Decision Making Units (DMU). There are several methods that are applicable for evaluating performance of ports including regression analysis (Tongzon, 1995). In recent years, Data Envelopment Analysis (DEA) has been an alternative technique for estimating an empirical efficient production frontier. The frontier defines the relationship between inputs and outputs by depicting graphically the maximum outputs obtainable from the given inputs.

Data Envelopment Analysis (DEA) is a non-parametric method of measuring the efficiency of decision making unit (DMU) with multiple outputs and inputs. DEA is an appealing technique due to at least two reasons. First, its ability to analyze several outputs simultaneously and to derive efficiency rating within a set of analyzing units, are particular suitable for measuring port efficiency. Second, DEA technique does not require assumptions regarding associated functional forms. Instead, DEA will provide a piece-wise linear function to represent an empirical maximum possible frontier. In Figure 1, it plots the empirical relationship between an input and an output from a set of 7 hypothetical ports, A, B, C, D, E, F, and G. Using DEA will determine that ABCD form an efficient frontier.

Port output can be multi-dimensional depending on the objective that ports want to achieve. Roil and Hayuth (1993) have advocated the use of this approach in measurement of port efficiency and demonstrated, based on the port data, how the relative efficiency ratings of ports could be obtained.

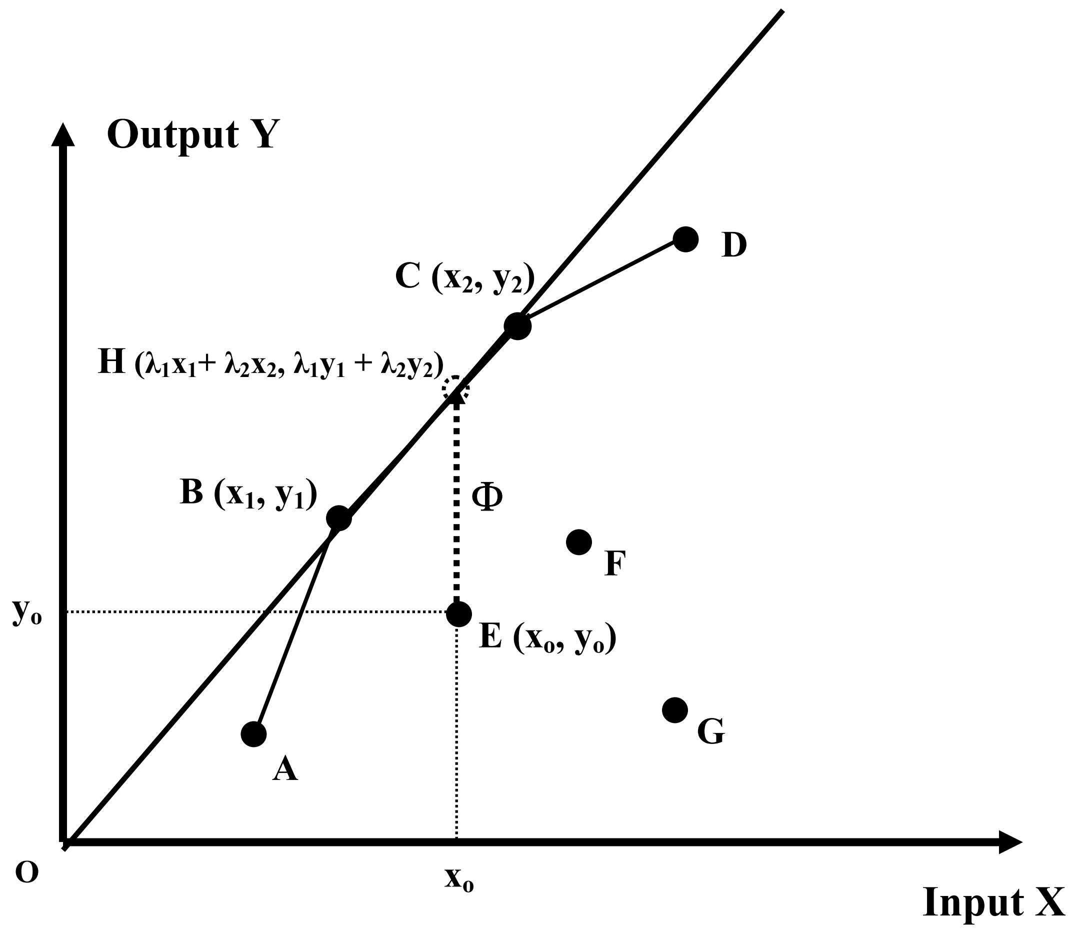

FIGURE 1: Output-Oriented Variable Return-to-Scale DEA Model: Single Input/Output

This study examines operational efficiency of ports with respect to containerized cargoes across regions in the US. One of the results is an index or a performance score which can be used for performance comparison across ports. The score can also be used for benchmarking purpose. In the subsequent study, we plan to develop the causal relationship between this performance score and port factors. Such relationship would be useful for port managers and policy makers to understand factor affecting productivity of ports and ultimately derive a strategy to enhance the operational efficiency. At this stage, we address the efficient measurement by using the DEA technique. The proposed methodology is implemented with a sample of 25 ports operating in the west and east coast of the U.S. during 1998 – 2003.

METHODOLOGY

Data Envelopment Analysis (DEA) is an efficiency evaluation model based on mathematical programming theory. DEA calculations are non-parametric and do not require an explicit determinations of relationships between input and outputs. The choice of one port representing the best national practice may be unfair due to differences in context. As a result, DEA is a more flexible tool as compared with conventional efficiency measures derived from stochastic production frontier or economic value added, which are based on a priori production function.

Since its introduction by Charnes et al. (1978), DEA technique has been applied in many different contexts. In transportation, there are applications in airports [Martin and Roman (2001), Bazargan and Vasigh (2003)], multi-airport systems (Pathomsiri et al. 2006), ports [Roll and Hayuth (1993), Cullianane et al. (2004), Turner et al. (2004)]. 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. Suppose we have n DMUs (ports), where each $DMU_j (j = 1,2,....,n)$ produces s output $y_{rj} (r = 1,........,s)$ by utilizing m inputs $x_{ij} (i = 1,........,m)$. DEA, use the following measure of performance for DMU_j.

$$h_j = \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}}$$

where:

$v_i (i = 1,....,m)$ and $u_r (r = 1,....,s)$ are weights assigned to output r and input i, for DMU_j, respectively. The above equation is determined for each DMU_j by the following mathematical programming problem (Charnes et al., 1978).

$$h_o^* = \underset{u_r v_i}{Max} h_o$$

$$\text{s.t. } h_j \leq 1 \quad j = 1,2,....,n$$

$$v_j, u_r \geq 0$$

where:

$$h_o = \frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=1}^{m} v_i x_{io}}$$

represents the ratio of aggregated outputs to aggregated inputs for one of the n DMUs denoted $DMU_i (i = 1,2,....,n)$ and y_{ro} are respectively the i^{th} input and r^{th} output of DMU_i.

For this fractional programming problem with potential infinite number of optimal solutions, Charnes et al. (1978) were able to specify an equivalent linear programming problem. This requires the introduction of a scalar quantity (θ) to adjust the input and output weights:

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

In above DEA, the LP is known as the CCR model, as Charnes et al. (1978) proposed. Later on there are many variations to deal with certain type of data and assumptions. One form that we use in this study is an output-oriented and variable return-to-scale (VRS) DEA model. The idea may be explained by using a graphical illustration of hypothetical single input/output ports, as shown in Figure 1. The mathematical form is shown in the following LP:

$$\begin{aligned}
&\max \quad Z_0 = \Phi \\
&\text{Subject to} \\
&\Phi y_{ro} \le \sum_{j=1}^{n} \lambda_j y_{rj} \qquad r = 1,2,......s \\
&x_{i0} \ge \sum_{j=1}^{n} \lambda_j x_{ij} \qquad i = 1,2,......m \\
&\sum_{j=1}^{n} \lambda_j = 1 \\
&\lambda_j \ge 0
\end{aligned} \tag{1}$$

To determine whether a port is on the frontier, we simply solve (1). The LP problem above is a generalized formulation for multiple input and output cases. In this formulation, n, s and m represent number of samples, number of outputs and number of inputs respectively. λ_j is a scalar vector associated with each airport and has n elements. x_{ij}, y_{rj} are quantity of input i and output r of port j respectively. x_{io}, y_{ro} are quantities of input i and output r of an airport o for which the productivity is to be measured. Φ or the performance score is a number by which the current output level has to be multiplied in order to reach the frontier. If a port is on the frontier, solving this LP will result in an optimal objective function $Z_0 = \Phi = 1$. In other words, it is sufficiently productive and does not need to increase output. The performance score Φ can be used as an index to measure total productivity of an airport in terms of how far it is from the efficient production frontier. The LP needs to be solved n times, each time for an individual port. This process can be automated in many off-the-shelf optimization packages including Microsoft Excel's Solver that is used in this study.

ANALYSIS

The input and output variables should reflect actual objectives and process of container terminal productivity as accurately as possible. As far as the former is concerned the port performance could be closely related to its objective. In this study, the main port objective assumed to be the minimization of the use of inputs and maximization of the outputs. This is justified by the fact that container ports (terminals) depend upon "Smart" equipment and information technology rather than being labor intensive, and by the increasing competition faced by each port.

A container and Ro/Ro shipping lines are the most important clients of a container port. The loading / unloading procedure of cargo across a quay is very critical for port efficiency, and vital to its competitive position. In this transfer process the most important equipment is the gantry cranes. Also the space of the container yard is really important for this kind of operations. Ports many times are used as a storage area, because the container yards act as buffer between sea and inland transportation or transshipment. The measurement of terminal production, therefore, is a mean of quantifying efficiency in the utilization of these three variables. Given the characteristics of container port production, the total quay length and the terminal are the most suitable proxies for the land factor and the quay gantry cranes is the most suitable proxy for the equipment factor input. Measures of these variables are going to be the inputs in the model.

Container throughput is the most important terminal output. Almost all previous studies used it as an output variable, because it is closely related to cargo facilities, with which container ports are compared. Another important issue is that container throughput is the most appropriate and analytical indicator of effectiveness of port production.

The sampling frame for this study consists of the most important U.S. Container Ports in the last decade. Although twenty five ports of all the regions (West-Gulf-East) have been included in this study, a couple of ports in some years had to be removed due to incomplete input data. Five years of annual data from 1998 to 2003 are collected for each port. Therefore the sample size for the analysis comprises a total of 150 observations. The secondary data has been collected from the Containerization International Yearbook and the U.S. Department of Transportation Maritime Administration. Table 1 lists all ports along with their TEU outputs during 1998 – 2003. Among them, Los Angles (LA) port served the most TEU whereas Galveston (GAL) port served the least with only 6,402 TEU in 2003.

TABLE 1: List of Ports with the annual TEU*

PORT	1998	1999	2000	2001	2003	2003
Baltimore (BAL)	255,312	255,378	275,955	273,418	301,944	306,845
Boston (BOS)	67,502	78,582	73,500	64,078	80,079	92,609
Charleston (CHA)	1,034,918	1,169,552	1,246,181	1,158,751	1,197,398	1,249,770
Galveston (GAL)	3,526	6,588	3,505	10,179	15,174	6,402
Houston (HOU)	657,210	713,677	733,134	783,316	850,663	932,883
Hampton Roads (HR)	866,964	908,902	924,167	940,424	1,038,989	1,172,761
Jacksonville (JAC)	207,034	148,074	110,471	103,502	114,149	113,354
Los Angeles (LA)	2,292,923	2,551,565	3,227,743	3,428,408	4,059,550	4,663,899
Long Beach (LB)	2,851,516	3,047,960	3,203,555	3,195,120	3,183,629	3,090,712
Miami (MIA)	602,473	618,436	683,504	717,100	751,986	763,930
New Orleans (NOLA)	219,062	236,906	229,441	217,134	216,055	236,945
New York/New Jersey (NYNJ)	1,884,268	2,027,188	2,200,343	2,355,133	2,627,116	2,803,036
Oakland (OAK)	901,679	914,915	988,773	963,484	978,816	1,064,278
Port Everglades (PEV)	474,441	473,123	439,217	416,839	370,266	422,811
Philadelphia (PHI)	114,981	89,345	83,256	83,408	114,659	103,408
Portland (POR)	187,857	210,218	211,505	206,400	185,134	210,301
Savannah (SAV)	557,642	624,497	720,231	812,984	1,013,893	1,124,409
Seattle (SEA)	976,484	961,847	959,883	824,392	849,855	814,742
San Francisco (SF)	15,217	28,969	35,918	22,817	16,615	14,912
Tacoma (TAC)	496,104	581,162	647,017	611,893	768,770	931,289
Wilmington DE (WDE)	126,586	131,608	122,690	128,028	133,186	195,028
Wilmington NC (WNC)	84,116	73,664	72,035	66,722	71,175	71,957
Mobile (MOB)	13,883	14,004	14,152	13,687	14,307	13,339
GulfPort (GULF)	112,654	123,483	155,667	158,946	172,800	204,089
Freeport (FREE)	37,870	41,593	44,515	43,509	54,261	50,179

* TEU is the abbreviation for "Twenty foot Equivalent Unit", referring to the most common standard size of 20 ft. in length.

RESULTS AND ANALYSIS

Given 25 seaports studied over a six year period, the maximum sample size would be 150 observations. However, data availability affected the actual sample size. For the model, any variations on the model, missing data within an observation resulted in the exclusion of that observation from the sample.

In the analysis, Wilmington (DE), San Francisco (SF), Mobile (AL), Freeport (TX), Philadelphia (PA) ports were not included for the years 1998 to 2003 as they either have no OSG cranes or lack reliable information during such period. For purposes of this study then, they were not considered as a containerport during this period. Overall, DEA scores were obtained for only 120 port-years.

Table 2 shows performance scores from solving DEA model in (1). The results indicate that Baltimore, Charleston, Long Beach, Los Angeles (for some years), New York/New Jersey, Oakland, and Wilmington (NC) define the efficiency production frontier for this set of samples. These airports earned efficiency scores of one, as emphasized in bold typeface. Given the input/output this not surprising because this two regions are the most productive as pointed out in the Table 1. The scores may be used to rank performance of ports. A port with higher score means that its performance is less efficient. For example, the least efficient port is Galveston (GAL) since it earned a score of 323.

Table 2 indicates that the results for the three regional grouping vary. In the Gulf Coast region we had port with the worst productivity from 1998-2003. However, productivity generally rose from 2001 to 2003. The West Coast region showed a steady improvement or good scores in productivity across the entire sample period. The East Coast region had mix results with some ports being steady and others falling short in all three inputs from 1998 to 2003. Overall, we conclude that during this study period, on average, gross infrastructure productivity increased for U.S. container ports.

During the 2000-2003, Los Angeles (LA) and Long Beach (LB) ports are at the top of the list. However, sometimes port congestion is already plaguing the ports of Los Angeles and Long

Beach, as turnaround times recorded in early October 2004 has been extending from 2-3 to 6-8 days (Marine Exchange, 2004). The reason that Long Beach earned a perfect score is because it served high container throughput with fairly small amount of inputs i.e., 105 acres of land and eight structures. Its terminal is located adjacent to deep water, the deepest dredged dockside of any US Pacific Coast ports. Its proximity to the southern end of the Long Beach Freeway between the harbor and San Diego Freeway provides expedient routes to land transportation. Also, during 1990s the terminal built an on-dock rail system to expand the movement of intermodal containers directly from the terminal to destinations in the east. The Port of Los Angeles has eight major container terminals and four dockside intermodal rail yards with direct access to the Alameda Corridor, a 20-mile express railway connecting the Port to the rail hubs in downtown Los Angeles. There are several ports that earned good scores or scores near one such as Gulfport, and Wilmington N.C. These two ports are in two regions, which consist of two fast growing ports with a lot of investment in infrastructure and equipments.

In general Galveston (TX) and Port Everglades (FL) are rather low in efficiency since they earned very high performance scores. This is because the port authorities of these ports have also concentrated in all types of cargo including dry and liquid bulk, break-bulk, refrigerated and project cargoes. In addition, a thriving cruise industry and a major petroleum storage and distribution hubs play a significant role in the performance score. Port Everglades the last year has invested in a growing containerized cargo business which improve productivity score from 2002-2003.

TABLE 2: Efficiency Scores 1998 – 2003

Port Code	1998	1999	2000	2001	2002	2003
BAL	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**
BOS	14.1154	14.9355	14.5369	16.6184	10.2522	11.4006
CHA	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**
GAL	323.1368	199.8360	373.6096	126.9688	87.2993	202.9620
GULF	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HOU	2.2782	2.2857	2.3376	2.1245	2.0386	1.8172
HR	3.2891	3.3535	3.4664	3.3975	3.0642	2.6354
JAC	13.7732	20.5840	29.0572	31.4682	29.9259	30.9481
LA	1.2168	1.1686	**1.0000**	**1.0000**	**1.0000**	**1.0000**
LB	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**
MIA	2.6193	2.7151	2.5802	2.4517	2.0305	2.3080
NOLA	11.3279	11.1871	12.1772	12.9235	12.9650	12.0099
NYNJ	1.2272	1.2118	1.1742	1.0939	**1.0000**	1.0874
OAK	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	1.2168
PEV	2.1060	2.2344	2.5244	2.6515	**1.0000**	**1.0000**
POR	9.2821	9.0202	9.3411	N.A.	10.6044	9.1690
SAV	2.2829	2.1641	2.0022	1.7080	1.3897	1.6006
SEA	1.4000	1.5102	1.5934	1.8622	1.2640	1.9265
TAC	5.3223	4.8542	4.5876	4.8504	3.8357	3.1380
WNC	**1.0000**	**1.0000**	**1.0000**	**1.0000**	N.A.	**1.0000**
Sum	399.3772	283.0604	465.9881	215.1186	172.6695	289.2193
Average	19.9689	14.1530	23.2994	11.3220	9.0879	14.4610
Std. Dev.	71.49	44.04	82.74	29.05	20.24	44.94

We also computed the projection of TEU output of each port onto the efficient frontier in order to provide the target TEU output, if a port wants to be regarded as efficient. Table 3 shows the results. Clearly, given the current level of inputs, ports with the worst performance scores would need a huge amount of container throughput to reach the efficiency frontier. For example, for Galveston in Gulf port region to be regarded as efficient, it should have served 1,299,282 TEU in 2003, rather than 6,402 at the current level. The bold typeface emphasizes that these ports are already operated efficiently. Therefore their outputs are at the current levels. These results should be interesting to port managers and port authorities who want to know the magnitude of potential for improvement in target achievements among its operational units. This information may be useful when setting targets.

TABLE 3: Target TEU Output 1998 – 2003

Port Code	1998	1999	2000	2001	2002	2003
BAL	**255,312**	**255,378**	**275,955**	**273,418**	**301,944**	**306,845**
BOS	952,808	1,173,651	1,068,468	1,064,872	820,990	1,055,791
CHA	**1,034,918**	**1,169,552**	**1,246,181**	**1,158,751**	**1,197,398**	**1,249,770**
GAL	1,139,380	1,316,588	1,309,666	1,292,471	1,324,713	1,299,282
GULF	**112,654**	**123,483**	**155,667**	**158,946**	**172,800**	**204,089**
HOU	1,497,228	1,631,275	1,713,809	1,664,193	1,734,189	1,695,188
HR	2,851,516	3,047,960	3,203,555	3,195,120	3,183,629	3,090,712
JAC	2,851,516	3,047,960	3,209,972	3,257,013	3,416,016	3,508,088
LA	2,789,978	2,981,821	**3,227,743**	**3,428,408**	**4,059,550**	**4,663,899**
LB	**2,851,516**	**3,047,960**	**3,203,555**	**3,195,120**	**3,183,629**	**3,090,712**
MIA	1,578,082	1,679,098	1,763,565	1,758,119	1,526,886	1,763,124
NOLA	2,481,510	2,650,291	2,793,935	2,806,125	2,801,157	2,845,671
NYNJ	2,312,413	2,456,572	2,583,608	2,576,187	**2,627,116**	3,047,988
OAK	**901,679**	**914,915**	**988,773**	**963,484**	**978,816**	1,295,004
PEV	999,191	1,057,152	1,108,778	1,105,256	**370,266**	**422,811**
POR	1,743,708	1,896,213	1,975,699	N.A.	1,963,223	1,928,258
SAV	1,273,024	1,351,457	1,442,018	1,388,555	1,408,972	1,799,715
SEA	1,367,114	1,452,581	1,529,452	1,535,191	1,074,230	1,569,566
TAC	2,640,435	2,821,098	2,968,241	2,967,933	2,948,810	2,922,360
WNC	**84,116**	**73,664**	**72,035**	**66,722**	N.A.	**71,957**
Summation	31,718,097	34,148,668	35,840,676	33,855,883	35,094,333	37,830,832
Average	1,585,905	1,707,433	1,792,034	1,781,889	1,847,070	1,891,542
Std. Dev.	939,993	1,000,104	1,061,365	1,113,526	1,165,551	1,241,769

CONCLUSION

By employing Data Envelopment Analysis (DEA) as the technique to measure port productivity, this paper has addressed several methodological hurdles presented by industry characteristics and data limitations. The results indicate that port efficiency can fluctuate over time to different extents. Indeed, the empirical results reveal that substantial inefficiencies exist in container ports at some point in time.

Regarding rail service, the relationship between seaports and the rail industry appears to remain a critical determinant of container port infrastructure productivity. In this study we found that a few ports, such as Baltimore, Charleston, Long Beach, Los Angeles (for a few years), New York/ New Jersey, Oakland, and Wilmington (NC) which have railroad service, tend to be more efficient than others. The provision of railroad service is therefore possibly correlated with higher productivity of ports. However, the rail service is a factor that it is beyond the control of seaport management. Further, if on-dock rail facilities appear at port, they may attract large carries to the container port.

This seems to imply that port competition and competitiveness may have a major impact on the measured levels of relative efficiency within container ports. Some other possible reasons which explain differences in port production includes differences in port ownership or governance, location attributes and the form and label competition level. By examining the influence of port authority, ocean carrier and rail carrier on container port productivity valuable guidance is provided for those with policy interests directed at improving the performance of this complex and critical system.

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