Efficiency of world ports in container and bulk cargo (oil, coal, ores and grain)

Please cite this paper as:

Merk, O., Dang, T. (2012) "Efficiency of world ports in container and bulk cargo (oil, coal, ores and grain)", *OECD Regional Development Working Papers*, 2012/09, OECD Publishing
http://dx.doi.org/10.1787/5k92vgw39zs2-en

OECD Regional Development Working Papers, 2012/09

Olaf Merk, Thai Thanh Dang

JEL classification: R41, R11, L91

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ABSTRACT

Port efficiency is an important indicator of port performance; more efficient ports lower transportation costs and facilitate imports and exports of a country. Despite the importance of the subject, the exisiting port efficiency studies have almost exclusively focused on container ports. This Working Paper aims to fill that gap by calculating efficiency scores of world ports per cargo type (containers, oil, coal, iron ore and grain). These calculcations have been made using a database constructed for this purpose. Several findings can be derived from these calculations. Significant improvements can be made when the technical efficiency of ports is increased. Among the sample, gaps between terminal efficiency mostly reflected gaps in pure technical efficiency. When comparing the level of efficiency achieved by ports across commodities, technical gaps were more marked for container and oil terminals. Promoting policies to raise throughput levels in order to minimise production scale inefficiencies is another important area for improvement. Production scale inefficiencies arise when throughput levels are below or above optimal levels given the current capacity of terminal infrastructure. Such inefficiencies were mostly found in a substantial number of ports handling crude oil and iron ore, suggesting that efficiency is more sensitive and driven by exogenous factors related to traffic flows. The analysis also shows that the size of ports matters for port efficiency. The crude oil, iron-ore and grain ports have higher efficiency scores at larger total port size, suggesting that this size is more efficient because they can drive technological development. Finally, there are regional patterns emerging across commodities. Terminals in China are among the most efficient in handling coal bulk and containers with terminals in Southeast Asia. By contrast, the most efficient grain and iron-ore terminals are located in Latin America, and the most efficient crude-oil transhipment terminals are mostly found in the Gulf region. Further, Australia is also found to perform well in handling coal bulk and grains.

JEL classification: R41, R11, L91

Keywords: port efficiency, ports, transportation

FOREWORD

This working paper is one in a series of *OECD Working Papers on Regional Development* published by the OECD Public Governance and Territorial Development Directorate. It forms part of the *OECD Port Cities Programme*. This paper was written by Olaf Merk, (Administrator, OECD Regional Development Policy Division) and Thai Thanh Dang (Consultant). The paper benefits from data collection by Xiao Wang, Mathieu Bordes and Rachel Silberstein. The publication was edited by Caitlin Connelly.

The paper can be downloaded on the OECD website: www.oecd.org/regional/portcities

Further enquiries about this work in this area should be addressed to:

Olaf Merk (olaf.merk@oecd.org), OECD Public Governance and Territorial Development Directorate

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1. INTRODUCTION

Port efficiency is an important factor to stimulate port competitiveness and boost regional development. With growing international sea traffic and changing technology in the maritime transport industry (containerisation, integrated logistic services, etc.), seaports are coping with mounting pressures to upgrade and provide cutting-edge technology. They are also being forced to improve port efficiency to provide comparative advantages that will attract more traffic. Some of the key challenges ports are surmounting to secure traffic flows and prevent diversion to nearby ports include handling containers and goods more rapidly, providing more adequate and performing equipment, reducing berth times and delays, enabling large storage capacity and ensuring multi-modal connections to hinterland. The benefits of port efficiency extend beyond traffic volume: they have direct and indirect effects on related activities, such as maritime insurance, finance, and logistics, because of their strategic position in the transport chain. They create value added and employment, which affect the prospect of regional and urban growth.

Seaport efficiency is often associated with productivity and performance; however, their focus is narrow, measuring operating technology or total traffic volumes of seaports, which are not the only indicators. There are additional factors that are associated with the more organisational side of production, such as how efficiently ports use inputs to produce current output levels and whether the technologies adopted by ports are the most efficient, that are critical to determining port efficiency.

The indicator of productive port efficiency is thus defined along: *i)* an efficient production frontier, which maximises port output for different input levels; *ii)* a benchmark of best practices, based on ports located on the efficient production frontier; *iii)* observable gaps between what ports currently produce and what they would optimally produce if they were operating efficiently. The efficiency indicator is really a measure of existing inefficiencies, which is assessed against the most efficient ports and relative differences in adopted technologies, production scales and input utilisations. This Working Paper should indicate where potential efficiency gains could be improved, providing insights for guiding development policy strategies that yield more efficient ports.

One important aspect in measuring port efficiency that is often overlooked in related literature is related to the multi-activity nature of ports. With the exception of a study by Oliveira and Cariou (2011), the existing literature tends to measure port efficiency based on volume and technology at container terminals or the containerised part of ports. Although container activity represents an important segment of many ports, the measurement of global port efficiency should not be limited to this port use. Other port activities, which can be very large for some ports, include dry bulk, liquid bulk and general cargo traffic, and to a lesser extent, passenger traffic. In 2009, average liquid and dry bulk cargo throughput at the top 20 EU ports amounted to 65% of total port traffic in tonnage against 27% for containers, according to Eurostat-statistics.

This report intends to achieve three main objectives: *i)* reflect, with the use of a new database, port multi-activities in assessing port efficiency; *ii)* estimate port efficiency by activity (*e.g.* container, oil, coal, iron ore and grain) and identify the key performance factors, along technology, scale and input efficiencies; and *iii)* discuss some general issues on regional and port size patterns across world port efficiency.

2. THE METHODOLOGICAL APPROACH TO MEASURE PORT EFFICIENCY

2.1 Methodology

The methodology used to measure efficiency relies on the data envelopment analysis (DEA) technique. This empirical methodology derives efficiency scores for each decision-making unit (DMU) involved in a homogeneous production process such as firms or seaports. An efficient port is defined as one maximising output level for the same level of inputs across all observed ports (efficient output-oriented DMU) or minimising quantity of inputs for a given level of output (efficient input-oriented DMU). The efficient production frontier is delineated by a set of efficient DMUs referred to as the benchmark of most performing seaports. The potential gains for less efficient ports (*e.g.* located below the efficient production frontier) are measured by their distance, both from an output- or input-oriented approach, relative to the efficiency frontier. This methodology has been widely used in the most recent mainstream literature[1] [2](Cheon, *et al.*, 2010; Wu and Goh, 2010; Martinez-Budria, *et al.*, 1999; Wang and Cullinane, 2006; Al-Eraqui, *et al.*, 2007; Tongzon, 2001).

The DEA approach has advantages as well as limitations. Among its positive characteristics, DEA does not impose any functional form to the production function or on the shape of returns to scale (*i.e.* non-parametric), such as when adopting a Cobb Douglas production function. For seaports, in particular, it is very difficult to guess or impose whether returns to scale should be increasing or decreasing. Dealing with multiple output processes is another useful property of DEA, especially when addressing port multi-activities and when a certain degree of homogeneity in the production process is observable across ports. DEA also has some negative characteristics, including its deterministic property, which does not allow random noises or measurement errors to be isolated from the measure of pure inefficiency[3]. However, use of the Bonilla (2000) and Barros (2007) bootstrapping[4] technique can help limit this effect.

This sampling technique enables generation of a stochastic distribution and intervals of confidence around the estimators (Simar and Wildon, 2000). The efficiency estimates derived from using this technique are often lower compared to DEA estimates derived from a standard sample. In addition, atypical efficient ports (characterised by low density of observations in the region of the frontier) are characterised by higher degrees of uncertainty. However, because efficiency is a relative measure, depending on observable seaports and inputs considered, any omission may affect the results. A sample excluding potentially efficient seaports or including outliers would respectively shift downward/upward on the efficient production frontier and affect (upward/downward) the relative efficiency scores. To the same extent, omitting input factors or including them with non-documented values (zero or not available [n.a.]) may yield higher efficiency scores for ports that are using high quantities of the omitted input factor or those producing output with "no" input.

There are three different types of efficiency that can be distinguished: *i)* overall efficiency, *ii)* technical efficiency, and *iii)* scale efficiency.

i) **Overall efficiency**. This general indicator, derived from a model assuming constant returns to scale (CRS), provides a measure of overall port efficiency. This DEA-CCR indicator, developed by Charnes, Coopers and Rhodes (1978), assumes that all observed production combinations could be scaled up and down proportionally. Varying production sizes or scales are considered to have no effect on efficiency scoring, which means that small or large ports can equally operate in an efficient way. Efficient ports are both technically and scale efficient. Conversely, inefficiencies (efficiency gap measured in per cent of most efficient port scores) reflect both technical and scale inefficiencies.

ii) **Technical efficiency.** Pure technical efficiency is estimated by relaxing the constraint on scale efficiency, allowing output to vary unproportionally more or less with a marginal increase in inputs. This DEA-BCC indicator, developed by Banker, Charnes and Cooper (1984), is derived from a model assuming varying returns to scale (VRS), and recognises that smaller ports may face disadvantages caused by production scale effects (Cheon, 2008). By taking into account and neutralising scale inefficiencies, relative gaps in efficiency between ports would thus only reflect differences in operational inefficiency, so-called pure technical inefficiency.

iii) **Scale inefficiencies.** Scale inefficiencies arise when the scale of production is inappropriate, being above or below optimal levels and generating production wastes. Formally, they are identified when a difference appears between efficiency achieved at technical and overall levels, as measured by the following ratio (Cooper, *et al.,* 2000; see also Fare, *et al.,* 1994).[5]

$$SE=CRS/VRS \text{ and where } SE<1$$

In the equation, CRS and VRS are the efficiency estimates derived from respectively assuming constant and varying returns to scale. When SE<1, ports face scale inefficiency, driving higher overall inefficiency compared to pure technical inefficiency. By contrast, when SE=1, ports are operating at efficient scales, producing at the optimal level for which they were designed. However, the appropriate direction in scale adjustments can be identified only with the nature of returns to scale, that is, increasing (IRS) or decreasing (DRS). For ports operating at IRS (output rises proportionally more than the increase in inputs), production level should be expanded. This is usually the case for ports operating below optimal levels as long as current business traffic, while building up gradually, remains below the optimal capacity of port infrastructure. By contrast, when ports operate at DRS (output rises proportionally less than the increase in inputs) they should scale down their production toward lower optimal levels to limit inefficiencies lead, for example, by bottlenecks. In a long-run perspective, however, the alternative of raising the optimal level of production through investing in higher port infrastructure capacity should also be considered.

2.2 Input, output variables and dataset

Defining and identifying appropriate output and input variables for port production function is crucial. The input/output variables must reflect the main objectives of a port, which in this study is about maximising cargo throughput and productivity while efficiently using infrastructure and equipment. Along the economic theory, output as measured by handling cargo throughput (loaded/unloaded) depends to the same extent on labour and capital inputs. In port literature, labour input is known as the most challenging issue due to lack of data reliability and comparability. One of the main reasons is that port labour organisation is particularly complex, consisting of different types of full- and part-time contracts and contracts partly managed by private, public and port authorities, which make it difficult to collect complete and consistent data. Proxies are often used along the argument that labour is usually closely and negatively correlated to handling equipment: equipment is thus considered to be a proxy for labour. As such, for this study the number of loading/unloading equipment from ship-to-quay and quay-to-shore is collected per port for container terminals and the different dry and liquid bulk cargo terminals (oil, coal, iron ore and grain). Capital inputs, on the other hand, are more readily available as long as they concern land and infrastructure. Such inputs mainly include terminal surface, quay length or storage capacity.

The aim of this study – to extend the assessment of port efficiency beyond container terminals and container ports – brings with it major complexities with regard to data collection of port output. Earlier studies focusing on container ports have benefited from relatively comprehensive existing datasets on container port output, with output measured in twenty-foot equivalent units (TEUs), being the equivalent to a small container. This measure is widely accepted and administered, which allows for comprehensive analysis. Such a comprehensive and comparative dataset does not exist for other port cargo categories. Most port authorities publish their total annual throughput in metric tonnes, often differentiated by containerised, bulk and general cargo, but rarely in more specific categories. While this study aims to give port efficiency scores for bulk categories, it acknowledges the major differences that exist in the equipment needed for the different bulk categories such as coal, iron ore, grain and oil. Not surprisingly, almost all large ports dealing with bulk have one or more specialised terminals in these different bulk cargo categories. This makes it possible to collect input data per port for these cargo categories (*e.g.* by adding up the equipment for all grain terminals in that port). However, the corresponding output data (*e.g.* grain throughput per port) are in many cases lacking or not in the public domain. Despite considerable efforts to collect comprehensive port throughput data per cargo category, this proved to be impossible

In order to overcome this complexity, this study uses a new output dataset, based on a volume output measure: aggregated ship volume in deadweight tonnes (dwt) calling each port. These data can be derived from existing comprehensive databases of vessel movements, which include detailed information on ship types (including volume), as well as arrival and departure times at the different ports. This approach assumes that the volume of a ship calling a port is correlated with the number of metric tonnes loaded or unloaded from that ship. This assumption will hold especially for cargo categories with point-to-point deliveries, as in most bulk cargo categories, but probably less so for cargo categories or containerised cargo with service loops in which several ports are called (as it would be likely that some ports in the loops, serviced by the same vessel, will load/unload more cargo than others in the same loop). For this reason, in this study the number of TEUs, where available, is also considered as an output indicator. The availability of information on different ship types in the database, most of these specialised in carrying one specific cargo type (*e.g.* ore carriers, crude oil tankers, etc.), makes it possible to estimate the aggregated ship volume per port and per cargo category. While "total dwt calling the port" (output measure) is not perfectly correlated with actual throughput, it is no more imperfect than throughput as reported in metric tonnes and TEUs. Both methods risk double counting due to variations in port calculation of throughput. For example, in instances of transport from an inland to a deep-sea terminal (counted as an incoming and outgoing container in the river terminal and then incoming and outgoing for the deep sea terminal) one container could end up being counted four times.

For the purpose of this study, a database was built to analyse port efficiency across worldwide ports at aggregated and disaggregated activity levels, gathering data for the most recent available year (2011). The database covers approximately 100 ports, including all major container and dry and liquid bulk ports in a wide range of ports located in almost all OECD and non-OECD countries. Most of the input data are drawn from Lloyd's Port of the World 2011 Yearbook, whereas the Lloyd's Marine Intelligence Unit's (for May 2011) comprehensive database of vessel movements was used to derive output data. Given limitations in the data and the DEA methodology, a number of aggregations/approximations were performed in order to ensure estimate reliability. The input and output variables used to derive efficiency indicators are described in the following paragraphs on the efficiency per cargo type. The database reflects existing heterogeneity across equipment and ports into the differences in productivity and thus technology efficiency.

3. MAIN RESULTS

3.1. Container terminals

Container traffic has grown very rapidly over the last decade, increasing by about 9% per year on average compared to 4% for total seaborne trade (UNCTAD, 2011). While containerised goods broadly account for one-quarter of total world traffic volume (*i.e.* manufacturing goods), container traffic remains one of the most value added and profitable activities. With ports facing growing and lucrative container traffic, questioning and improving their efficiency in a competitive environment remain a crucial policy challenge. Based on a worldwide sample of major ports, this section estimates efficiency scores and ranking for container ports, and explores the ways to improve potential gains.

Sample description

The sample used includes the 63 largest container ports around the world. The regional profile broadly reflects the worldwide geographic distribution. About half of the container ports are found in Asia (*e.g.* 34% in eastern/south-eastern Asia and 19% in western/southern Asia), while the remaining half is equally split between Europe and America (*e.g.* respectively 20% each). In terms of traffic volumes, the sub-sample covers a total of 687 million dwt in 2011 and 287 thousand TEUs in 2009 based on the latest data available.

Output variables for container ports consider two distinct measures: the volume estimates in deadweight tonnes (see Section 2.2) and the number of TEUs. The use of multi-output measures is meant to reconcile both standard analysis based on TEUs (as seen in the literature review) and the methodology specific to this analysis (inclusion of dwt). While output measures are not strongly correlated (the rank correlation coefficient is equal to 0.77), the sensitivity analysis shows that the benchmark group remains broadly the same: among the 15 most efficient ports identified by different output measures, about 10 common ports are found in both groups. Score estimates and the ranking associated to individual ports, however, differ to some degree (see Table A.1).

Identified input variables are specific to container terminals. Capital inputs are proxied by the infrastructure of container terminals, such as total quay lengths, terminal surface and the number of reefer (or plugging) points for refrigerated container ships. Storage capacity, both in TEUs and ha (hectare), has not been taken into account due to incomplete data. Inputs collected at terminal levels are thus aggregated at the port level. Labour inputs are proxied by equipment, such as the number of container cranes (*e.g.* type of large dockside gantry cranes for loading/unloading intermodal containers from container ships), including both quay cranes and yard cranes which differ depending on whether the supporting framework can traverse the length of the quay or yard. The size of container cranes (specific to the size of container ships such as Panamax, post-Panamax, super-post-Panamax) and handling equipment (*e.g.* straddle carriers, sidelifts, reach stackers, or container lorries used to manoeuvre underneath the crane base and collect the containers) were taken into account.

Table 1. Descriptive statistics of input and output variables of the container ports sample

Container terminal sample	TEUs 2009	Output May 2011	Quay length	Surface terminal (ha)	Reefer points	Quay cranes (no)	Yard cranes (no)
Average	4,639	10,944,765	4,814	229	1,875	45	97
Max	25,866	61,351,881	19,410	854	5,444	208	522
Min	723	34,202	540	13	24	4	1
Total sample	287,601	678,575,427	298,476	8,691	82,501	2,602	4,383
Normalised standard deviation	1	1	1	1	1	1	1
N (non missing)	62	62	62	38	44	58	45

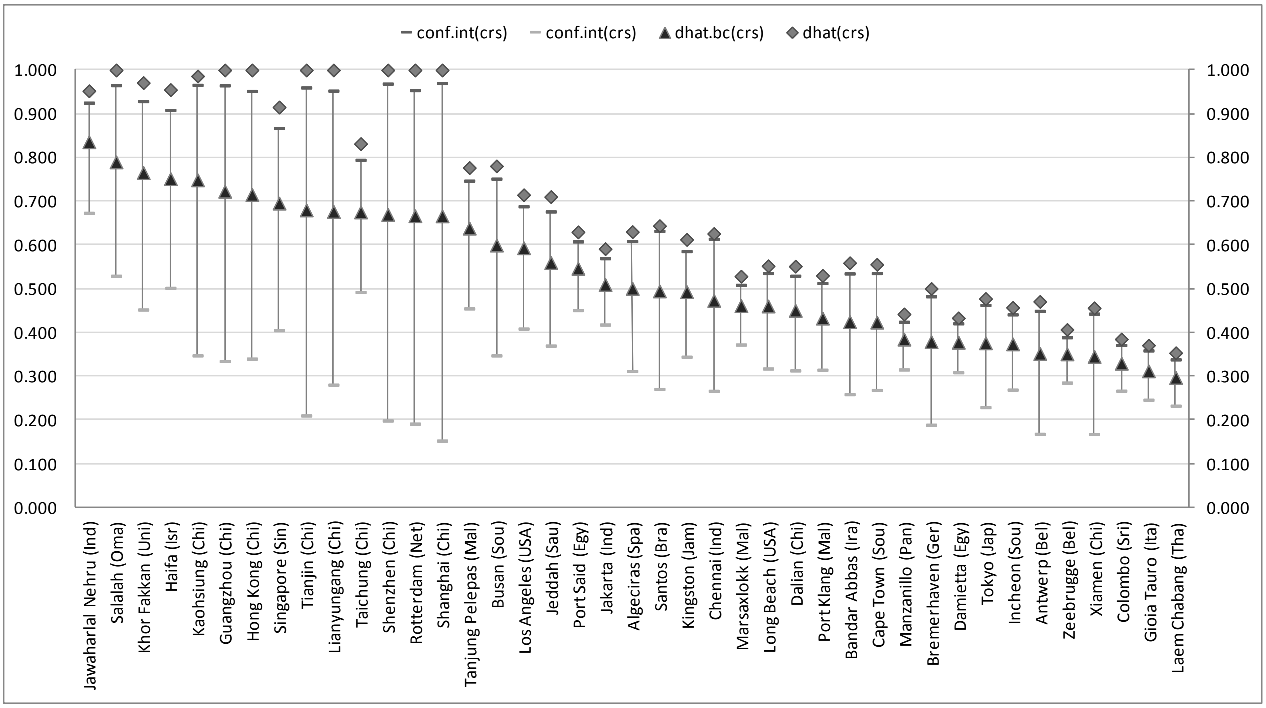
Source: OECD database

Overall efficiency scores

Overall efficiency scores were derived using the DEA methodology (dhat) and plotted next to the scores derived from the bootstrapping approach (dhat.bc), including intervals of confidence (conf.int) as shown in Figure 1. The efficiency assessment of one port relative to another is confirmed when both scores are closed in values and characterised by a small confidence interval. By contrast, a significant gap between the two different scores is an indicator that the estimates could be sample biased.

To facilitate the interpretation of results, Figure 1 plots the efficiency scores for a sub-sample of around 40 ports. Those showing the highest scores can be considered the benchmark group or “leader” ports, against which the relative scores of the “follower” ports are assessed. In addition, standardising the efficiency score plots with a fixed number of ports allows for comparison with efficiency profiles for other commodities that are derived later on in the study.

Figure 1. Efficiency scores for a sub-sample of container ports (output-dwt, TEUs)



Source: Authors’ own calculations.

Note: (dhat) refers to efficiency scores derived using the standard DEA methodology; (dhat.bc) indicates scores derived using the bootstrapping method and (conf.int) indicates the upper/lower bound values of the interval of confidence; (crs) is the abbreviation of constant returns to scale, assumption used in both methodologies.

The main features emerging from the efficiency profile of container terminals are (see Annex Table A.2 for detailed estimates):

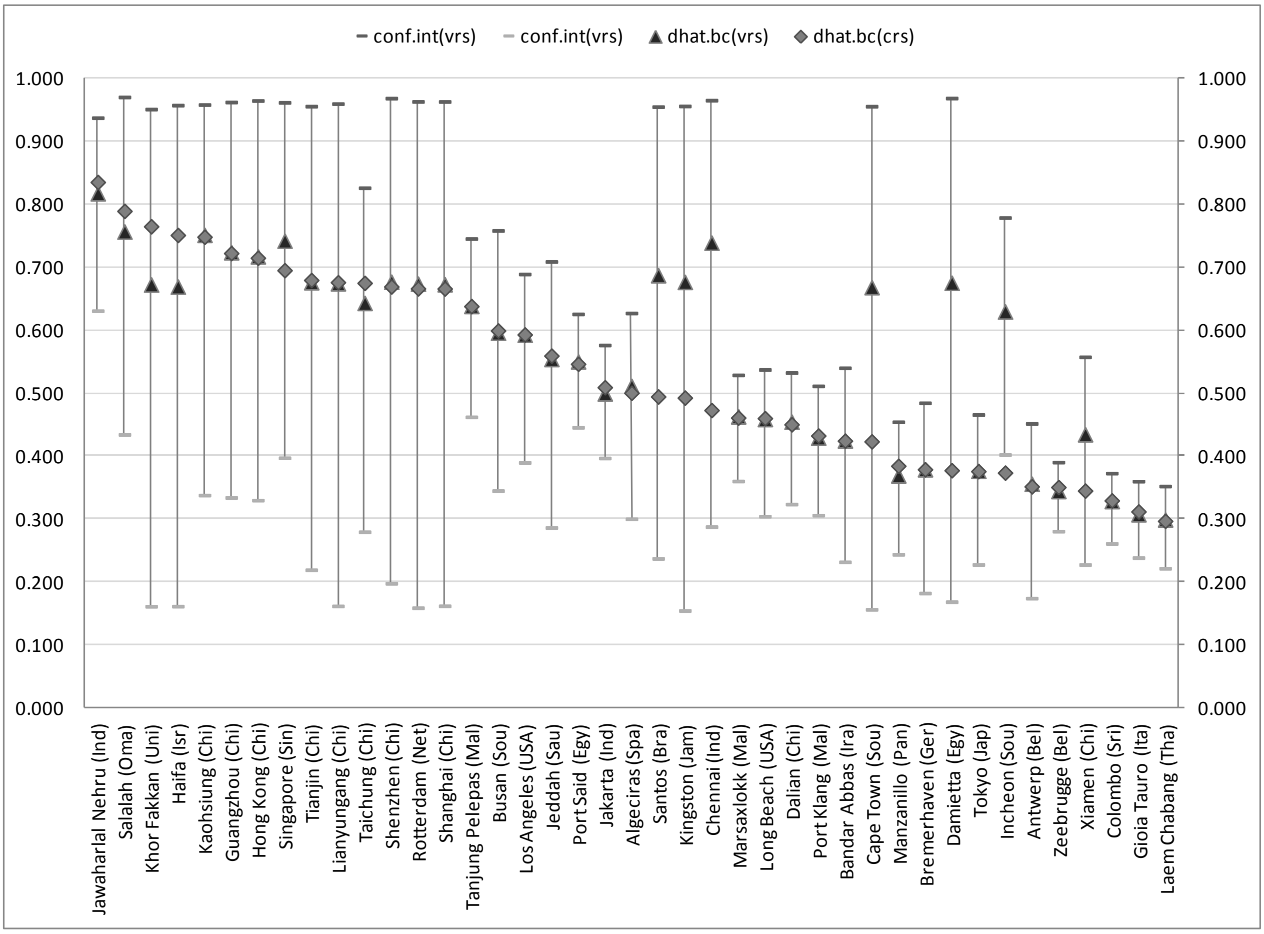
Most efficient container ports operate at 70% to 80% of the maximum efficiency level. These ports are mostly located in Asia, with the exception of Rotterdam. Most efficient ports are operating at high efficiency values according to both standard and bootstrapped estimates. However, they still operate under their optimal levels, suggesting that overall efficiency could be improved by 20% to 35% compared to their current levels. The regional pattern shows that these ports are partly located in western/central Asia and in China.

Most efficient container ports are not necessarily the largest ports. Among most efficient ports, are some of the largest global container ports: *e.g.* Hong Kong, Singapore, Shenzhen and Shanghai (handling from 20 to 60 million dwt per port per month), but also medium to small size ports (handling 3 to 7 million dwt per port per month). Further, when measuring the rank correlation between efficiency scores and output, as measured by dwt, the coefficient is 0.27, which indicates that there is not a strong correlation between terminal/port size and efficiency, at least for containers.

Efficiency potential gains

Figure 2 plots technical and overall efficiency estimates respectively assuming varying and constant returns to scale. The comparison allows for identification of inefficiency sources: inefficiencies related to production scale arise when both pure technical estimates (by neutralising production scale inefficiencies) and overall estimates (without neutralising production scale inefficiencies) differ in values. The gap indicates the degree by which production scale inefficiencies undermine the level of technological efficiency. By contrast, inefficiencies related to technology are identifiable by the relative gap in technical efficiency scores between a given terminal and the benchmark level (the efficiency frontier). The larger the technical gap, the greater the efforts needed to improve efficiency towards the benchmark level (see Annex Table A.2 for detailed estimates).

Figure 2. Technical efficiency scores for sub-sample of container ports (output=dwt, TEU)



Source: Authors' own calculations.

Note: (dhat.bc) indicates scores derived using the bootstrapping method and (conf.int) indicates the upper/lower bound values of the interval of confidence; (crs) and (vrs) respectively refer to constant returns to scale and varying returns to scale, assumptions used in the methodology.

The technical efficiency profile of container terminals points to several key conclusions:

The technical gap is the major source of inefficiencies across container ports. In most cases, technical and overall efficiency estimates are almost equal in value indicating that the main source of inefficiency is closely related to the technical gap. As such, most efficient ports are also technically efficient. Generally speaking, both "follower" container ports and most efficient ports have some room to improve their level of technical efficiency, as most efficient ports still operate between 70% to 80% of the efficiency frontier.

High technical efficiency is sometimes undermined by production scale inefficiencies. High technical efficiency scores are mostly concentrated in western/central Asia, Brazil and Jamaica, though not in the most developed OECD regions. Among these ports, one-third operate at lower (overall) efficiency levels, reflecting inefficiencies related to inappropriate production levels. For these ports, the adjustments to limit production scale inefficiencies depend on whether ports are operating at increasing (irs) or decreasing returns (drs). Table 2 shows the VRS/NIRS ratio, which compares efficiency scores relaxing the assumption on returns to scale (VRS) and imposing decreasing returns to scale (NIRS). Ports are operating at decreasing returns when the VRS/NIRS ratio is around the unit value. When the ration differs from the unit value, ports are operating at increasing returns. As such, Table 2 indicates that the selected ports are all operating at increasing returns, suggesting that ports are operating under their optimal levels and that production should be scaled up in order to reduce such inefficiencies.

Table 2. Production returns to scale ratio for selected container ports

Output ranking	Port names	vrs	nirs	ratio	irs/drs
54	Damietta (Egy)	0.676	0.375	0.55	irs
53	Chennai (Ind)	0.739	0.472	0.64	irs
46	Incheon (Sou)	0.630	0.370	0.59	irs
61	Cape Town (Sou)	0.669	0.421	0.63	irs
35	Santos (Bra)	0.688	0.491	0.71	irs
43	Kingston (Jam)	0.677	0.489	0.72	irs

Source: Authors' own calculations.

3.2. Oil terminals

Crude oil, petroleum and liquid gas are among the major commodities handled by seaborne traffic, amounting to about half of total traffic volume. Fluctuations in world oil supply and demand are important factors in determining traffic volumes, but they are not the sole factors. Other key challenging factors include the efficiency of port infrastructure to berth oil tankers, handle liquid oil/gas via pipelines, or to provide substantial storage capacity and the existence of chemical industries and refineries on port sites. This section estimates efficiency scores, not yet analysed in literature, for a sample of crude oil ports across and identifies/discusses the potential sources of improvement for oil port efficiency

Sample description

The sample includes 71 major worldwide ports. The regional pattern reflects a noticeable imbalance in the distribution of terminals across the world. About two-thirds of the sample oil ports are concentrated in Asia (with 34% in the East/Southeast and 24% in the western/southern), while the remaining ports are located in Europe and North America (respectively accounting for 24% and 10% of the total sample).

Table 3 shows input variables specific to the sample oil ports. Capital inputs are proxied by the capacity of terminal reception of oil tankers, such as quay lengths, maximum vessel capacity, canal draught/depth and tank storage capacity. Labour input is proxied by the loading capacity of equipment as measured by their discharge rates (tonne/hour) and pipeline/loading arm capacity (diameter in mm).

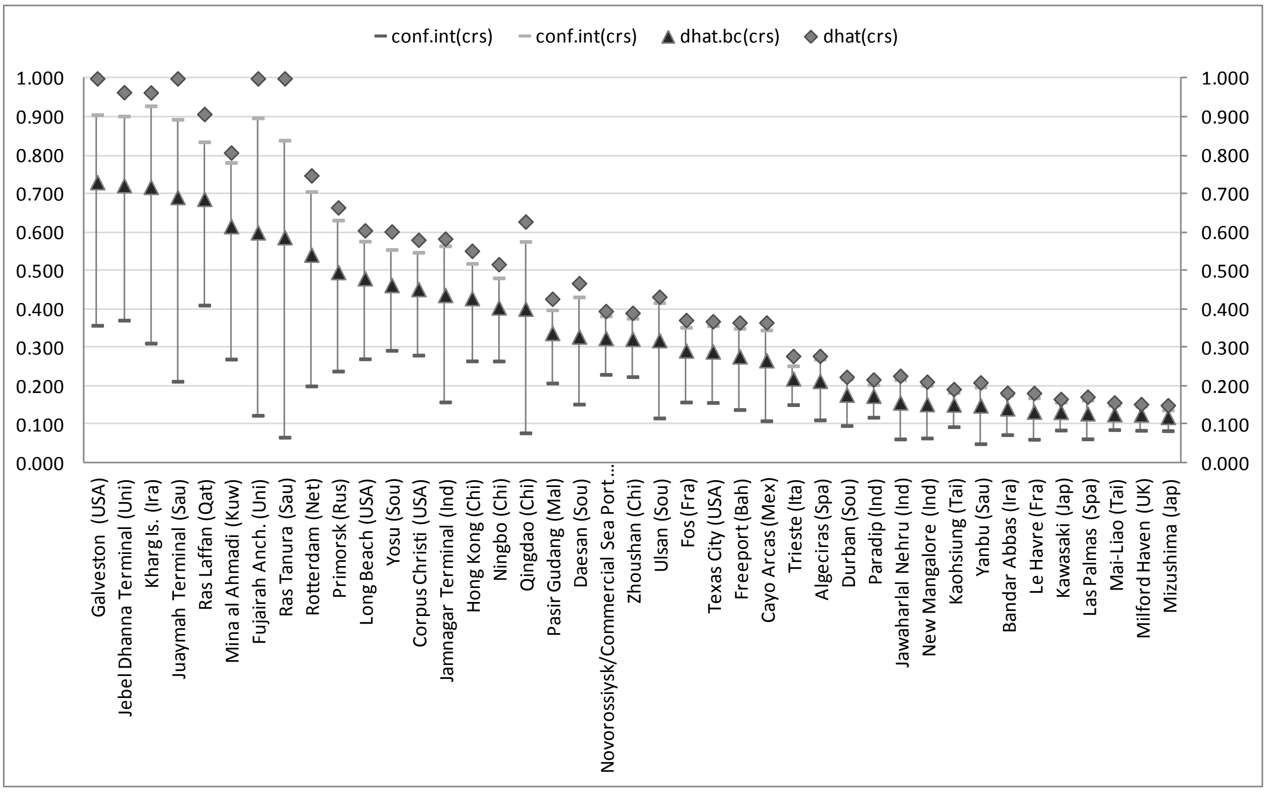
Table 3. Descriptive statistics of input/output variables of the crude oil port sample

Oil terminal sample	Output May 2011	Quay length	Max vessel capacity (dwt)	Max draught/depth	Tank storage capacity	Discharge rate (t/h)	Pipeline/loading arm capacity
Average	**2,665,512**	**1,833**	**250,346**	**19**	**2,300,030**	**32,016**	**9,623**
Max	33,557,799	16,222	750,000	50	7,092,000	112,000	25,245
Min	2,247	100	2,000	5	123,211	382	2,040
Normalised standard deviation	1.98	1.40	0.66	0.44	1.04	1.13	0.85
N (non missing)	71	52	47	66	9	11	12

Source: OECD database.

Overall efficiency scores

Figure 3. Efficiency scores for a sub-sample of crude oil ports/terminals



Source: Authors' own calculations.

Note: (dhat) refers to efficiency scores derived using the standard DEA methodology; (dhat.bc) indicates scores derived using the bootstrapping method and (conf.int) indicates the upper/lower bound values of the interval of confidence; (crs) is the abbreviation of constant returns to scale, assumptions used in both methodologies.

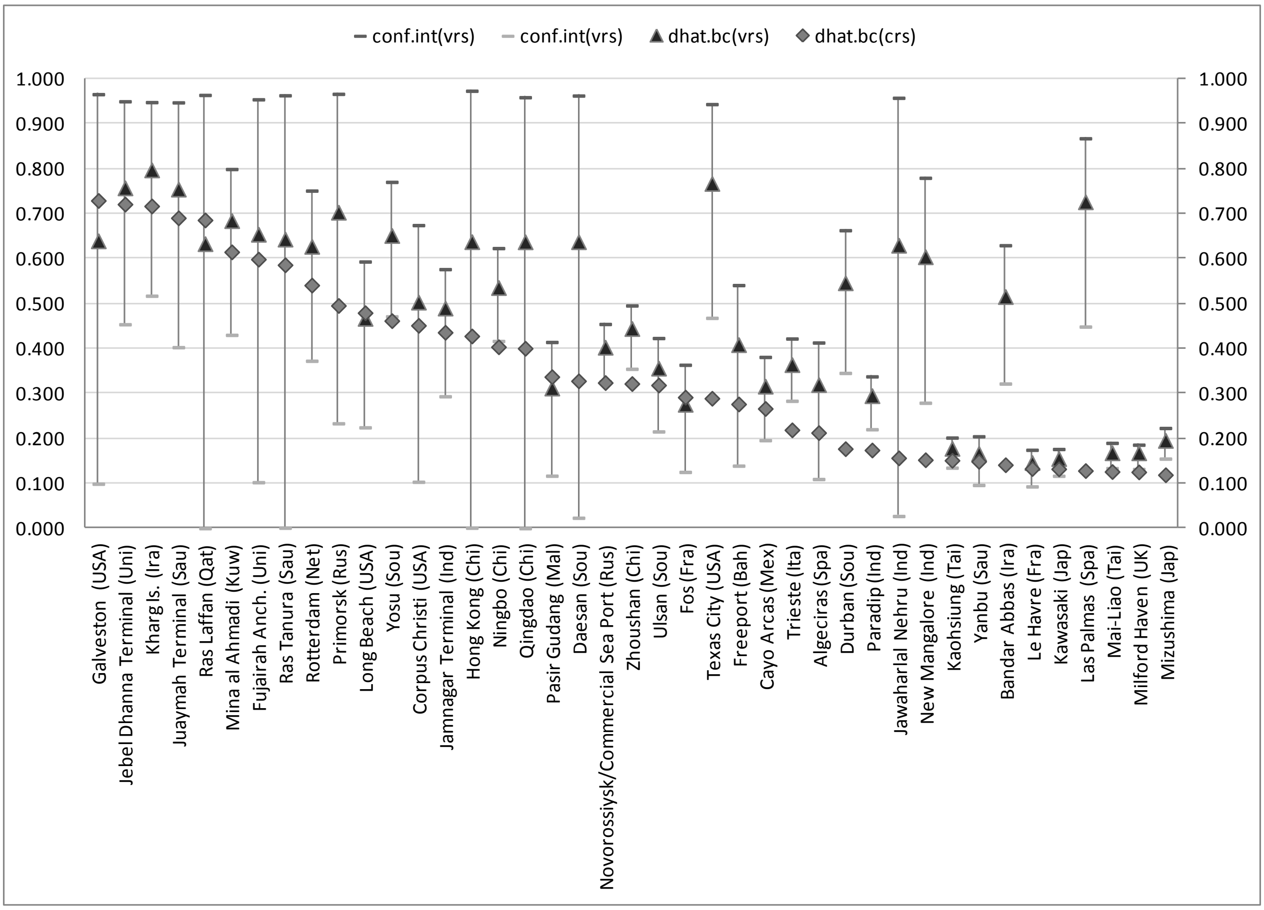
Figure 3 plots both the standard DEA and bootstrapped efficiency estimates for crude oil ports/terminals. The main features include (see Annex Table A.3 for detailed estimates):

Most efficient terminals still have potentials to improve efficiency. Efficient ports are mostly located in the Gulf region, excluding Galveston (USA) and Rotterdam (NLD), but not all ports in the Gulf region are operating efficiently (see Mina El Hamadi (KUW), Fujhaira (UAE) and Ras Tamura (SAU) ports). On average, most efficient terminals achieve around 60% to 70% of the efficiency frontier, suggesting that 30 % gains in production could be achieved given their existing inputs/infrastructure.

Oil terminal size matters. Most efficient terminals also tend to rank among the top ten terminals in terms of volume. Rank correlation between port size/volume and port efficiency scores shows a strong and positive correlation (coefficient of 0.95), suggesting that efficiency is strongly and significantly associated to oil traffic volumes.

Sources of efficiency/inefficiency

Figure 4. Technical efficiency scores for a sub-sample of crude oil ports/terminals



Source: Authors' own calculations.

Note: (dhat.bc) indicates scores derived using the bootstrapping method and (conf.int) indicates the upper/lower bound values of the interval of confidence; (crs) and (vrs) respectively refer to constant returns to scale and varying returns to scale, assumption used in the methodology.

Marked gaps between technical and overall efficiency estimates as shown in Figure 4 indicate important sources of inefficiencies related to production scales ranging from point loses of 10% to 40%. Figure 4 highlights several key findings:

Technical efficiency is the key driver of overall efficiency for most oil ports/terminals. Most technically efficient ports are also most overall efficient ones. As such, the major source of potential gains for these ports is to catch-up the technological ladder towards the efficiency frontier. To the same extent, a similar assessment would also apply to all "follower" ports/terminals with closed estimates (between technical and overall scores).

Inefficiencies are also partly driven by production scales. Some of the crude oil ports/terminals are particularly marked by large gaps between pure technical and overall efficiency scores. These gaps mainly reflect efficiency losses due to production scales, pointing out that the production level is below/above optimal values given the existing infrastructure. Production scale inefficiencies are usually found to negatively affect technical efficiency scores by 40% to 50% points, especially for small (Bangkok [THA], Djakarta [IDN] and London [GBR] and Salalah [OMA] Savannah [USA]) and medium size terminals (Las Palmas [ESP], Jawaharlal Nehru, New Mangalore [IND] and Texas City [USA]) (see Annex tables A.3).

Increasing oil production volumes towards optimal levels would improve efficiency. The comparison between efficiency estimates derived by imposing or not decreasing returns indicates that most crude oil ports/terminals facing production scale inefficiencies are operating at increasing returns to scale. This suggests that terminal efficiency could be improved by adjusting oil production towards upward optimum levels.

Table 4. Production returns to scale for selected crude oil ports

Output ranking	Port names	vrs	nirs	ratio	irs/drs
24	Texas City (USA)	0.768	0.292	0.38	irs
43	Jawaharlal Nehru (Ind)	0.630	0.157	0.25	irs
37	New Mangalore (Ind)	0.605	0.154	0.25	irs
41	Las Palmas (Spa)	0.727	0.129	0.18	irs
58	Savannah (USA)	0.730	0.026	0.04	irs
60	Bangkok (Tha)	0.636	0.016	0.03	irs
63	Jakarta (Ind)	0.632	0.014	0.02	irs
66	London (UK)	0.642	0.011	0.02	irs
65	Salalah (Oma)	0.638	0.006	0.01	irs

Source: Authors' own calculations.

3.3. Coal bulk terminals

Dry bulk goods in seaborne traffic amount to one-quarter of total volume of minerals (coal, iron ore, etc.) and vegetables (grain, wood, edible foods, etc.). Dry bulk maritime traffic, despite being relatively less valuable and profitable than crude oil and container traffic, also faces lower entry costs driven by cutting edge technology used to operate container and liquid bulk terminals. As such, diversification strategies and fierce competition are likely to be more intense across worldwide ports handing dry bulk cargoes. The following three sections provide efficiency analysis (*e.g.* score estimates, ranking and source of improvement) for ports/terminals handling coal, iron ore and grain bulk cargoes.

Sample description

The coal bulk port sample includes 34 of the largest ports across the world. The regional distribution of the sample is broadly well balanced across Asia, America and Oceania, while Europe tends to be under-represented. Capital inputs used by dry bulk terminals dedicated to handling coal are proxied by specific terminal quay length and their storage capacity. Labour input is approximated by the capacity of terminal handling equipment ranging from 1 to 39 thousand tonnes per hour over the sample.

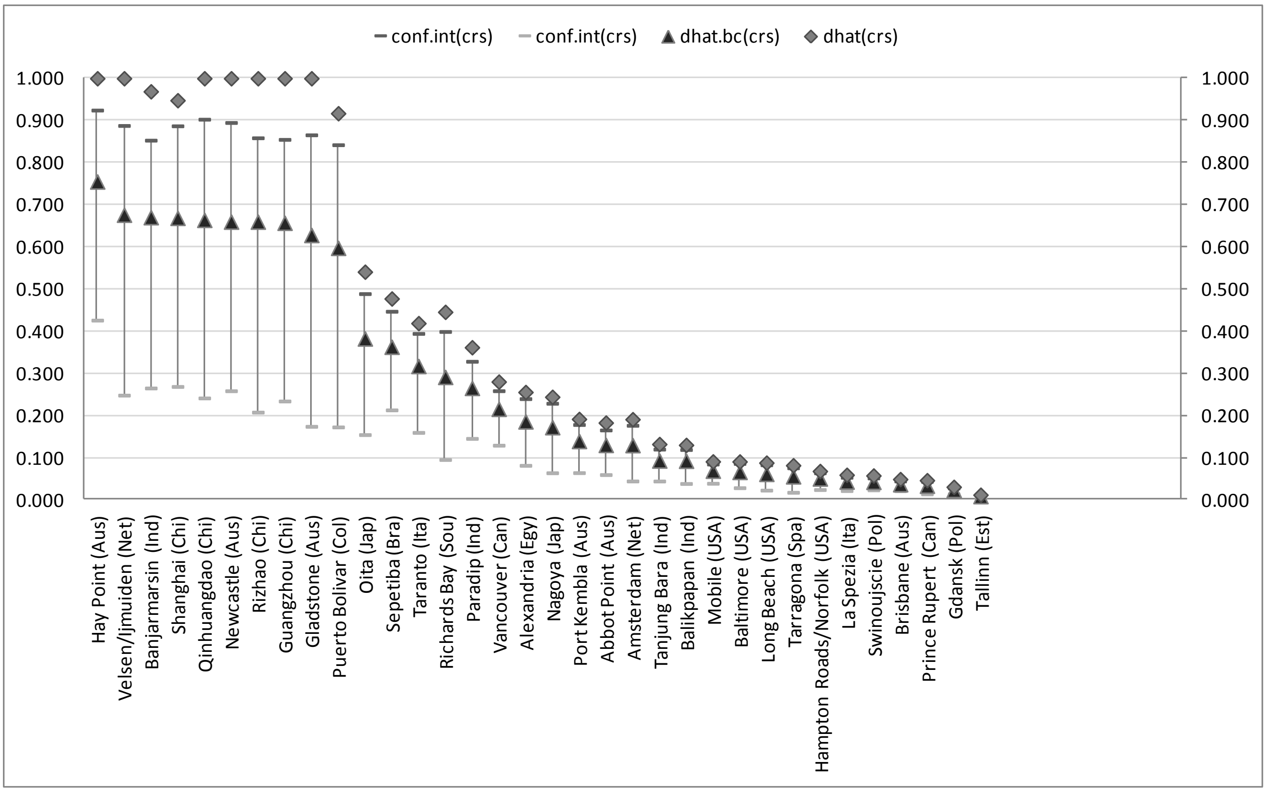
Table 5. Descriptive statistics of coal bulk terminals/ports sample

Coal bulk terminal sample	Output May 2011	Quay length (m)	Storage capacity (tonnes)	Loading/unloading (total capacity per h)
Average	2,178,910	1,020	2,648,195	10,863
Max	7,787,066	4,215	10,425,000	39,000
Min	41,688	235	350,000	1,000
Normalised standard deviation	1.00	0.94	0.95	0.97
N (non missing)	34	33	28	27

Source: OECD database.

Overall efficiency scores

Figure 5. Efficiency scores for coal bulk terminals



Source: Author's own calculations.

Note: (dhat) refers to efficiency scores derived using the standard DEA methodology; (dhat.bc) indicates scores derived using the bootstrapping method and (conf.int) indicates the upper/lower bound values of the interval of confidence; (crs) is the abbreviation of constant returns to scale, assumption used in both methodologies.

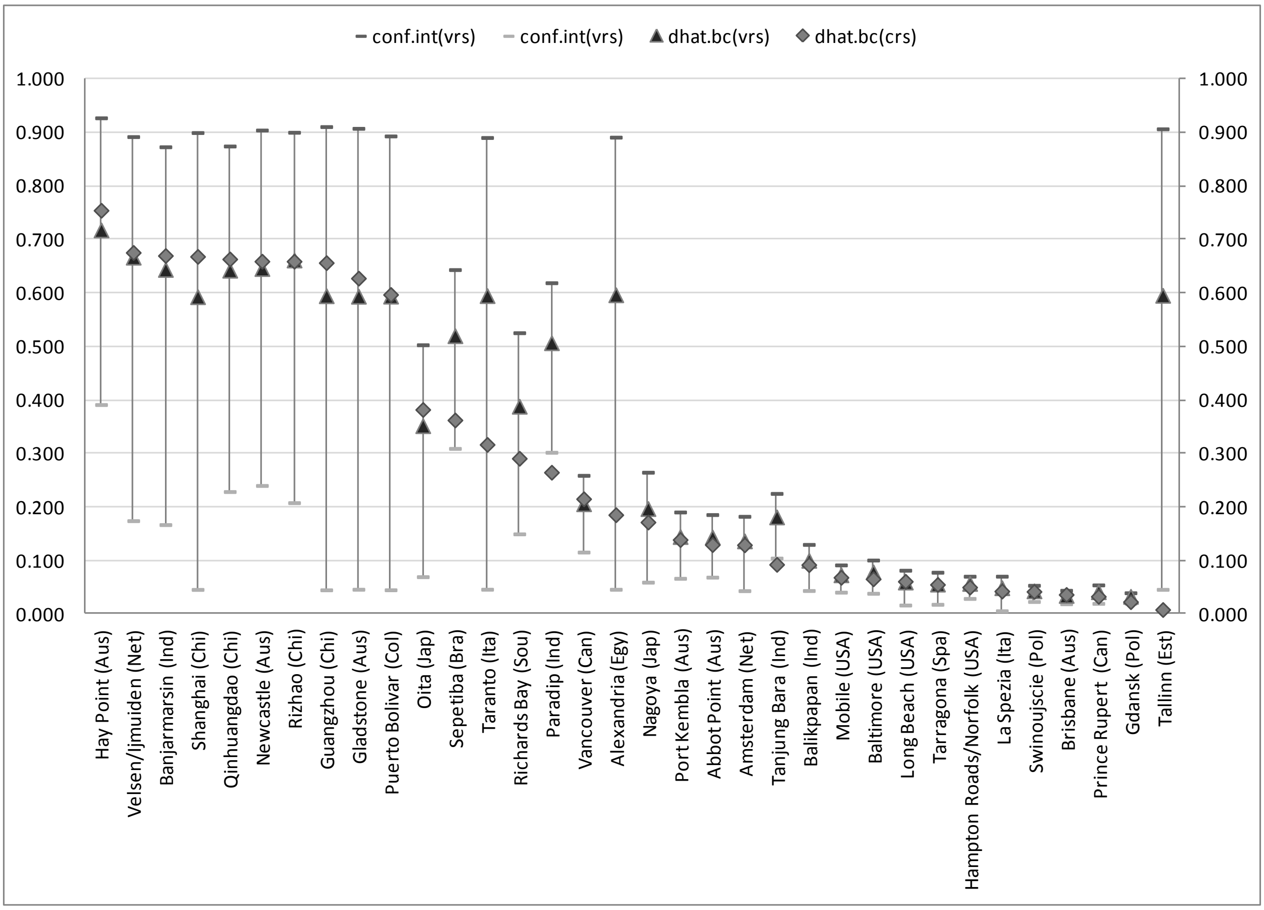
The main findings shown in Figure 5, which plots both efficiency scores based on standard and bootstrapped DEA, include:

A clear group of efficient terminals is emerging from the sample, mostly located in Australia and China. According to both estimates (standard and bootstrapped), about one-third of the coal bulk ports figures among the benchmark of efficient terminals. Most of these terminals are located in Australia and China, excluding those located in the Netherlands, India and Colombia (see Annex Table A.4 for detailed estimates). Operating at 65% to 75% of the efficiency frontier, there is also room to improve operational efficiency

"Follower" terminals are significantly lagging behind. Indeed, "follower" ports/terminals drop down to less than 40% efficiency, and the least performing terminals fall below 10% efficiency. Further, many of the least performing ports are located in developed countries in Europe and the USA.

Efficiency potential gains

Figure 6. Technical efficiency scores for coal bulk terminals



Source: Authors' own calculations.

Note: (dhat.bc) indicates scores derived using the bootstrapping method and (conf.int) indicates the upper/lower bound values of the interval of confidence; (crs) and (vrs) respectively refer to constant returns to scale and varying returns to scale, assumption used in the methodology.

Figure 6 highlights the importance of efficiency gains from improved technology (*e.g.* equipment) and infrastructure.

The main source of efficiency gains is based on improving the technological ladder of the infrastructure and equipment. For almost all coal bulk ports, overall and pure technical estimates are found to be very closed in values, indicating the absence of inefficiencies driven by non-optimal production levels. As such, the main driving factor of overall efficiency is related to gaps in pure technical efficiency. Improving the technological ladder appears as a key lever, including for terminals located in most developed countries. This assessment excludes a few terminals (Alexandria [EGY], Toranto [ITA] and Paradip [IND]) where efficiency gains rely on the adjustment of production scales towards optimal levels.

3.4. Iron bulk terminals

Sample description

The sample of iron bulk terminals includes only 15 ports/terminals around the world, reflecting the availability of the data. The regional distribution is relatively well balanced, though Africa is under-represented.

Input variables specific to bulk terminal infrastructure dedicated to iron ore are proxied by quay lengths and the maximum depth of canals for bulks carriers. For a limited number of terminals, inputs also include storage capacity. Labour input is proxied by the equipment capacity in loading/unloading minerals ranging from 1.5 to 60 thousand tonnes per hour.

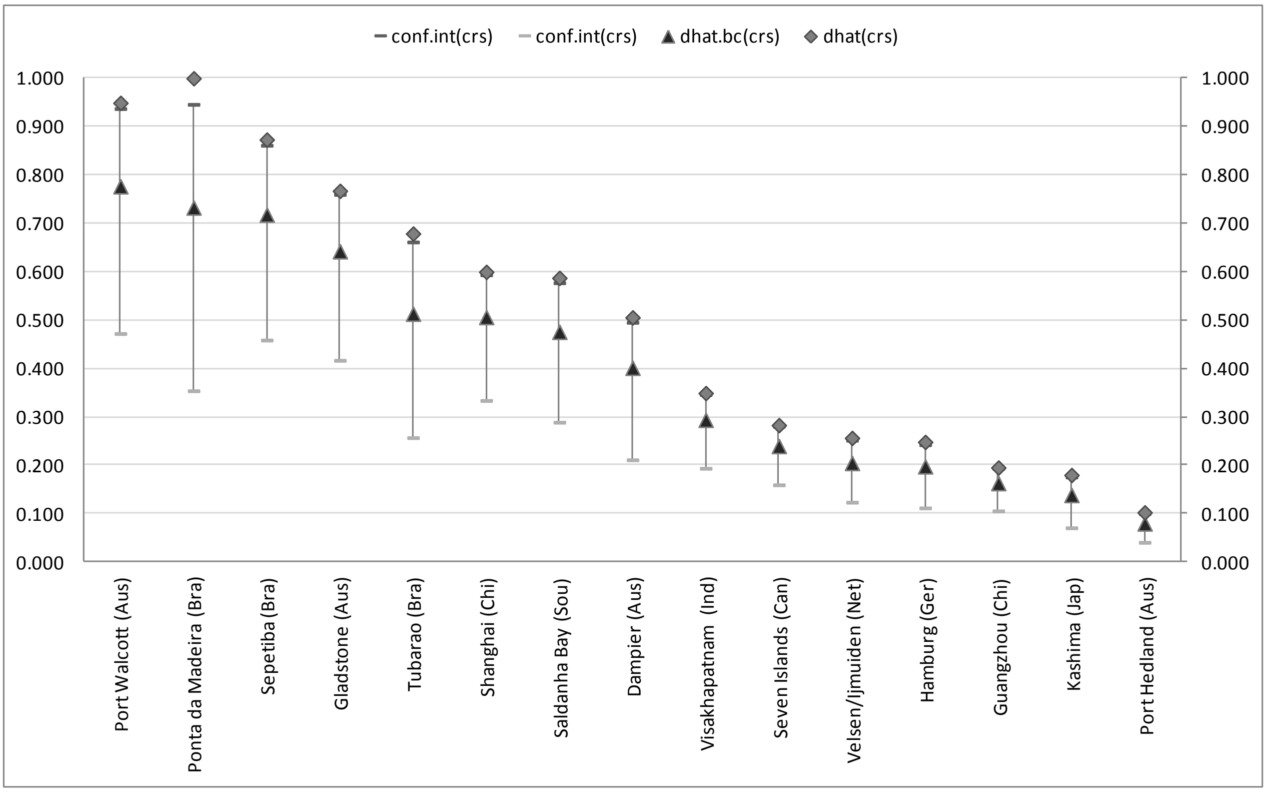
Table 6. Descriptive statistics of grain ports/terminals sample

Iron bulk terminal sample	Output May 2011	Quay length	Maximum depth (m)	Loading/unloading capacity (t/h)	Storage capacity (tonnes)
Average	771,650	981	18	15,820	2,061,250
Max	3,039,118	2,825	24	60,000	2,975,000
Min	100,912	168	10	1,500	1,150,000
Normalised standard deviation	1.11	0.70	0.28	1.10	0.39
N (non missing)	15	15	15	13	4

Source: OECD database.

Overall efficiency scores

Figure 7. Efficiency scores for iron bulk terminals



Source: Authors' own calculations.

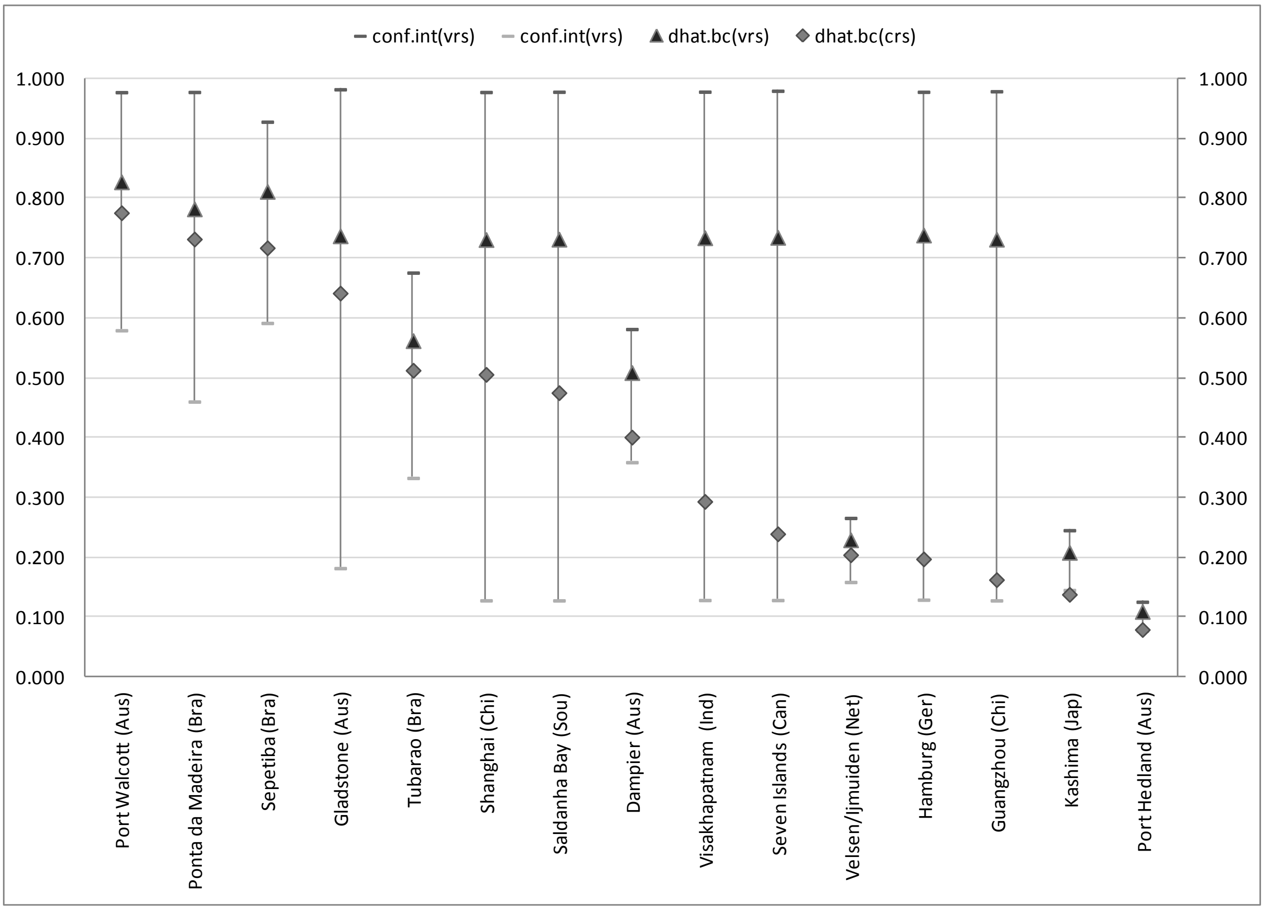
Note: (dhat) refers to efficiency scores derived using the standard DEA methodology; (dhat.bc) indicates scores derived using the bootstrapping method and (conf.int) indicates the upper/lower bound values of the interval of confidence; (crs) is the abbreviation of constant returns to scale, assumption used in both methodologies.

Figure 7 represents efficiency scores based on standard and bootstrapped DEA. Its main findings highlight a strong relationship between terminal size and efficiency of iron ore terminals.

Most efficient iron ore ports/terminals are mostly large. Achieving 70% to 80% of the frontier of efficiency, the scores suggest potential room for improvement. These ports principally appear in the top five terminals in terms of iron ore transhipment volume. The rank correlation between port volume and efficiency score is around 0.72, which confirms a strong link between the size/volume and efficiency gains for iron ore ports. However, some caution should be used when considering the results given the relatively small size of the sample (see Annex Table A.5 for detailed estimates).

Efficiency potential gains

Figure 8. Technical efficiency scores for iron bulk terminals



Source: Authors' own calculations.

Note: (dhat.bc) indicates scores derived using the bootstrapping method and (conf.int) indicates the upper/lower bound values of the interval of confidence; (crs) and (vrs) respectively refer to constant returns to scale and varying returns to scale, assumption used in the methodology.

Technical efficiency scores show how production scale inefficiencies are an important factor in the creation of efficiency gaps across iron ore ports/terminals (see Figure 8).

Production scale inefficiencies are major source of efficiency gaps across iron ore ports/terminals. With the exception of a few cases, iron ore ports are mostly operating at high levels of technical efficiency, achieving more than 70% of the frontier. The interesting finding is that the overall efficiency is proportionally decreasing while inefficiencies in production scale are increasing (as identified by the gaps between both technical and overall estimates). This indicates that, on the basis of the sample, the major driver for improving efficiency of iron bulk ports/terminals is to reduce production scale inefficiencies rather than improving technology. As seen in Table 7, showing state of production returns to scale, adjustments for most of these ports must focus on increasing output volumes as all concerned terminals are found to operate at increasing returns to scale.

Table 7. Production returns to scale for iron ore commodities for selected terminals/ports

Output ranking	Port names	vrs	nirs	ratio	drs/irs
12	Shanghai (Chi)	0.731943	0.506149	0.692	irs
6	Saldanha Bay (Sou)	0.732501	0.47488	0.648	irs
13	Visakhapatnam (Ind)	0.734986	0.293871	0.400	irs
14	Seven Islands (Can)	0.735622	0.239893	0.326	irs
10	Hamburg (Ger)	0.739479	0.198004	0.268	irs
15	Guangzhou (Chi)	0.732503	0.163193	0.223	irs

Source: Authors' own calculations.

3.5. Grain terminals

Sample representativity and input proxies

The data sample covers 41 grain ports/terminals worldwide. The sample is equally distributed across the main regions, such as Asia, North and South America, followed by Oceania, Europe and to a smaller extent, Africa. However, the sample is marked by a greater volatility in output around the mean (as indicated by the normalised standard deviation compared to other commodities) suggesting that the sample may reflect very large imbalances in size across grain ports/terminals.

Input variables collected are specific to grain terminals. Capital inputs are proxied by quay lengths, and grain storage capacity, and labour input is proxied by loading grain equipment as measured by the loading capacity ranging from 400 tonnes to 20 000 tonnes loaded per hour.

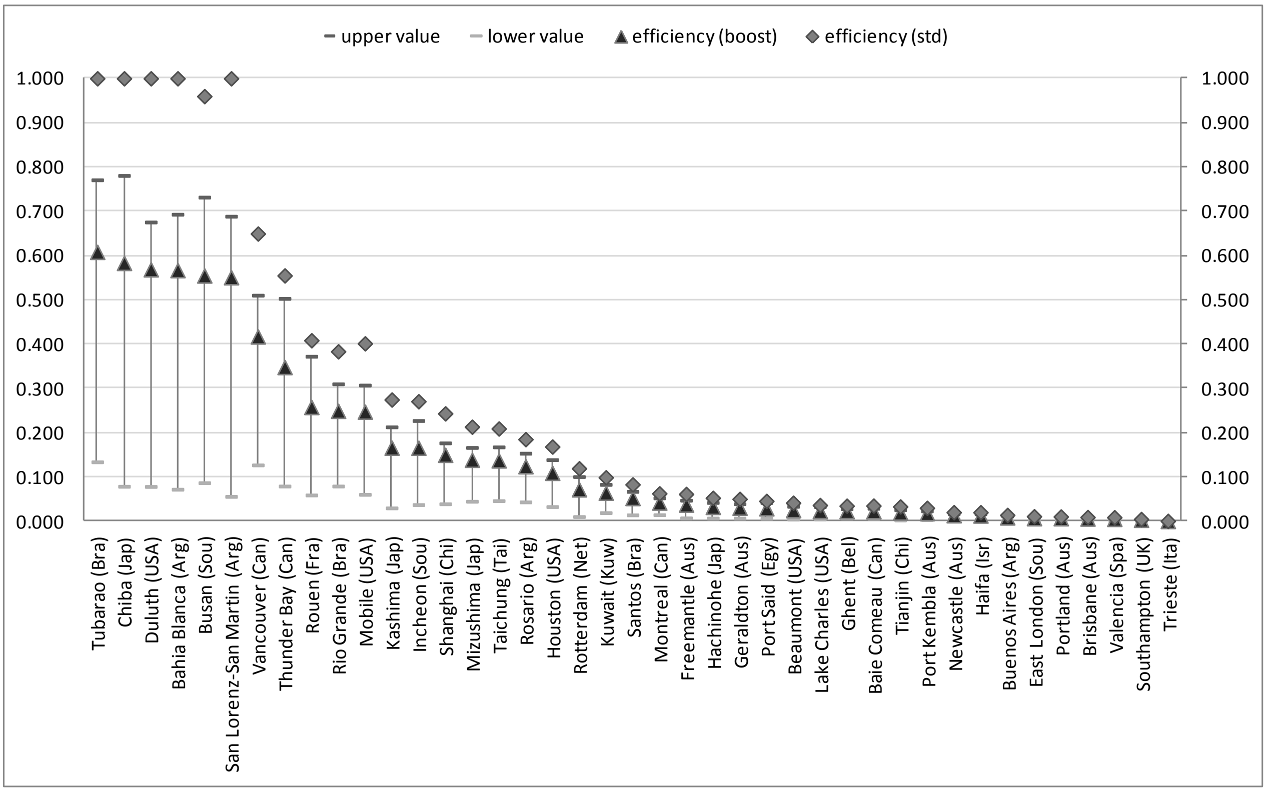
Table 8. Descriptive statistics of grain ports/terminals sample

Grain terminal sample	Output May 2011	Quay length (m)	Storage capacity (Tonnes)	Loading capacity (per h)
Average	**769,881**	**656**	**413,097**	**4,963**
Max	3,450,208	3,484	2,470,000	20,000
Min	4,942	100	27,945	400
Normalised standard deviation	1.26	1.04	1.38	1.05
N (non missing)	41	39	33	36

Source: OECD database.

Overall efficiency scores

Figure 9. Efficiency scores for grain terminals



Source: Authors' own calculations.

Note: (dhat) refers to efficiency scores derived using the standard DEA methodology; (dhat.bc) indicates scores derived using the bootstrapping method and (conf.int) indicates the upper/lower bound values of the interval of confidence; (crs) is the abbreviation of constant returns to scale, assumption used in both methodologies.

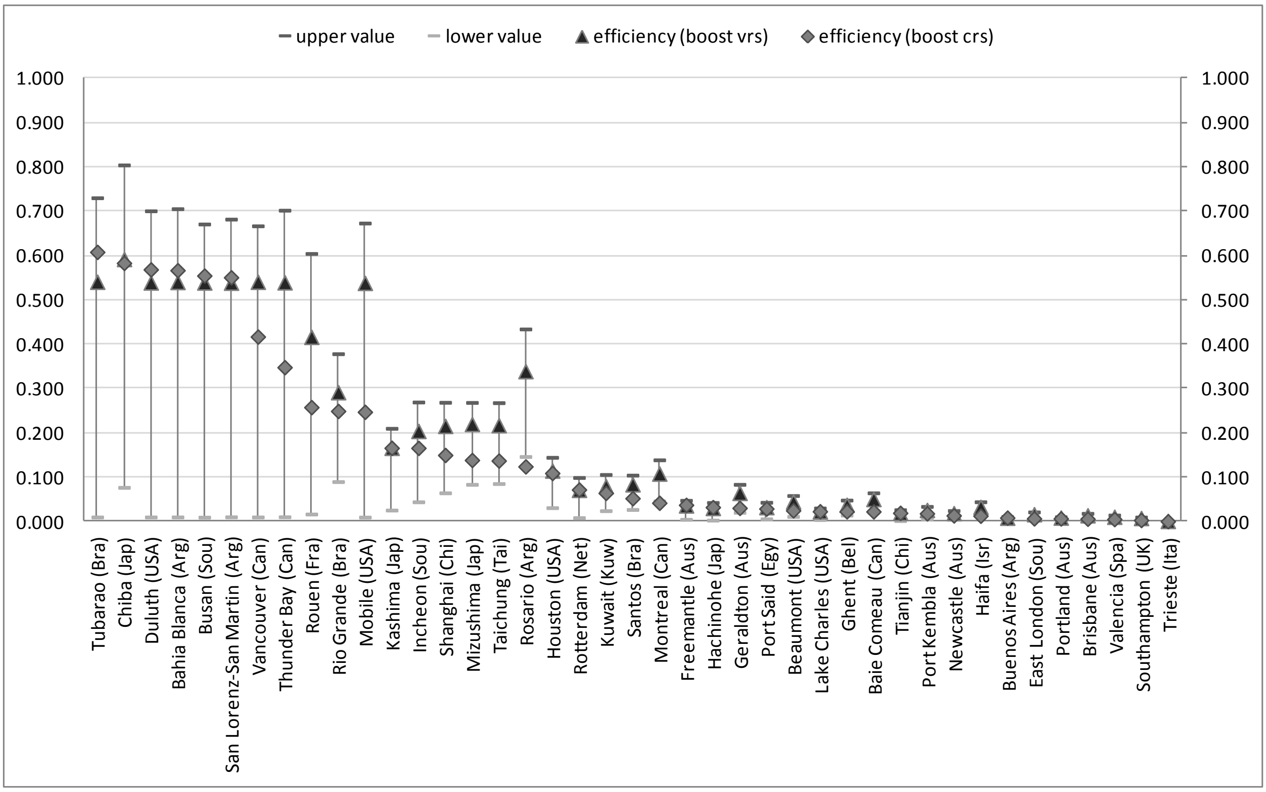
There are two main findings from Figure 9 (see Annex Table A.6 for detailed estimates):

Port size matters. Most efficient terminals are among the top ten largest grain ports/terminals. There is a clear emerging group of efficient terminals, which according to both standard and bootstrapped estimates are operating at relatively high standard values. These terminals are also figure among the top ten largest grain ports/terminals loading more than 1.5 million tonnes of grains per year. However, the bootstrapped estimates indicate that these terminals operate at more than 55% of the efficiency frontier, suggesting that the room to increase their efficiency is even larger compared to other commodities. These terminals are mostly located in Latin America with two terminals in Argentina (Bahia Bianca and San Lorenz San Martin), in Brazil (Tubarao), Japan (Chiba) and Korea (Busan) but also Duluth in the US.

Terminals in developed countries are poorly performing. Efficiency scores (according to standard and bootstrapped estimates) rapidly drop down to 30% after the benchmark group and down below 10% after the first 20 terminals. These relative poorly scores suggest that substantial room exists to improve efficiency. Surprisingly, least performing terminals tend to be found in developed OECD countries such as Italy, UK, Spain and Australia.

Sources of efficiency/inefficiency

Figure 10. Technical efficiency scores for grain terminals



Source: Authors'own calculations.

Note: (dhat.bc) indicates scores derived using the bootstrapping method and (conf.int) indicates the upper/lower bound values of the interval of confidence; (crs) and (vrs) respectively refer to constant returns to scale and varying returns to scale, assumption used in the methodology.

The main findings from Figure 10 are:

Improving technical efficiency is the major driver to increase overall efficiency. In most cases, overall and technical estimates of efficiency have closed values, indicating that overall efficiency reflects the level of pure technical efficiency. The technical gaps are surprisingly marked across grain ports/terminals. The correlation between the two efficiency scores is equal to 0.97, which confirms that upgrading technical efficiency towards the efficiency frontier is a key lever to increase grain port/terminal efficiency. As a result, a large majority of grain ports/terminals are operating at optimal levels.

4. CONCLUSIONS

Port efficiency is a key driver of port competitiveness and can play an important role in boosting regional development. The analysis in this report provides several insights on where and how to gain port efficiency.

Technical efficiency is the most important factor to improving port efficiency. Significant improvements can be made when the technical efficiency of ports is increased. Among the sample, gaps between terminal efficiency mostly reflected gaps in pure technical efficiency. Most of the performing ports still have some room to improve pure technical efficiency as long as they are already achieving between 65% to 75% of the efficiency frontier, whereas "follower" ports need to catch up the technological ladder in order to see improvements. When comparing the level of efficiency achieved by ports across commodities, technical gaps were more marked for container and oil terminals. Most of the performing container and oil terminals use technology more efficiently compared to iron ore, coal and grain terminals. This probably reflects the nature of container and crude oil terminals, which when compared to other commodity terminals are generally more technology embedded and likely to face greater pressures to provide cutting-edge technology.

Promoting policies to raise throughput levels in order to minimise production scale inefficiencies is another important area for improvement. Production scale inefficiencies arise when throughput levels are below or above optimal levels given the current capacity of terminal infrastructure. Such inefficiencies were mostly found in a substantial number of ports handling crude oil and iron ore, suggesting that efficiency is more sensitive and driven by exogenous factors related to traffic flows. By contrast, for containers, grain and coal bulks, production scale inefficiencies were more focused on individual/specific ports. The handling of these cargo categories were mostly found to operate at increasing return to scales indicating that throughput levels have to be increased towards higher optimal levels. However, ports with recent infrastructure investments also face production scale inefficiencies over a period until current business reach their optimal levels.

The analysis shows that the size of ports matters for port efficiency. The crude oil, iron-ore and grain ports have higher efficiency scores at larger total terminal size, suggesting that this size is more efficient because they can drive technological development. However, larger-scale ports are more likely to operate at decreasing return to scale (*e.g.* above certain optimal levels) and face overheating inefficiencies. Policies aimed at relieving traffic congestions in the short run, or increasing terminal infrastructure for large-scale ports in the long run, would reinforce port efficiency for these specific commodities.

Regional patterns are also seen in port efficiency. There are regional patterns emerging across commodities. For example, in general, terminals in China are among the most efficient in handling coal bulk and containers with terminals in Southeast Asia. By contrast, the most efficient grain and iron-ore terminals are located in Latin America, and the most efficient crude-oil transhipment terminals are mostly found in the Gulf region. Further, Australia is also found to perform well in handling coal bulk and grains.

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ANNEX TABLES

Table A.1: Sensitivity analysis for DEA scores[1] container terminals

DMU (A)	Country	Port	Model A (dwt, teu) CRS std Score	Model A (dwt, teu) CRS boot Score[2]	Rank CRS Boots (A)	DMU (B)	Model B (dwt) CRS Std Score	Model B (dwt) CRS Boot Score[2]	Rank CRS Boots (B)	Comm on ports in the efficiency benchmark
	Correlations A/B	all ports					0.640	0.557	0.559	
21	India	Jawaharlal Nehru	0.952	0.836	1	44	0.302	0.228	35	
24	Oman	Salalah	1.000	0.790	2	79	1.000	0.701	8	x
31	United Arab Emirates	Khor Fakkan	0.971	0.765	3	106	1.000	0.826	1	x
57	Israel	Haifa	0.955	0.752	4	50	1.000	0.718	7	x
9	Chinese Taipei	Kaohsiung	0.986	0.749	5	28	1.000	0.679	11	x
6	China	Guangzhou	1.000	0.723	6	20	0.532	0.426	26	
3	China	Hong Kong	1.000	0.715	7	21	1.000	0.637	14	x
1	Singapore	Singapore	0.915	0.696	8	91	0.727	0.538	20	
8	China	Tianjin	1.000	0.680	9	26	1.000	0.765	3	x
29	China	Lianyungang	1.000	0.676	10	22	0.181	0.143	44	
55	Chinese Taipei	Taichung	0.832	0.675	11	30	1.000	0.757	5	x
4	China	Shenzhen	1.000	0.670	12	24	1.000	0.642	12	x
7	Netherland	Rotterdam	1.000	0.667	13	77	1.000	0.641	13	x
2	China	Shanghai	1.000	0.666	14	23	1.000	0.608	17	x
14	Malaysia	Tanjung Pelepas	0.777	0.638	15	73	0.381	0.277	34	
5	South Korea	Busan	0.781	0.600	16	93	1.000	0.781	2	
13	USA	Los Angeles	0.715	0.593	17	116	0.772	0.548	18	
27	Saudi Arabia	Jeddah	0.710	0.560	18	89	1.000	0.689	9	
26	Egypt	Port Said	0.630	0.547	19	36	0.279	0.219	36	
23	Indonesia	Jakarta	0.591	0.510	20	46	0.092	0.064	53	
28	Spain	Algeciras	0.630	0.501	21	95	0.712	0.547	19	
35	Brazil	Santos	0.644	0.495	22	12	1.000	0.726	6	
43	Jamaica	Kingston	0.613	0.493	23	58	0.583	0.491	22	
53	India	Chennai	0.626	0.473	24	43	0.207	0.153	42	
34	Malta	Marsaxlokk	0.528	0.461	25	74	0.153	0.110	49	
15	USA	Long Beach	0.552	0.460	26	115	0.260	0.211	37	
19	China	Dalian	0.551	0.450	27	19	0.003	0.002	62	
11	Malaysia	Port Klang	0.530	0.433	28	72	0.660	0.502	21	
37	Iran	Bandar Abbas	0.559	0.424	29	47	0.575	0.449	24	

61	South Africa	Cape Town	0.556	0.423	30	92	0.590	0.429	25
49	Panama	Manzanillo	0.442	0.385	31	82	0.003	0.002	61
17	Germany	Bremerhaven	0.500	0.379	32	40	0.951	0.761	4
54	Egypt	Damietta	0.433	0.377	33	35	0.138	0.096	51
22	Japan	Tokyo	0.477	0.376	34	65	0.525	0.391	28
46	South Korea	Incheon	0.457	0.374	35	94	0.089	0.064	54
10	Belgium	Antwerp	0.471	0.352	36	8	0.883	0.617	16
33	Belgium	Zeebrugge	0.407	0.351	37	9	0.163	0.130	47
16	China	Xiamen	0.456	0.345	38	27	0.649	0.464	23
25	Sri Lanka	Colombo	0.385	0.329	39	100	0.172	0.135	46
30	Italy	Gioia Tauro	0.371	0.312	40	52	0.219	0.166	40
20	Thailand	Laem Chabang	0.353	0.297	41	102	0.252	0.199	39
40	Panama	Balboa	0.338	0.293	42	81	0.255	0.203	38
58	Spain	Las Palmas	0.341	0.291	43	98	0.151	0.107	50
42	USA	Houston	0.289	0.243	44	113	0.064	0.048	57
38	Japan	Nagoya	0.315	0.243	45	63	0.773	0.619	15
59	Australia	Brisbane	0.274	0.226	46	2	0.462	0.396	27
41	Spain	Barcelona	0.256	0.225	47	96	0.079	0.060	55
47	USA	Tacoma	0.256	0.211	48	125	0.077	0.058	56
18	USA	New York	0.261	0.209	49	120	0.207	0.159	41
12	Germany	Hamburg	0.268	0.205	50	41	0.512	0.365	30
36	France	Le Havre	0.257	0.192	51	39	0.852	0.684	10
44	USA	Seattle	0.225	0.186	52	124	0.159	0.122	48
39	USA	Oakland	0.229	0.184	53	121	0.420	0.335	33
50	Pakistan	Karachi	0.212	0.174	54	80	0.188	0.140	45
45	Chinese Taipei	Keelung	0.224	0.170	55	29	0.445	0.339	32
52	Saudi Arabia	Dammam	0.204	0.166	56	88	0.044	0.033	59
60	Lebanon	Beirut	0.209	0.158	57	69	0.437	0.349	31
56	USA	Charleston	0.188	0.147	58	110	0.454	0.370	29
32	USA	Savannah	0.191	0.146	59	123	0.202	0.145	43
48	Italy	Genoa	0.153	0.128	60	51	0.122	0.094	52
62	Japan	Hakata	0.146	0.112	61	60	0.063	0.044	58
51	Canada	Montreal	0.137	0.107	62	14	0.036	0.026	60

Notes:

1 Authors' calculation

2 Ports ranked by bootstrapped DEA scores

Table A.2: DEA scores[1] under varying assumptions on returns to scale for container terminals

DEA Model specification

Outputs: y1=containers (DWT) , y2=containers (TEUs),
Inputs: x1=quay length, x2=surface terminal, x3=refeer points, x4=quay cranes, x5=yard cranes

			Constant returns to scale (CRS)				Varying returns to scale (VRS)				Non increasing returns to scale (NIRS)			
			Standard DEA	Bootstrapped DEA			Standard DEA	Bootstrapped DEA			Standard DEA	Bootstrapped DEA		
DMU	Country	Port	Score	Score[2]	Upper value	Lower value	Score	Score	Upper value	Lower value	Score	Score	Upper value	Lower value
1	Singapore	Singapore	0.915	0.696	0.867	0.405	1.000	0.742	0.962	0.397	1.000	0.735	0.952	0.394
2	China	Shanghai	1.000	0.666	0.970	0.153	1.000	0.673	0.964	0.162	1.000	0.660	0.960	0.149
3	China	Hong Kong	1.000	0.715	0.952	0.340	1.000	0.718	0.965	0.330	1.000	0.711	0.950	0.336
4	China	Shenzhen	1.000	0.670	0.969	0.198	1.000	0.677	0.969	0.198	1.000	0.676	0.957	0.205
5	South Korea	Busan	0.781	0.600	0.752	0.347	0.783	0.596	0.759	0.345	0.781	0.588	0.749	0.326
6	China	Guangzhou	1.000	0.723	0.965	0.334	1.000	0.724	0.963	0.334	1.000	0.718	0.972	0.331
7	Netherland	Rotterdam	1.000	0.667	0.954	0.191	1.000	0.674	0.964	0.159	1.000	0.670	0.955	0.190
8	China	Tianjin	1.000	0.680	0.960	0.210	1.000	0.676	0.956	0.219	1.000	0.671	0.962	0.220
9	Chinese Taipei	Kaohsiung	0.986	0.749	0.966	0.347	0.986	0.752	0.959	0.338	0.986	0.741	0.970	0.346
10	Belgium	Antwerp	0.471	0.352	0.449	0.168	0.471	0.356	0.452	0.174	0.471	0.353	0.454	0.174
11	Malaysia	Port Klang	0.530	0.433	0.513	0.315	0.532	0.429	0.512	0.306	0.532	0.425	0.510	0.302
12	Germany	Hamburg	0.268	0.205	0.258	0.124	0.349	0.266	0.340	0.149	0.349	0.261	0.334	0.141
13	USA	Los Angeles	0.715	0.593	0.688	0.409	0.715	0.593	0.689	0.390	0.715	0.589	0.687	0.396
14	Malaysia	Tanjung Pelepas	0.777	0.638	0.747	0.455	0.777	0.639	0.746	0.462	0.777	0.632	0.753	0.437
15	USA	Long Beach	0.552	0.460	0.536	0.317	0.552	0.459	0.538	0.304	0.552	0.457	0.534	0.310
16	China	Xiamen	0.456	0.345	0.443	0.168	0.570	0.435	0.558	0.228	0.456	0.343	0.441	0.172
17	Germany	Bremerhaven	0.500	0.379	0.482	0.189	0.500	0.379	0.485	0.182	0.500	0.374	0.479	0.179
18	USA	New York	0.261	0.209	0.251	0.148	0.276	0.218	0.268	0.144	0.276	0.214	0.264	0.140
19	China	Dalian	0.551	0.450	0.529	0.313	0.555	0.455	0.533	0.324	0.551	0.449	0.532	0.311
20	Thailand	Laem Chabang	0.353	0.297	0.338	0.232	0.366	0.299	0.352	0.222	0.366	0.295	0.350	0.213
21	India	Jawaharlal Nehru	0.952	0.836	0.925	0.673	0.968	0.818	0.938	0.631	0.952	0.829	0.928	0.652
22	Japan	Tokyo	0.477	0.376	0.463	0.229	0.480	0.376	0.466	0.228	0.477	0.373	0.460	0.227
23	Indonesia	Jakarta	0.591	0.510	0.570	0.418	0.597	0.500	0.577	0.397	0.591	0.501	0.565	0.399
24	Oman	Salalah	1.000	0.790	0.965	0.529	1.000	0.757	0.971	0.434	1.000	0.785	0.945	0.517
25	Sri Lanka	Colombo	0.385	0.329	0.371	0.267	0.387	0.328	0.373	0.261	0.387	0.328	0.377	0.262
26	Egypt	Port Said	0.630	0.547	0.608	0.451	0.647	0.551	0.626	0.446	0.630	0.540	0.603	0.427
27	Saudi Arabia	Jeddah	0.710	0.560	0.677	0.370	0.743	0.554	0.709	0.286	0.710	0.556	0.684	0.353
28	Spain	Algeciras	0.630	0.501	0.609	0.312	0.652	0.512	0.627	0.300	0.630	0.492	0.611	0.303
29	China	Lianyungang	1.000	0.676	0.953	0.280	1.000	0.675	0.960	0.162	1.000	0.677	0.954	0.271
30	Italy	Gioia Tauro	0.371	0.312	0.359	0.246	0.374	0.307	0.360	0.238	0.371	0.307	0.356	0.234
31	United Arab	Khor Fakkan	0.971	0.765	0.929	0.452	1.000	0.673	0.952	0.161	0.971	0.756	0.930	0.443

	Emirates													
32	USA	Savannah	0.191	0.146	0.185	0.082	0.191	0.147	0.185	0.083	0.191	0.144	0.184	0.079
33	Belgium	Zeebrugge	0.407	0.351	0.389	0.285	0.408	0.344	0.390	0.281	0.407	0.344	0.393	0.277
34	Malta	Marsaxlokk	0.528	0.461	0.509	0.372	0.548	0.463	0.529	0.360	0.528	0.458	0.510	0.354
35	Brazil	Santos	0.644	0.495	0.632	0.271	1.000	0.688	0.956	0.237	0.644	0.491	0.622	0.262
36	France	Le Havre	0.257	0.192	0.250	0.083	0.257	0.190	0.252	0.071	0.257	0.189	0.251	0.082
37	Iran	Bandar Abbas	0.559	0.424	0.535	0.259	0.559	0.425	0.540	0.232	0.559	0.423	0.535	0.247
38	Japan	Nagoya	0.315	0.243	0.305	0.132	0.321	0.244	0.311	0.126	0.315	0.241	0.308	0.133
39	USA	Oakland	0.229	0.184	0.221	0.124	0.229	0.184	0.222	0.121	0.229	0.183	0.220	0.126
40	Panama	Balboa	0.338	0.293	0.330	0.233	0.381	0.321	0.364	0.262	0.338	0.290	0.328	0.233
41	Spain	Barcelona	0.256	0.225	0.250	0.182	0.273	0.236	0.265	0.192	0.256	0.223	0.249	0.182
42	USA	Houston	0.289	0.243	0.279	0.199	0.303	0.252	0.292	0.206	0.289	0.241	0.276	0.199
43	Jamaica	Kingston	0.613	0.493	0.586	0.344	1.000	0.677	0.957	0.154	0.613	0.489	0.594	0.329
44	USA	Seattle	0.225	0.186	0.217	0.131	0.228	0.189	0.220	0.131	0.225	0.186	0.217	0.132
45	Chinese Taipei	Keelung	0.224	0.170	0.216	0.086	0.224	0.169	0.216	0.086	0.224	0.167	0.216	0.087
46	South Korea	Incheon	0.457	0.374	0.441	0.269	0.812	0.630	0.779	0.402	0.457	0.370	0.442	0.268
47	USA	Tacoma	0.256	0.211	0.250	0.146	0.259	0.211	0.252	0.141	0.256	0.211	0.249	0.149
48	Italy	Genoa	0.153	0.128	0.147	0.099	0.153	0.127	0.149	0.095	0.153	0.125	0.145	0.094
49	Panama	Manzanillo	0.442	0.385	0.424	0.315	0.468	0.369	0.454	0.244	0.442	0.381	0.423	0.299
50	Pakistan	Karachi	0.212	0.174	0.205	0.120	0.213	0.174	0.205	0.119	0.212	0.172	0.206	0.113
51	Canada	Montreal	0.137	0.107	0.132	0.070	0.137	0.107	0.132	0.066	0.137	0.106	0.131	0.067
52	Saudi Arabia	Dammam	0.204	0.166	0.196	0.121	0.221	0.183	0.216	0.139	0.221	0.182	0.214	0.138
53	India	Chennai	0.626	0.473	0.614	0.266	1.000	0.739	0.966	0.288	0.626	0.472	0.602	0.273
54	Egypt	Damietta	0.433	0.377	0.421	0.309	1.000	0.676	0.969	0.168	0.433	0.375	0.420	0.307
55	Chinese Taipei	Taichung	0.832	0.675	0.795	0.492	0.863	0.643	0.827	0.280	0.832	0.669	0.804	0.470
56	USA	Charleston	0.188	0.147	0.182	0.085	0.189	0.146	0.178	0.087	0.188	0.144	0.181	0.084
57	Israel	Haifa	0.955	0.752	0.909	0.502	1.000	0.670	0.958	0.161	0.955	0.746	0.923	0.497
58	Spain	Las Palmas	0.341	0.291	0.330	0.232	0.422	0.332	0.406	0.211	0.341	0.290	0.332	0.226
59	Australia	Brisbane	0.274	0.226	0.265	0.154	0.334	0.254	0.327	0.123	0.274	0.223	0.265	0.148
60	Lebanon	Beirut	0.209	0.158	0.202	0.079	0.212	0.155	0.202	0.065	0.209	0.157	0.199	0.081
61	South Africa	Cape Town	0.556	0.423	0.536	0.268	1.000	0.669	0.956	0.156	0.556	0.421	0.528	0.262
62	Japan	Hakata	0.146	0.112	0.142	0.066	0.177	0.140	0.170	0.085	0.177	0.140	0.170	0.096

Notes:

1 Author's calculation

2 Ports ranked by Bootstrapped DEA scores

Table A.2 (cont'd): DEA scores[1] under varying assumptions on returns to scale for container terminals

DEA Model specification

Output: y1=containers (DWT)
Inputs: x1=quay length, x2=surface terminal, x3=refeer points, x4=quay cranes, x5=yard cranes

			Constant returns to scale (CRS)				Varying returns to scale (VRS)				Non increasing returns to scale (NIRS)			
			Standard DEA	Bootstrapped DEA			Standard DEA	Bootstrapped DEA			Standard DEA	Bootstrapped DEA		
DMU	Country	Port	Score	Score [2]	Upper value	Lower value	Score	Score	Upper value	Lower value	Score	Score	Upper value	Lower value
1	Argentina	Buenos Aires	0.398	0.283	0.384	0.079	0.422	0.293	0.407	0.071	0.398	0.287	0.386	0.077
2	Australia	Brisbane	0.462	0.396	0.448	0.307	0.600	0.493	0.583	0.333	0.462	0.391	0.438	0.305
3	Australia	Melbourne	0.152	0.119	0.139	0.082	0.156	0.118	0.142	0.077	0.156	0.122	0.144	0.084
4	Australia	Newcastle	0.011	0.008	0.010	0.006	0.091	0.059	0.086	0.005	0.011	0.008	0.010	0.005
5	Australia	Port Kembla	0.002	0.002	0.002	0.001	0.002	0.001	0.002	0.001	0.002	0.002	0.002	0.001
6	Australia	Sydney	0.005	0.004	0.005	0.002	0.005	0.004	0.005	0.002	0.005	0.004	0.005	0.002
7	Bangladesh	Chittagong	0.049	0.038	0.045	0.022	0.049	0.037	0.045	0.022	0.049	0.038	0.046	0.023
8	Belgium	Antwerp	0.883	0.617	0.840	0.234	0.918	0.624	0.846	0.224	0.883	0.613	0.836	0.234
9	Belgium	Zeebrugge	0.163	0.130	0.154	0.099	0.166	0.127	0.153	0.091	0.163	0.128	0.154	0.093
10	Brazil	Itajai	0.587	0.447	0.555	0.289	0.587	0.410	0.548	0.127	0.587	0.444	0.551	0.286
11	Brazil	Navegantes	0.115	0.082	0.109	0.039	0.115	0.081	0.111	0.038	0.115	0.083	0.111	0.039
12	Brazil	Santos	1.000	0.726	0.942	0.390	1.000	0.642	0.929	0.174	1.000	0.728	0.942	0.385
13	Brazil	Sepetiba	0.146	0.120	0.143	0.074	0.147	0.119	0.145	0.070	0.146	0.121	0.143	0.077
14	Canada	Montreal	0.036	0.026	0.034	0.012	0.036	0.026	0.033	0.012	0.036	0.026	0.034	0.012
15	Canada	Vancouver	1.000	0.714	0.923	0.402	1.000	0.599	0.926	0.003	1.000	0.704	0.936	0.364
16	Chile	San Antonio	0.048	0.038	0.044	0.028	0.062	0.049	0.058	0.034	0.062	0.050	0.058	0.036
17	Chile	Valparaiso	0.527	0.429	0.501	0.286	0.527	0.400	0.498	0.230	0.527	0.429	0.498	0.294
18	China	Beilun	0.727	0.539	0.684	0.288	0.763	0.532	0.709	0.242	0.763	0.550	0.730	0.276
19	China	Dalian	0.003	0.002	0.002	0.001	0.003	0.002	0.002	0.001	0.003	0.002	0.002	0.001
20	China	Guangzhou	0.532	0.426	0.499	0.281	0.532	0.419	0.500	0.283	0.532	0.429	0.496	0.303
21	China	Hong Kong	1.000	0.637	0.949	0.173	1.000	0.623	0.920	0.138	1.000	0.635	0.944	0.177
22	China	Lianyungang	0.181	0.143	0.178	0.075	0.183	0.141	0.179	0.073	0.181	0.144	0.177	0.074
23	China	Shanghai	1.000	0.608	0.935	0.075	1.000	0.599	0.924	0.038	1.000	0.605	0.919	0.073
24	China	Shenzhen	1.000	0.642	0.926	0.180	1.000	0.634	0.936	0.155	1.000	0.643	0.913	0.187
25	China	Taicang	0.042	0.034	0.040	0.023	0.042	0.032	0.039	0.021	0.042	0.034	0.040	0.023
26	China	Tianjin	1.000	0.765	0.944	0.395	1.000	0.748	0.941	0.377	1.000	0.768	0.951	0.394
27	China	Xiamen	0.649	0.464	0.594	0.221	0.700	0.480	0.650	0.194	0.649	0.458	0.609	0.215
28	Chinese Taipei	Kaohsiung	1.000	0.679	0.909	0.292	1.000	0.673	0.932	0.283	1.000	0.688	0.954	0.295
29	Chinese Taipei	Keelung	0.445	0.339	0.421	0.204	0.445	0.332	0.415	0.195	0.445	0.343	0.422	0.209
30	Chinese Taipei	Taichung	1.000	0.757	0.936	0.510	1.000	0.675	0.929	0.235	1.000	0.762	0.950	0.502
31	Colombia	Cartagena	0.778	0.604	0.717	0.428	0.778	0.551	0.715	0.264	0.778	0.605	0.728	0.411
32	Costa Rica	Puerto Limon	0.203	0.150	0.190	0.092	0.235	0.162	0.216	0.076	0.203	0.150	0.193	0.092
33	Ecuador	Guayaquil	0.175	0.138	0.166	0.090	0.177	0.133	0.163	0.082	0.175	0.137	0.166	0.092

34	Egypt	Alexandria	0.052	0.036	0.051	0.008	0.052	0.035	0.050	0.008	0.052	0.036	0.050	0.009
35	Egypt	Damietta	0.138	0.096	0.132	0.033	0.186	0.127	0.175	0.038	0.138	0.096	0.131	0.035
36	Egypt	Port Said	0.279	0.219	0.259	0.146	0.285	0.217	0.262	0.139	0.285	0.224	0.268	0.151
37	Estonia	Tallinn	0.030	0.022	0.028	0.012	0.051	0.035	0.046	0.015	0.030	0.022	0.028	0.011
38	France	Dunkirk	0.183	0.148	0.173	0.095	0.183	0.140	0.171	0.082	0.183	0.149	0.173	0.098
39	France	Le Havre	0.852	0.684	0.821	0.402	0.852	0.671	0.823	0.377	0.852	0.689	0.825	0.423
40	Germany	Bremerhaven	0.951	0.761	0.906	0.473	0.951	0.743	0.893	0.442	0.951	0.764	0.910	0.494
41	Germany	Hamburg	0.512	0.365	0.472	0.159	0.524	0.362	0.481	0.142	0.524	0.371	0.485	0.147
42	Greece	Piraeus	0.169	0.127	0.159	0.069	0.169	0.124	0.159	0.066	0.169	0.127	0.162	0.071
43	India	Chennai	0.207	0.153	0.194	0.073	0.294	0.210	0.273	0.076	0.207	0.153	0.194	0.076
44	India	Jawaharlal Nehru	0.302	0.228	0.282	0.123	0.308	0.230	0.283	0.122	0.302	0.231	0.284	0.131
45	India	Kolkata (Calcutta)	0.149	0.119	0.138	0.090	0.434	0.333	0.403	0.185	0.149	0.117	0.137	0.084
46	Indonesia	Jakarta	0.092	0.064	0.088	0.026	0.184	0.139	0.168	0.083	0.184	0.144	0.171	0.089
47	Iran	Bandar Abbas	0.575	0.449	0.535	0.310	0.575	0.417	0.529	0.226	0.575	0.449	0.539	0.312
48	Iran	Bandar Imam Khomeini	0.121	0.096	0.111	0.069	1.000	0.600	0.921	0.003	0.121	0.093	0.114	0.063
49	Israel	Ashdod	0.664	0.545	0.633	0.374	0.753	0.558	0.727	0.284	0.664	0.541	0.635	0.373
50	Israel	Haifa	1.000	0.718	0.925	0.453	1.000	0.595	0.921	0.017	1.000	0.718	0.946	0.442
51	Italy	Genoa	0.122	0.094	0.112	0.064	0.148	0.113	0.138	0.075	0.148	0.115	0.140	0.081
52	Italy	Gioia Tauro	0.219	0.166	0.206	0.110	0.264	0.199	0.245	0.128	0.264	0.205	0.250	0.139
53	Italy	La Spezia	0.610	0.481	0.573	0.321	0.660	0.488	0.610	0.264	0.610	0.483	0.575	0.315
54	Italy	Leghorn	0.280	0.219	0.262	0.139	0.280	0.210	0.264	0.114	0.280	0.222	0.265	0.136
55	Italy	Taranto	0.152	0.119	0.141	0.081	0.152	0.116	0.136	0.074	0.152	0.120	0.145	0.082
56	Italy	Trieste	0.041	0.029	0.039	0.012	0.046	0.031	0.043	0.012	0.046	0.032	0.043	0.014
57	Ivory Coast	Abidjan	0.583	0.441	0.551	0.285	0.583	0.389	0.544	0.091	0.583	0.437	0.552	0.272
58	Jamaica	Kingston	0.583	0.491	0.553	0.387	0.852	0.678	0.806	0.445	0.583	0.481	0.541	0.375
59	Japan	Chiba	0.031	0.022	0.029	0.009	0.041	0.029	0.039	0.009	0.031	0.023	0.029	0.009
60	Japan	Hakata	0.063	0.044	0.061	0.014	0.065	0.044	0.061	0.013	0.063	0.044	0.061	0.015
61	Japan	Kitakyushu	0.081	0.064	0.078	0.043	0.256	0.166	0.243	0.024	0.081	0.061	0.077	0.038
62	Japan	Kobe	0.280	0.195	0.262	0.081	0.287	0.191	0.267	0.064	0.280	0.194	0.264	0.079
63	Japan	Nagoya	0.773	0.619	0.744	0.412	0.794	0.609	0.744	0.382	0.773	0.611	0.721	0.420
64	Japan	Osaka	0.482	0.335	0.461	0.084	0.491	0.333	0.469	0.077	0.482	0.339	0.467	0.082
65	Japan	Tokyo	0.525	0.391	0.502	0.228	0.525	0.380	0.482	0.202	0.525	0.391	0.500	0.225
66	Japan	Yokohama	1.000	0.682	0.915	0.161	1.000	0.665	0.914	0.149	1.000	0.689	0.940	0.158
67	Kenya	Mombasa	0.082	0.061	0.079	0.029	0.082	0.060	0.078	0.027	0.082	0.062	0.079	0.029
68	Kuwait	Kuwait	0.006	0.005	0.006	0.002	0.006	0.004	0.006	0.002	0.006	0.005	0.006	0.002
69	Lebanon	Beirut	0.437	0.349	0.418	0.217	0.479	0.368	0.448	0.203	0.437	0.349	0.416	0.215
70	Malaysia	Pasir Gudang	0.047	0.036	0.045	0.021	0.047	0.035	0.043	0.020	0.047	0.036	0.044	0.021
71	Malaysia	Penang	0.282	0.212	0.270	0.132	0.328	0.217	0.307	0.058	0.282	0.212	0.263	0.131
72	Malaysia	Port Klang	0.660	0.502	0.614	0.336	0.896	0.683	0.809	0.447	0.896	0.703	0.858	0.501
73	Malaysia	Tanjung Pelepas	0.381	0.277	0.356	0.128	0.381	0.274	0.358	0.131	0.381	0.280	0.359	0.141
74	Malta	Marsaxlokk	0.153	0.110	0.145	0.046	0.153	0.107	0.144	0.045	0.153	0.110	0.145	0.049
75	Mexico	Manzanillo	0.517	0.372	0.488	0.159	0.573	0.398	0.531	0.154	0.517	0.370	0.487	0.159
76	Morocco	Tangier	0.269	0.190	0.253	0.077	0.271	0.187	0.254	0.066	0.269	0.191	0.256	0.080
77	Netherland	Rotterdam	1.000	0.641	0.939	0.171	1.000	0.611	0.900	0.094	1.000	0.630	0.923	0.158
78	Netherlands	Amsterdam	0.000	0.000	0.000	0.000	0.005	0.003	0.004	0.001	0.000	0.000	0.000	0.000
79	Oman	Salalah	1.000	0.701	0.951	0.379	1.000	0.661	0.929	0.283	1.000	0.697	0.947	0.382
80	Pakistan	Karachi	0.188	0.140	0.177	0.084	0.191	0.141	0.179	0.085	0.188	0.142	0.176	0.085
81	Panama	Balboa	0.255	0.203	0.237	0.141	0.261	0.195	0.239	0.117	0.261	0.201	0.242	0.131
82	Panama	Manzanillo	0.003	0.002	0.003	0.001	0.003	0.002	0.003	0.001	0.003	0.002	0.003	0.001

83	Peru	Callao	0.198	0.158	0.190	0.103	0.198	0.154	0.187	0.100	0.198	0.158	0.188	0.108
84	Philippines	Manila	0.001	0.001	0.001	0.000	0.001	0.001	0.001	0.000	0.001	0.001	0.001	0.000
85	Romania	Constantza	0.161	0.130	0.155	0.087	0.168	0.129	0.156	0.077	0.161	0.130	0.154	0.087
86	Russia	Novorossisk	0.038	0.029	0.036	0.015	0.038	0.028	0.035	0.015	0.038	0.029	0.037	0.017
87	Russia	St. Petersburg	0.021	0.017	0.019	0.012	0.031	0.023	0.029	0.015	0.031	0.024	0.029	0.016
88	Saudi Arabia	Dammam	0.044	0.033	0.041	0.018	0.050	0.036	0.045	0.019	0.050	0.037	0.047	0.020
89	Saudi Arabia	Jeddah	1.000	0.689	0.930	0.388	1.000	0.657	0.911	0.316	1.000	0.689	0.939	0.397
90	Saudi Arabia	Yanbu	0.003	0.002	0.003	0.001	0.003	0.002	0.003	0.001	0.003	0.002	0.003	0.001
91	Singapore	Singapore	0.727	0.538	0.681	0.296	0.926	0.662	0.858	0.355	0.926	0.679	0.881	0.397
92	South Africa	Cape Town	0.590	0.429	0.563	0.174	0.787	0.547	0.746	0.142	0.590	0.429	0.558	0.166
93	South Korea	Busan	1.000	0.781	0.916	0.517	1.000	0.732	0.927	0.418	1.000	0.755	0.916	0.467
94	South Korea	Incheon	0.089	0.064	0.083	0.034	0.092	0.064	0.085	0.030	0.089	0.064	0.083	0.034
95	Spain	Algeciras	0.712	0.547	0.667	0.330	0.712	0.529	0.664	0.286	0.712	0.553	0.684	0.317
96	Spain	Barcelona	0.079	0.060	0.074	0.034	0.115	0.085	0.110	0.047	0.115	0.087	0.111	0.053
97	Spain	Bilbao	0.040	0.028	0.038	0.009	0.050	0.033	0.046	0.008	0.040	0.027	0.038	0.008
98	Spain	Las Palmas	0.151	0.107	0.147	0.040	0.151	0.103	0.143	0.031	0.151	0.106	0.146	0.039
99	Spain	Tarragona	0.090	0.073	0.086	0.043	0.096	0.077	0.093	0.043	0.090	0.073	0.086	0.043
100	Sri Lanka	Colombo	0.172	0.135	0.159	0.092	0.198	0.150	0.182	0.094	0.198	0.155	0.187	0.100
101	Sweden	Stockholm	0.010	0.008	0.010	0.006	0.012	0.010	0.012	0.006	0.010	0.008	0.010	0.006
102	Thailand	Laem Chabang	0.252	0.199	0.239	0.142	0.315	0.243	0.291	0.168	0.315	0.249	0.297	0.182
103	Turkey	Ambarli	0.483	0.373	0.467	0.195	0.486	0.367	0.471	0.187	0.483	0.375	0.470	0.195
104	Turkey	Mersin	0.197	0.156	0.193	0.083	0.199	0.155	0.196	0.081	0.197	0.157	0.193	0.082
105	United Arab Emirates	Jebel Ali	0.365	0.289	0.352	0.205	0.461	0.357	0.425	0.247	0.461	0.366	0.431	0.266
106	United Arab Emirates	Khor Fakkan	1.000	0.826	0.955	0.593	1.000	0.694	0.919	0.330	1.000	0.819	0.946	0.586
107	United Kingdom	Felixstowe	1.000	0.738	0.935	0.450	1.000	0.707	0.913	0.390	1.000	0.742	0.944	0.465
108	United Kingdom	Southampton	0.100	0.072	0.096	0.031	0.104	0.072	0.098	0.028	0.100	0.071	0.096	0.031
109	Uruguay	Montevideo	0.249	0.189	0.234	0.113	0.249	0.184	0.234	0.105	0.249	0.191	0.238	0.118
110	USA	Charleston	0.454	0.370	0.426	0.266	0.455	0.359	0.432	0.249	0.454	0.371	0.427	0.271
111	USA	Hampton Roads	0.869	0.741	0.847	0.518	0.949	0.790	0.927	0.509	0.869	0.742	0.845	0.533
112	USA	Honolulu	0.356	0.278	0.336	0.187	1.000	0.628	0.921	0.079	0.356	0.268	0.334	0.168
113	USA	Houston	0.064	0.048	0.060	0.030	0.071	0.053	0.065	0.032	0.071	0.054	0.066	0.034
114	USA	Jacksonville	0.239	0.203	0.231	0.141	0.259	0.214	0.253	0.137	0.239	0.203	0.232	0.145
115	USA	Long Beach	0.260	0.211	0.257	0.118	0.260	0.204	0.255	0.108	0.260	0.212	0.256	0.117
116	USA	Los Angeles	0.772	0.548	0.726	0.214	0.822	0.544	0.773	0.136	0.772	0.541	0.725	0.202
117	USA	Miami	0.137	0.098	0.127	0.046	0.137	0.094	0.126	0.034	0.137	0.097	0.129	0.042
118	USA	Mobile	0.059	0.047	0.058	0.025	0.060	0.047	0.059	0.024	0.059	0.048	0.058	0.025
119	USA	New Orleans	0.391	0.329	0.366	0.257	0.413	0.318	0.387	0.192	0.391	0.326	0.371	0.255
120	USA	New York	0.207	0.159	0.191	0.108	0.251	0.190	0.231	0.122	0.251	0.194	0.238	0.127
121	USA	Oakland	0.420	0.335	0.413	0.184	0.420	0.324	0.407	0.171	0.420	0.336	0.411	0.184
122	USA	Port Everglades	0.209	0.166	0.205	0.086	0.209	0.163	0.206	0.083	0.209	0.167	0.206	0.085
123	USA	Savannah	0.202	0.145	0.191	0.053	0.202	0.141	0.187	0.053	0.202	0.145	0.192	0.054
124	USA	Seattle	0.159	0.122	0.154	0.066	0.159	0.118	0.151	0.060	0.159	0.123	0.153	0.065
125	USA	Tacoma	0.077	0.058	0.075	0.031	0.077	0.057	0.073	0.027	0.077	0.059	0.074	0.030
126	Venezuela	Puerto Cabello	0.246	0.199	0.226	0.144	0.395	0.305	0.377	0.162	0.246	0.196	0.231	0.141

Notes:

1 Author's calculation

2 Ports ranked by Bootstrapped DEA scores

Table A.3: DEA scores[1] under varying assumptions on returns to scale for crude oil terminals

DEA Model specification

Output: y1=crude oil (DWT)
Inputs: x1=Quay length, x2=Max vessel capacity (dwt), x3=Max draught/depth, x4=Tank storage capacity (m3), x5=Discharge rate (t/h) , x6=Pipeline/loading arm capacity (mm)

			Constant returns to scale (CRS)				Varying returns to scale (VRS)				Non increasing returns to scale (NIRS)			
			Standard DEA	Bootstrapped DEA			Standard DEA	Bootstrapped DEA			Standard DEA	Bootstrapped DEA		
DMU	Country	Port	Score	Score[2]	Upper value	Lower value	Score	Score	Upper value	Lower value	Score	Score	Upper value	Lower value
7	USA	Galveston	1.000	0.730	0.906	0.358	1.000	0.640	0.967	0.099	1.000	0.736	0.907	0.356
8	United Arab Emirates	Jebel Dhanna Terminal	0.964	0.722	0.902	0.371	1.000	0.758	0.951	0.454	0.964	0.720	0.903	0.368
3	Iran	Kharg Is.	0.963	0.718	0.929	0.311	0.968	0.798	0.949	0.518	0.963	0.718	0.926	0.324
2	Saudi Arabia	Juaymah Terminal	1.000	0.691	0.894	0.212	1.000	0.755	0.949	0.403	1.000	0.690	0.874	0.226
16	Qatar	Ras Laffan	0.907	0.687	0.835	0.410	1.000	0.634	0.965	0.000	0.907	0.686	0.833	0.396
5	Kuwait	Mina al Ahmadi	0.807	0.616	0.781	0.270	0.817	0.685	0.800	0.431	0.807	0.613	0.778	0.270
1	United Arab Emirates	Fujairah Anch.	1.000	0.599	0.897	0.124	1.000	0.655	0.955	0.103	1.000	0.602	0.890	0.125
4	Saudi Arabia	Ras Tanura	1.000	0.587	0.839	0.066	1.000	0.644	0.964	0.001	1.000	0.583	0.881	0.070
6	Netherlands	Rotterdam	0.748	0.542	0.706	0.200	0.782	0.628	0.752	0.373	0.748	0.540	0.702	0.208
13	Russia	Primorsk	0.664	0.496	0.631	0.239	1.000	0.704	0.968	0.234	0.664	0.500	0.629	0.231
14	USA	Long Beach	0.605	0.480	0.577	0.270	0.605	0.467	0.594	0.225	0.605	0.484	0.580	0.290
10	South Korea	Yosu	0.602	0.462	0.555	0.293	0.800	0.652	0.771	0.472	0.602	0.464	0.549	0.293
28	USA	Corpus Christi	0.580	0.452	0.548	0.280	0.711	0.504	0.675	0.104	0.580	0.451	0.545	0.272
9	India	Jamnagar Terminal	0.583	0.436	0.564	0.158	0.590	0.490	0.577	0.294	0.583	0.437	0.565	0.170
33	China	Hong Kong	0.551	0.428	0.519	0.265	1.000	0.638	0.974	0.001	0.551	0.428	0.518	0.261
11	China	Ningbo	0.517	0.404	0.481	0.265	0.646	0.536	0.624	0.417	0.517	0.405	0.479	0.269
15	China	Qingdao	0.628	0.401	0.576	0.078	1.000	0.638	0.960	0.000	0.628	0.401	0.576	0.078
20	Malaysia	Pasir Gudang	0.427	0.338	0.398	0.208	0.429	0.312	0.415	0.117	0.427	0.340	0.400	0.202
27	South Korea	Daesan	0.467	0.328	0.431	0.153	1.000	0.638	0.964	0.023	0.467	0.330	0.435	0.145
17	Russia	Novorossiysk/ Commercial Sea Port	0.395	0.324	0.382	0.230	0.469	0.403	0.455	0.327	0.395	0.325	0.379	0.231
18	China	Zhoushan	0.390	0.322	0.376	0.224	0.511	0.445	0.496	0.355	0.390	0.323	0.374	0.229
12	South Korea	Ulsan	0.432	0.319	0.416	0.117	0.437	0.357	0.424	0.216	0.432	0.319	0.415	0.124
22	France	Fos	0.371	0.292	0.352	0.158	0.371	0.276	0.364	0.126	0.371	0.295	0.357	0.169
24	USA	Texas City	0.368	0.290	0.357	0.157	1.000	0.768	0.945	0.469	0.368	0.292	0.357	0.153
25	Bahamas	Freeport	0.365	0.277	0.350	0.138	0.550	0.409	0.542	0.139	0.365	0.279	0.351	0.132
19	Mexico	Cayo Arcas	0.365	0.267	0.345	0.109	0.395	0.316	0.382	0.196	0.365	0.266	0.343	0.112
23	Italy	Trieste	0.278	0.219	0.252	0.151	0.438	0.364	0.423	0.284	0.278	0.220	0.258	0.154

31	Spain	Algeciras	0.278	0.213	0.270	0.112	0.419	0.320	0.414	0.110	0.278	0.215	0.269	0.107
36	South Africa	Durban	0.224	0.177	0.218	0.097	0.698	0.547	0.664	0.346	0.224	0.179	0.220	0.100
32	India	Paradip	0.217	0.174	0.203	0.118	0.353	0.295	0.338	0.221	0.217	0.175	0.204	0.121
43	India	Jawaharlal Nehru	0.226	0.157	0.216	0.062	1.000	0.630	0.959	0.027	0.226	0.157	0.218	0.058
37	India	New Mangalore	0.211	0.153	0.201	0.064	0.798	0.605	0.781	0.280	0.211	0.154	0.201	0.065
29	Taiwan	Kaohsiung	0.192	0.151	0.183	0.094	0.209	0.178	0.202	0.135	0.192	0.152	0.183	0.095
21	Saudi Arabia	Yanbu	0.209	0.149	0.197	0.050	0.212	0.167	0.205	0.096	0.209	0.149	0.193	0.052
39	Iran	Bandar Abbas	0.182	0.141	0.176	0.073	0.650	0.516	0.630	0.322	0.182	0.143	0.175	0.070
26	France	Le Havre	0.182	0.133	0.169	0.061	0.184	0.146	0.175	0.093	0.182	0.132	0.165	0.060
30	Japan	Kawasaki	0.166	0.132	0.158	0.085	0.183	0.155	0.177	0.117	0.166	0.132	0.156	0.086
41	Spain	Las Palmas	0.172	0.128	0.163	0.062	0.894	0.727	0.869	0.449	0.172	0.129	0.164	0.058
35	Taiwan	Mai-Liao	0.157	0.126	0.150	0.086	0.196	0.168	0.190	0.134	0.157	0.127	0.147	0.087
34	UK	Milford Haven	0.153	0.126	0.147	0.084	0.192	0.168	0.186	0.132	0.153	0.126	0.147	0.087
38	Japan	Mizushima	0.150	0.119	0.137	0.084	0.230	0.196	0.223	0.155	0.150	0.120	0.137	0.086
44	Australia	Brisbane	0.148	0.111	0.140	0.060	0.453	0.351	0.434	0.195	0.148	0.112	0.139	0.060
47	South Korea	Incheon	0.128	0.102	0.123	0.061	0.186	0.151	0.182	0.082	0.128	0.102	0.123	0.062
50	Sweden	Gothenburg	0.129	0.100	0.122	0.056	0.138	0.111	0.134	0.070	0.129	0.101	0.124	0.055
46	India	Visakhapatnam	0.131	0.095	0.124	0.050	0.233	0.184	0.225	0.124	0.131	0.095	0.119	0.051
49	Spain	Bilbao	0.104	0.085	0.102	0.052	0.158	0.129	0.156	0.067	0.104	0.086	0.103	0.053
51	Pakistan	Karachi	0.099	0.076	0.094	0.044	0.221	0.170	0.213	0.095	0.099	0.076	0.094	0.044
45	China	Xingang	0.086	0.071	0.083	0.048	0.096	0.084	0.094	0.068	0.086	0.071	0.083	0.048
48	Japan	Yokohama	0.084	0.070	0.081	0.048	0.106	0.093	0.103	0.074	0.084	0.070	0.081	0.049
40	Italy	Genoa	0.095	0.069	0.091	0.023	0.095	0.077	0.093	0.044	0.095	0.069	0.091	0.024
53	India	Chennai	0.052	0.043	0.050	0.029	0.083	0.068	0.080	0.051	0.052	0.043	0.050	0.029
52	Japan	Nagoya	0.044	0.037	0.044	0.026	0.053	0.046	0.051	0.037	0.044	0.038	0.043	0.026
55	USA	Honolulu	0.047	0.035	0.045	0.017	0.243	0.201	0.239	0.123	0.047	0.035	0.046	0.016
57	Romania	Constantza	0.040	0.032	0.039	0.018	0.060	0.047	0.059	0.020	0.040	0.032	0.039	0.019
58	USA	Savannah	0.038	0.026	0.037	0.009	1.000	0.730	0.947	0.353	0.038	0.026	0.037	0.009
54	Italy	Taranto	0.030	0.022	0.028	0.013	0.037	0.030	0.035	0.021	0.030	0.022	0.028	0.013
56	South Korea	Gwangyang	0.025	0.020	0.024	0.013	0.029	0.024	0.027	0.019	0.025	0.020	0.024	0.013
60	Thailand	Bangkok	0.024	0.016	0.023	0.006	1.000	0.636	0.947	0.000	0.024	0.016	0.023	0.006
42	Japan	Chiba	0.025	0.016	0.024	0.004	0.025	0.018	0.025	0.004	0.025	0.016	0.024	0.004
59	USA	Port Everglades	0.021	0.014	0.020	0.005	0.442	0.334	0.427	0.184	0.021	0.014	0.020	0.005
63	Indonesia	Jakarta	0.020	0.014	0.019	0.006	1.000	0.632	0.951	0.001	0.020	0.014	0.019	0.005
61	Kenya	Mombasa	0.017	0.012	0.015	0.007	0.023	0.016	0.023	0.001	0.017	0.012	0.015	0.006
66	UK	London	0.015	0.011	0.014	0.005	1.000	0.642	0.965	0.001	0.015	0.011	0.014	0.005
62	Russia	St. Petersburg	0.012	0.008	0.011	0.004	0.100	0.080	0.097	0.053	0.012	0.008	0.011	0.004
64	Peru	Callao	0.010	0.007	0.009	0.003	0.049	0.041	0.048	0.025	0.010	0.007	0.009	0.003
65	Oman	Salalah	0.008	0.006	0.008	0.003	1.000	0.638	0.953	0.001	0.008	0.006	0.008	0.003
67	Turkey	Ambarli	0.004	0.003	0.004	0.001	0.010	0.007	0.009	0.003	0.004	0.003	0.004	0.002
68	Japan	Kokura	0.001	0.000	0.001	0.000	0.001	0.001	0.001	0.001	0.001	0.000	0.001	0.000
70	Japan	Kobe	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
69	Malta	Marsaxlokk	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes:

1 Author's calculation

2 Ports ranked by Bootstrapped DEA scores

Table A.4: DEA scores[1] under varying assumptions on returns to scale for iron-ore terminals

DEA Model specification

Output: y1=iron ore (DWT)
Inputs: x1=Quay length, x2=Maximum depth (m), x3=Loading/unloading capacity (t/h), x4=Storage capacity (tonnes)

			Constant returns to scale (CRS)				**Varying returns to scale (VRS)**				**Non increasing returns to scale (NIRS)**			
			Standard DEA	Bootstrapped DEA			Standard DEA	Bootstrapped DEA			Standard DEA	Bootstrapped DEA		
DMU	Country	Port	Score	Score[2]	Upper value	Lower value	Score	Score	Upper value	Lower value	Score	Score	Upper value	Lower value
3	Australia	Port Walcott	0.949	0.777	0.937	0.472	1.000	0.828	0.978	0.580	0.949	0.764	0.934	0.460
1	Brazil	Ponta da Madeira	1.000	0.733	0.946	0.354	1.000	0.783	0.979	0.461	1.000	0.725	0.951	0.337
5	Brazil	Sepetiba	0.873	0.718	0.861	0.459	0.943	0.812	0.929	0.592	0.873	0.709	0.861	0.435
7	Australia	Gladstone	0.767	0.642	0.760	0.417	1.000	0.738	0.983	0.182	0.767	0.643	0.759	0.415
2	Brazil	Tubarao	0.679	0.513	0.662	0.257	0.684	0.563	0.677	0.333	0.684	0.510	0.668	0.237
12	China	Shanghai	0.600	0.506	0.594	0.334	1.000	0.732	0.979	0.128	0.600	0.506	0.594	0.330
6	South Africa	Saldanha Bay	0.587	0.476	0.577	0.289	1.000	0.733	0.979	0.128	0.587	0.475	0.578	0.290
4	Australia	Dampier	0.506	0.401	0.496	0.211	0.592	0.509	0.582	0.360	0.506	0.398	0.494	0.206
13	India	Visakhapatnam	0.349	0.294	0.346	0.194	1.000	0.735	0.979	0.129	0.349	0.294	0.346	0.189
14	Canada	Seven Islands	0.283	0.240	0.281	0.160	1.000	0.736	0.981	0.129	0.283	0.240	0.281	0.158
8	Netherlands	Velsen/Ijmuiden	0.257	0.205	0.252	0.124	0.272	0.230	0.266	0.159	0.257	0.204	0.251	0.122
10	Germany	Hamburg	0.248	0.198	0.243	0.112	1.000	0.739	0.979	0.130	0.248	0.198	0.242	0.117
15	China	Guangzhou	0.195	0.163	0.193	0.106	1.000	0.733	0.980	0.128	0.195	0.163	0.193	0.105
9	Japan	Kashima	0.180	0.139	0.176	0.071	0.250	0.209	0.246	0.146	0.180	0.138	0.176	0.072
11	Australia	Port Hedland	0.103	0.080	0.100	0.041	0.128	0.110	0.126	0.078	0.103	0.079	0.100	0.041

Notes:

1 Author's calculation

2 Ports ranked by Bootstrapped DEA scores

Table A.5: DEA scores[1] under varying assumptions on returns to scale for coal bulk terminals

DEA Model specification

Output: y1=coal (DWT)
Inputs: x1=Quay length, x2=Storage capacity (tonnes), x3=Loading/unloading (total capacity per h)

			Constant returns to scale (CRS)				Varying returns to scale (VRS)				Non increasing returns to scale (NIRS)			
			Standard DEA	Bootstrapped DEA			Standard DEA	Bootstrapped DEA			Standard DEA	Bootstrapped DEA		
DMU	Country	Port	Score	Score[2]	Upper value	Lower value	Score	Score	Upper value	Lower value	Score	Score	Upper value	Lower value
3	Australia	Hay Point	1.000	0.755	0.925	0.426	1.000	0.718	0.928	0.392	1.000	0.724	0.890	0.393
9	Netherlands	Velsen/Ijmuiden	1.000	0.676	0.888	0.248	1.000	0.667	0.893	0.175	1.000	0.678	0.896	0.259
11	Indonesia	Banjarmarsin	0.969	0.670	0.853	0.265	0.969	0.644	0.874	0.167	0.969	0.670	0.867	0.276
10	China	Shanghai	0.948	0.669	0.887	0.269	1.000	0.593	0.900	0.046	0.948	0.676	0.894	0.272
2	China	Qinhuangdao	1.000	0.664	0.903	0.241	1.000	0.643	0.875	0.229	1.000	0.642	0.887	0.228
1	Australia	Newcastle	1.000	0.660	0.895	0.259	1.000	0.646	0.905	0.240	1.000	0.643	0.895	0.242
4	China	Rizhao	1.000	0.660	0.859	0.208	1.000	0.662	0.901	0.208	1.000	0.667	0.873	0.218
12	China	Guangzhou	1.000	0.657	0.855	0.234	1.000	0.595	0.912	0.045	1.000	0.655	0.890	0.236
7	Australia	Gladstone	1.000	0.628	0.866	0.174	1.000	0.594	0.908	0.046	1.000	0.628	0.887	0.173
13	Colombia	Puerto Bolivar	0.917	0.598	0.842	0.173	1.000	0.594	0.894	0.045	0.917	0.603	0.864	0.168
16	Japan	Oita	0.541	0.382	0.489	0.154	0.541	0.352	0.504	0.070	0.541	0.379	0.497	0.161
5	Brazil	Sepetiba	0.477	0.363	0.447	0.213	0.676	0.520	0.644	0.310	0.676	0.516	0.639	0.304
23	Italy	Taranto	0.419	0.317	0.395	0.160	1.000	0.595	0.891	0.046	0.419	0.309	0.388	0.159
8	South Africa	Richards Bay	0.446	0.291	0.399	0.095	0.576	0.389	0.526	0.150	0.576	0.386	0.525	0.151
6	India	Paradip	0.362	0.265	0.328	0.145	0.646	0.507	0.620	0.303	0.646	0.503	0.616	0.297
15	Canada	Vancouver	0.280	0.216	0.259	0.129	0.281	0.206	0.259	0.116	0.280	0.207	0.259	0.119
27	Egypt	Alexandria	0.256	0.186	0.240	0.082	1.000	0.597	0.892	0.046	0.256	0.182	0.234	0.084
19	Japan	Nagoya	0.244	0.172	0.229	0.064	0.294	0.197	0.265	0.060	0.244	0.175	0.231	0.068
18	Australia	Port Kembla	0.192	0.139	0.178	0.064	0.205	0.145	0.191	0.067	0.205	0.145	0.187	0.067
17	Australia	Abbot Point	0.183	0.130	0.165	0.060	0.204	0.144	0.186	0.069	0.204	0.143	0.180	0.067
20	Netherlands	Amsterdam	0.191	0.129	0.177	0.044	0.205	0.137	0.183	0.044	0.191	0.131	0.179	0.047
14	Indonesia	Tanjung Bara	0.132	0.093	0.120	0.044	0.239	0.182	0.226	0.105	0.239	0.180	0.225	0.102
25	Indonesia	Balikpapan	0.130	0.092	0.119	0.038	0.146	0.100	0.130	0.044	0.146	0.103	0.130	0.047
22	USA	Mobile	0.091	0.069	0.085	0.039	0.099	0.073	0.092	0.041	0.099	0.073	0.091	0.040
21	USA	Baltimore	0.091	0.066	0.086	0.028	0.109	0.079	0.101	0.039	0.109	0.078	0.100	0.036
29	USA	Long Beach	0.088	0.061	0.083	0.023	0.091	0.060	0.082	0.017	0.088	0.062	0.083	0.024
26	Spain	Tarragona	0.082	0.055	0.076	0.018	0.082	0.056	0.078	0.018	0.082	0.056	0.077	0.019
24	USA	Hampton Roads/Norfolk	0.068	0.050	0.064	0.024	0.079	0.057	0.071	0.029	0.079	0.057	0.071	0.028
33	Italy	La Spezia	0.059	0.043	0.053	0.022	0.077	0.049	0.071	0.006	0.059	0.043	0.053	0.022
30	Poland	Swinoujscie	0.057	0.042	0.052	0.023	0.060	0.043	0.054	0.023	0.060	0.044	0.054	0.024
31	Australia	Brisbane	0.049	0.037	0.044	0.021	0.049	0.035	0.044	0.019	0.049	0.035	0.044	0.019

28	Canada	Prince Rupert	0.046	0.033	0.043	0.014	0.058	0.042	0.054	0.020	0.058	0.041	0.054	0.019
32	Poland	Gdansk	0.031	0.023	0.028	0.014	0.043	0.033	0.040	0.020	0.043	0.033	0.040	0.020
34	Estonia	Tallinn	0.012	0.008	0.011	0.003	1.000	0.596	0.907	0.046	0.012	0.009	0.011	0.004

Notes:

1 Author's calculation

2 Ports ranked by Bootstrapped DEA scores

Table A.6: DEA scores[1] under varying assumptions on returns to scale for grain bulk terminals

DEA Model specification

Output: y1= grains (DWT)
Inputs: x1=Quay length, x2=Storage capacity (tonnes), x3=Loading/unloading (total capacity per h)

			Constant returns to scale (CRS)				Varying returns to scale (VRS)				Non increasing returns to scale (NIRS)			
			Standard DEA	Bootstrapped DEA			Standard DEA	Bootstrapped DEA			Standard DEA	Bootstrapped DEA		
DMU	Country	Port	Score	Score[2]	Upper value	Lower value	Score	Score	Upper value	Lower value	Score	Score	Upper value	Lower value
1	Japan	Chiba	1.000	0.583	0.781	0.079	1.000	0.592	0.805	0.077	1.000	0.608	0.831	0.109
2	Argentina	San Lorenz-San Martin	1.000	0.551	0.689	0.056	1.000	0.539	0.682	0.010	1.000	0.556	0.762	0.053
3	Argentina	Bahia Blanca	1.000	0.567	0.693	0.072	1.000	0.540	0.706	0.010	1.000	0.584	0.760	0.094
4	USA	Duluth	1.000	0.569	0.676	0.078	1.000	0.539	0.701	0.010	1.000	0.579	0.771	0.085
5	South Korea	Busan	0.960	0.555	0.732	0.087	1.000	0.539	0.671	0.010	0.960	0.566	0.817	0.097
6	Argentina	Rosario	0.185	0.124	0.154	0.044	0.455	0.339	0.434	0.146	0.455	0.351	0.437	0.176
7	Brazil	Rio Grande	0.383	0.249	0.310	0.079	0.463	0.292	0.378	0.090	0.463	0.304	0.398	0.115
8	Brazil	Tubarao	1.000	0.608	0.771	0.134	1.000	0.541	0.730	0.010	1.000	0.628	0.831	0.171
9	South Korea	Incheon	0.271	0.166	0.227	0.037	0.338	0.204	0.269	0.044	0.338	0.213	0.286	0.060
10	Japan	Mizushima	0.213	0.139	0.166	0.045	0.327	0.220	0.268	0.084	0.327	0.228	0.281	0.101
11	Taiwan	Taichung	0.209	0.137	0.168	0.046	0.321	0.217	0.268	0.085	0.321	0.225	0.283	0.102
12	China	Shanghai	0.243	0.150	0.177	0.039	0.343	0.215	0.269	0.065	0.343	0.224	0.289	0.084
13	Canada	Vancouver	0.649	0.417	0.510	0.127	1.000	0.541	0.667	0.010	0.649	0.414	0.501	0.142
14	Japan	Kashima	0.275	0.166	0.213	0.030	0.275	0.166	0.210	0.026	0.275	0.174	0.227	0.041
15	USA	Houston	0.169	0.109	0.139	0.033	0.187	0.115	0.145	0.031	0.187	0.120	0.156	0.041
16	USA	Mobile	0.402	0.247	0.307	0.061	1.000	0.538	0.673	0.010	0.402	0.254	0.328	0.072
17	Canada	Montreal	0.063	0.042	0.053	0.015	0.146	0.108	0.139	0.046	0.146	0.112	0.140	0.055
18	Canada	Thunder Bay	0.555	0.348	0.503	0.079	1.000	0.540	0.702	0.010	0.555	0.353	0.503	0.089
19	Brazil	Santos	0.083	0.052	0.067	0.014	0.131	0.084	0.104	0.027	0.131	0.087	0.113	0.033
20	Kuwait	Kuwait	0.099	0.064	0.083	0.019	0.125	0.080	0.106	0.024	0.125	0.083	0.112	0.031
21	Netherland	Rotterdam	0.119	0.072	0.101	0.010	0.119	0.071	0.099	0.009	0.119	0.074	0.104	0.012
22	France	Rouen	0.409	0.258	0.372	0.059	0.736	0.416	0.605	0.017	0.409	0.263	0.377	0.067
23	Australia	Geraldton	0.050	0.030	0.039	0.007	0.101	0.064	0.084	0.020	0.101	0.067	0.087	0.025
24	Canada	Baie Comeau	0.035	0.023	0.029	0.007	0.073	0.050	0.065	0.021	0.073	0.052	0.067	0.024
25	USA	Beaumont	0.042	0.025	0.033	0.005	0.073	0.045	0.058	0.011	0.073	0.047	0.063	0.015
26	Belgium	Ghent	0.035	0.023	0.028	0.007	0.055	0.038	0.048	0.014	0.055	0.039	0.049	0.017
27	Israel	Haifa	0.020	0.013	0.017	0.003	0.047	0.033	0.044	0.013	0.047	0.034	0.045	0.015
28	Australia	Port Kembla	0.030	0.018	0.023	0.004	0.043	0.026	0.034	0.006	0.043	0.027	0.037	0.007
29	Australia	Freemantle	0.061	0.037	0.047	0.008	0.061	0.036	0.048	0.005	0.061	0.039	0.050	0.010
30	China	Tianjin	0.033	0.019	0.026	0.003	0.033	0.019	0.026	0.002	0.033	0.020	0.028	0.004
31	Australia	Newcastle	0.020	0.013	0.017	0.005	0.028	0.019	0.024	0.007	0.028	0.019	0.026	0.008
32	USA	Lake Charles	0.036	0.023	0.033	0.005	0.038	0.023	0.030	0.004	0.036	0.023	0.031	0.006

33	Japan	Hachinohe	0.053	0.032	0.042	0.007	0.053	0.030	0.043	0.003	0.053	0.033	0.046	0.009
34	South Africa	East London	0.011	0.007	0.009	0.001	0.025	0.016	0.021	0.005	0.025	0.017	0.023	0.006
35	Egypt	Port Said	0.046	0.029	0.042	0.007	0.054	0.032	0.043	0.006	0.046	0.029	0.042	0.007
36	Australia	Brisbane	0.009	0.006	0.008	0.002	0.020	0.014	0.018	0.006	0.020	0.014	0.019	0.007
37	Spain	Valencia	0.009	0.005	0.006	0.001	0.017	0.010	0.014	0.002	0.017	0.011	0.015	0.003
38	Argentina	Buenos Aires	0.014	0.008	0.012	0.001	0.014	0.008	0.011	0.001	0.014	0.009	0.012	0.001
39	Australia	Portland	0.011	0.007	0.008	0.002	0.013	0.009	0.011	0.003	0.013	0.009	0.011	0.003
40	UK	Southampton	0.005	0.003	0.004	0.001	0.011	0.008	0.010	0.003	0.011	0.008	0.010	0.004
41	Italy	Trieste	0.001	0.000	0.001	0.000	0.001	0.001	0.001	0.000	0.001	0.001	0.001	0.001

Notes:

1 Author's calculation

2 Ports ranked by Bootstrapped DEA scores

NOTES

1 However, according to the review by Trujillo and Gonzales (2008) there are about an equal number of studies exploring efficiency via estimating a stochastic frontier production with a predefined functional form, suggesting the absence of consensus vis-à-vis the best approach to be used.

2 Cheon, *et al.*, 2010; Wu and Goh, 2010; Martinez-Budria, *et al.*, 2009; Wang and Cullinane, 2006; Al-Eraqui, *et al.*, 2007; Tongzon, 2001

3 This mainly legitimates stochastic frontiers and econometrics approaches though they impose a functional form to the production.

4 Bootstrapping is a re-sampling method consists in constructing a number of resamples of the observed dataset, and of equal size, where each of these is obtained by random sampling with replacement from the original dataset.