Operational Research (2022) 22:2667–2701
https://doi.org/10.1007/s12351-021-00626-5

ORIGINAL PAPER

Efficiency drivers for the South Pacific West coast port terminals: a two-stage non-convex metafrontier dea approach

Víctor Chang[1] · Beatriz Tovar[2]

Received: 26 November 2019 / Revised: 28 January 2021 / Accepted: 2 February 2021 / Published online: 28 February 2021

Abstract

We measure technical efficiency of Peruvian and Chilean port terminals, to evaluate the influence of certain contextual variables in the terminals' efficiency levels. The sample includes 14 port terminals from 2004 to 2014. Due to the potential differences, we have estimated a DEA model in a non-convex metafrontier framework. Afterwards, we estimated all the regression models proposed in the literature that could be used to explain not only the technical efficiency estimated with respect to the metafrontier (TE^*) but also each one of its components: the technical efficiency with respect to the group-specific frontier (TE^k) and the technological gap ratio (TGR). Results are robust across models.

Keywords Two-stage DEA non-convex metafrontier · Fractional regression models · Bootstrap truncated regression · Port terminals · Technological gap ratio · Efficiency drivers

Mathematics Subject Classification 90B30

✉ Beatriz Tovar
beatriz.tovar@ulpgc.es
http://www.personales.ulpgc.es/btovar.daea

Víctor Chang
c20795@utp.edu.pe

[1] Universidad Tecnológica del Perú, Av. Petit Thouars 385 / Av. Arequipa 265, Cercado de Lima 15046, Lima, Peru

[2] Tourism and Transport Research Unit, Institute of Tourism and Sustainable Economic Development, University of Las Palmas de Gran Canaria, Campus de Tafira, Modulo D, Despacho 2.20, 35017 Las Palmas de Gran Canaria, Spain

1 Introduction

Data envelopment analysis (DEA) and Stochastic frontier analysis (SFA) are well-known methods to measure productivity and/or efficiency and their drivers. However, whereas SFA does it in one step, DEA has to do it in a two-stage process: in the first step, the efficiency scores are measured and, in the second one, those measures are explained. DEA is the most popular method used in measuring efficiency/productivity in the port sector (Woo et al, 2011)[1] and it is also frequently used to evaluate, among others, the consequences of port reforms and the impact of regulation on port efficiency. For these reasons, it is paramount to analyse, from the methodological and empirical point of view, how these two stages are performed to obtain accurate estimates. For example, are the potential technological differences between the DMUs taken into account in the first-stage? How is the second-stage-regression model chosen?

Recently, Chang and Tovar (2014b) have measured technical efficiency (TE) of port terminals in Peru and Chile to identify efficiency drivers. They did it following a stochastic frontier approach. Due to the fact that Data Envelopment Analysis (DEA) has been used extensively for the measurement of port and terminal efficiency (Panayides et al. 2009), it might be worth revisiting Chang and Tovar (2014b) not only to check whether their conclusions could be upheld using a DEA approach but also, and more importantly, in order to discuss how those stages should be performed to obtain accurate results. This paper does that, using a database covering the same firms but in a longer period of time 2004–2014.[2]

When measuring TE of different terminals, usually it is assumed that they operate using the same production technology. If they do not, then the TE measurements obtained are erroneous. Thus, a DEA model used in the first stage should consider this issue. One solution would involve estimating a DEA model in a metafrontier framework. Afterwards, the regression model that tries to explain the TE measured in the first stage should be chosen.

The selection of a regression model for the second stage is not a minor econometric problem. The first models have been oriented to use Ordinary Least Squares (OLS) or Tobit regression (TR). However, after the academic debate between Simar and Wilson -henceforth SW-(2007, 2011) and Banker and Natarajan-henceforth BN-(2008), a greater use of bootstrapping techniques to make inferences about the estimated models was found, not only for OLS and Tobit but also for fractional regression models (FRMs).

The OLS estimator and TR have been criticized by SW (2007), because DEA efficiencies are defined on the interval (0, 1] and these estimators do not solve the

[1] These authors reviewed published port literature between 1980 and 2000 to investigate how seaport research has been conducted from the methodological perspective. They found that the main techniques used were descriptive statistics (35.5%), regression (16.9%), DEA (10.2%), Logit model (5.1%) and SFA (4.8%).

[2] Furthermore, the present paper complements a more recent paper (Chang and Tovar, 2017b), which evaluates, with the same dataset, how differences in the terminals' total factor productivity could be explained by certain explanatory variables. See also Tovar and Wall (2019).

problem linked to serial correlation among the efficiencies. These authors argue that the OLS and TR estimators are inconsistent in second-stage regression, thus, a truncated regression with a bootstrap procedure should be carried as it does give consistent estimators. In the meantime, Banker and Natarajan (2008) proposed a statistical model with a log-linear specification, that produces consistent estimations when OLS is used.

According to Ramalho et al. (2010) the data-generating process (DGP) suggested byBanker and Natarajan (2008) is less restrictive than the one proposed by Simar and Wilson (2007). Furthermore, these authors analyze the efficiency scores as descriptive measures of the relative performance of decision-making units (DMUs) within the sample, and suggest that using FRMs is the most natural way of modelling the endogenous variable values which are bounded between 0 and 1.

With this in mind, this paper analyzes, compares and contrasts the results obtained when using each of these approaches in the second stage of the DEA. Thus, to sum up, the aim of the present paper is fourfold: a) to identify the drivers explaining the TE for the South Pacific West Coast port terminals using a second DEA analysis in a metafrontier framework, b) to discuss the several approaches available in the two-stage DEA literature, such as, the linear regression model, estimated by OLS, TR, Simar and Wilson (2007) method, Banker and Natarajan (2008) approach and the FRMs; (c) to compare and test the results obtained when applied each of those models to our dataset, (d) to compare our results with those obtained by Chang and Tovar (2014b) to check whether their conclusions could also be upheld using a DEA approach.

The contributions of this paper to the available literature are the followings. Firstly, to the best of the author's knowledge, this paper is the first one using a second DEA approach in a non-convex metafrontier framework to analyse the technical efficiency with respect to the metafrontier (TE^*), its components (TE^k and TGR) and their determinants for the South Pacific West Coast port terminals. This approach means an upgrade in the methodology, which enables us to attain more accurate estimations asit takes into account that there could be a heterogeneity problem, due to the existence of potential technological differences among the terminals.This way, the possibility of the efficiency score being erroneous is eliminated. Secondly, nowadays there is no consensus about which regression model should be used for the second stage of DEA analysis. In this respect, our study summarizes the arguments proposed by the different authors (see Fig. 1), which is useful for easily understanding what the different options available in the literature are. Additionally, a survey of papers using a second stage DEA to explain port efficiency has been carried out. This allows us to assert that the present paper is the first to apply each of the different fractional models. Furthermore, all the other second stage models available in the empirical literature have also been estimated to check the robustness of our results. Finally, the results respond to the research question; i.e., the identification of the specific drivers that explain efficiency levels in those South Pacific West Coast terminals. Regardless of the approach used (SFA vs. DEA), the specific drivers show the potential utility of these measurements as support tools to port authorities, regulators and governments.

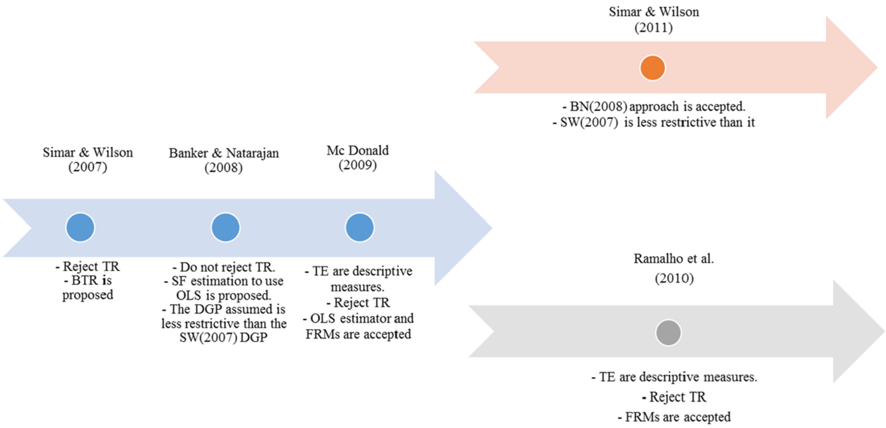

Fig. 1 DEA Second Stage conceptual development. *Note* TR = Tobit regression, BTR = Bootstrapped truncated regression, SF = Stochastic Frontier, OLS = Ordinary Least Square, DGP = Data-Generating Process, SW = Simar and Wilson, TE = Technical efficiency, FRM = Fractional Regression Model, BN = Banker and Natarajan

After the previous introduction, the second section presents the methodology used and a brief review, not only of the two-stage DEA, but also of its application to port literature. Section 3 shows the data. Section 4 discusses the results. Finally, Sect. 5 concludes and presents the policy implications.

2 Two-stage data envelopment analysis

2.1 Methodology

Since the appearance of the first DEA models, developed by Charnes et al (1978, 1979) and Färe et al. (1985), greater interest in this methodology has been taken by researchers and policy makers. This is due the non-complex way in which performance measurements of firms can be obtained, in order to be able to compare and identify best practices.

One of the relevant issues of research in DEA, studied in recent years, is the identification of the determinants of efficiency. Those articles that have attempted to explain technical efficiency have mainly chosen econometrical regression models. According to Coelli et al. (2005), they are called models of second stage analysis.

In the first stage, in order to estimate the technical efficiencies (TE_i), a DEA model is applied. This methodology estimates the production frontier and measures the efficiency relative to the frontier through a linear programming approach. The standard DEA method assumes that N DMUs have access to the same technology and that they can transform a set of p inputs$x$, into a set of q outputs$y$. Thus, given the technology set$T$, defined as:

$$T = \left\{ (x, y) \in \mathfrak{R}_{+}^{p+q} | x \in \mathfrak{R}_{+}^{p} canproducey \in \mathfrak{R}_{+}^{q} \right\} \tag{1}$$

the output set can be represented by:

$$P(x) = \left\{ y \in \mathfrak{R}_{+}^{q} | (x, y) \in T \right\} \tag{2}$$

Thus, output-oriented distance function is defined as:

$$D_i(x, y) = \inf_{\theta} \{ \theta | (x, y/\theta) \in P(x) \} \tag{3}$$

where $\theta \in (0, 1)$ measures the radial distance between the output vector and the production frontier, given the technology and inputs. The TE of the i^{th} unit could be recovered from the expression:

$$TE_i(x, y) = \left[D_i(x, y) \right]^{-1} \tag{4}$$

In practice, the technology set T and $P(x)$ are unobserved and they should be constructed from the data. Thus, the DEA method consists of enveloping the DMUs data linked to inputs and outputs through a frontier, called the "best practice frontier".

Although DEA was initially conceived to analyse cross-sectional data, there are several options available to take advantages of having a panel data when estimating the frontier. At one extreme, all data should be pooled and a unique (unvarying) best practice frontier should be estimated (Pooled model). At the other extreme, one frontier for each period (Yearly model) should be estimated. Finally, an intermediate option is to estimate a sequence of overlapping pooled panels (Window model). Results could vary considerably depending on the DEA model used.[3]

It should be noted that the envelopment surface differs depending on the scale assumptions of DEA model (constant returns to scale, CRS; variable returns to scale, VRS; or non-increasing return to scale, NIRS). Thus, the DEA method estimates the technology set $\hat{T}$ with CRS as:

$$\hat{T} = \left\{ (x, y) \in \mathfrak{R}_{+}^{p+q} \middle| \begin{array}{l} \sum_{k=1}^{N} \lambda_k y_r^k \geq y_r, \quad r = 1, \dots, q \\ \sum_{k=1}^{N} \lambda_k x_r^k \leq x_s, \quad s = 1, \dots, p \\ \lambda_k \geq 0, \quad k = 1, \dots, N \end{array} \right\} \tag{5}$$

where λ_K, to $K = 1, \dots, N$ is the intensity variables over which optimization (3) is made. In addition, DEA with VRS could be estimated if the restriction $\sum_{K=1}^{N} \lambda_K = 1$ is included in (5). Besides, DEA with NIRS would be related with the inclusion of $\sum_{K=1}^{N} \lambda_K \leq 1$ in (5).

[3] A detailed analysis about the relative merits of all of these models is out of the scope of this article. For a general reference, see Fried et al. (2008) and for a port terminals' application reference, see Cullinane and Wang (2010).

DEA with VRS can either take an input orientation or an output orientation. In this paper we follow an output orientation as Chang and Tovar 2014b. Moreover, it should be noted that, for the reasons raised in the introduction section, the DEA model will be estimated in a metafrontier framework, where the metafrontier envelops all the group-specific frontiers and, therefore, contains all technologically feasible input–output combinations.

Recent papers, such as Battese and Rao (2002), Rao et al. (2004) and O'Donnell et al. (2005, 2008) have introduced the concept of the metafrontiers technique, in order to take the technology differences among the production entities into account. Another relevant issue is related to convexity assumption of the metafrontiers analysis. As noted by Kerstens et al. (2015) "Even though each group technology may be a convex set, the meta-technology defined as the union of such sets is generally not convex. Ignoring this issue may result in a potentially poor approximation of the meta-frontier, and introduce bias in the evaluation of meta-efficiency".Therefore, and following to Kerstens, et al (2019) and Jin, et al (2019) we have decided to estimate a non-convex metafrontier.

Thus, the non-convex metafrontier can be represented similarly to (3) by:

$$D_i^*(x, y) = \inf_{\delta} \{\delta > 0 | (x, y/\delta) \in P^*(x)\} \tag{6}$$

and the TE with respect to the metafrontier as $TE_i^*(x, y) = \left[D_i^*(x, y)\right]^{-1}$.

We can link the TE efficiency with respect to k-th group $[TE_i^k\left(x^k, y^k\right)]$ and the metafrontier $[TE_i^*(x^*, y^*)]$ by a ratio of the two TEs, called *Technology Gap Ratio* (*TGR*).

$$TGR_i = \frac{D_i^k\left(x^k, y^k\right)}{D_i^*(x, y)} = \frac{TE_i^*(x, y)}{TE_i^k\left(x^k, y^k\right)} \tag{7}$$

O'Donnell et al. (2008) noticed that a convenient decomposition of the TE could be obtained from (7):

$$TE_i^*(x, y) = TE_i^k\left(x^k, y^k\right) \times TGR_i \tag{8}$$

Thus, TE measured with respect to the metafrontier (TE^*) can be decomposed into the product of how close a firm is operating to the group-specific frontier (TE^k) and how close the technology-specific frontier is to the metafrontier (TGR^k).

Once the TE_i^*, TE_i^k and TGR_i scores [4]have been obtained, in the second stage they are taken as the dependent variable to be regressed with a set of z_i independent variables that could explain the difference of efficiencies among port terminals. Thus, and for example, for TE_i^*,a regression model is specified

$$TE_i^* = f\left(z_i, \boldsymbol{\beta}\right) + \mu_i \; with \, i = 1, \dots, N \tag{9}$$

2.2 Review of the two-stage DEA literature

The choice of regression model for the second stage of DEA analysis has undergone an important conceptual development in the last ten years. This conceptual development has been in the context of the academic debate between BN (2008) and SW (2007, 2011), as summarized by Fig. 1.

The first econometric model that appeared in this second stage was the classic linear regression model. This model considers that there is a linear relationship between the TEs and the parameters (β) of the independent variables (z_i). Thus, $TE_i = z_i{}'\beta + \mu_i$, OLS was chosen to estimate the regression model, and to infer the estimated parameters. However, this approach does not guarantee the estimated TE lying inside the interval (0, 1]. In addition, the constant marginal effects are not compatible with the bounded efficiencies scores and the existence of a mass point at unity in their distribution; i.e., there are usually several values at 1 (Ramalho et al. 2010).

In order to solve these problems, censored regression models such as the two-limit Tobit method have been used by some authors, with limits at zero and unity. In other words, there is an unobservable latent variable $TE_i{}^*$.

$$TE_i^* = f\left(z_i, \boldsymbol{\beta}\right) + \epsilon_i \tag{10}$$

If $TE_i^* \leq 0$, the efficiency score for the i-th firm is zero ($TE_i = 0$), if $TE_i^* \geq 1$, the efficiency score is one ($TE_i = 1$), and if $0 < TE_i^* < 1$, $TE_i^* = TE_i$. Nevertheless, this approach has been criticized by SW (2007 and McDonald (2009). Both authors agree that there is not a data censured problem, and that the concentration of technical efficiencies at unity is due to how the efficiencies are defined in the frontier model.

[4] To test the robustness of our TE results depending on the DEA model used, the DEA efficiency scores were calculated from four different models: The Pooled model, the Yearly model, and, finally, two Window DEA models, where DEA scores are calculated using moving 5-year and 3-year windows, respectively. We have decided to keep the results from the yearly model for the second stage for two reasons. First and foremost, we are interested in discovering which determinants explain the TE_i^*, TE_i^k and TGR_i scores on a yearly base. (For a similar analysis regarding the changes in those variables, as opposed to the levels, interested readers are referred to our paper Chang and Tovar 2017b). The second reason is that due to the fact that the TE DEA scores are highly correlated across models, in this way we avoid the problem identified by Cooper et al. (2004) of choosing the width for a window and the theoretical implications of representing each port terminal as if it were a different one for each period in the window.

According to SW (2007), in order to use a second stage approach properly and to know what is being estimated, it is very important that the DGP of the DEA scores is clearly defined. However, the studies that have used censored models (Tobit) have not described, in a coherent way, how the censure has arisen. On the other hand, there are authors who have proposed using a linear regression model, estimated by OLS, in the second stage. In order to avoided boundary problems, they have transformed the DEA score using log, logistic, or log-normal functions. Nevertheless, they have not clearly described the DGP.

Another problem that SW (2007) have identified, linked to second stage analysis, is the fact that technical efficiencies estimated by DEA are serially correlated. As a consequence, the inferences used in these studies are invalid. In that sense, these authors describe a data-generating process which is consistent with the DEA approach and let us do valid inference. They propose single and double bootstrap procedures in a second stage regression context with a truncated model. The first algorithm improves the inference, but without taking into account the bias term; the latter not only improves the inference, but also produces bias-corrected parameters.

In addition, the censored regression models (Tobit) have been questioned by other authors such as BN (2008). They do not find theoretical justification to support a second stage with the Tobit method. However, they agree with the linear regression model estimated by OLS, because under some assumptions, the OLS estimator produces consistent estimators. According to Ramalho et al. (2010) the DGP proposed by these authors is less restrictive than that suggested by SW (2007).

In the words of McDonald (2009), there are good arguments for treating TE estimated by DEA as descriptive measures in a second stage context. The DEA efficiency scores can be treated as any other dependent variable in econometric analysis, and be estimated by OLS, which is a consistent estimator. In that sense, the Tobit method is an erroneous estimation procedure, because the technical efficiencies are not generated by a censoring process, but by fractional data. The author found that the fractional data estimator of Papke and Wooldridge (1996) is asymptotically more efficient than the OLS estimator.

The fractional regression models have been proposed in a second stage DEA context by Ramalho et al. (2010). These models consider that the dependent variable is in the interval (0, 1], without assuming that boundary values are observed. Different fractional models that use cumulative distribution function, such as log model, probit model, loglog model and complementary loglog model have been proposed.

$$f\left(z_i, \boldsymbol{\beta}\right) = \begin{cases} \frac{\exp\left(z_i'\boldsymbol{\beta}\right)}{1+\exp\left(z_i'\boldsymbol{\beta}\right)}, & \textit{Logitmodel} \\ \Phi\left(z_i'\boldsymbol{\beta}\right), & \textit{Probitmodel} \\ \exp\left(-\exp(-z_i'\boldsymbol{\theta})\right), & \textit{loglogmodel} \\ 1-\exp\left(-\exp(z_i'\boldsymbol{\theta})\right), & \textit{Complementaryloglog} \end{cases} \tag{11}$$

All models were estimated by Quasi Maximum Likelihood based on the Bernoulli log-likelihood function to ith firm

$$LL_i(\boldsymbol{\beta}) = TE_i \log f\left(z_i, \boldsymbol{\beta}\right) + \left(1 - TE_i\right) \log\left(1 - f\left(z_i, \boldsymbol{\beta}\right)\right) \tag{12}$$

And the Quasi Maximum Likelihood estimator of $\boldsymbol{\beta}$ is defined by

$$\hat{\boldsymbol{\beta}} = \arg\max \sum_{i=1}^{N} LL_i(\boldsymbol{\beta}) \tag{13}$$

According to Ramalho et al. (2010) linear regression models and censured models do not constitute a reasonable data-generating process for DEA scores. Nevertheless, fractional regression models are better for modelling the boundary, especially the complementary loglog model. However, in order to solve the serial correlation, and ensure that the inference made will be valid, it is necessary to apply bootstrap methods when the fractional regression models are estimated.

Although, there is no consensus about the choice of the regression model for the second stage, in our second stage we chose to estimate different fractional models, such as log model, probit, loglog and complementary loglog (where the TE_i^*, TE_i^k and TGR_i scores are the dependent variables analysed) because we agree with the arguments proposed by Ramalho et al. (2010). However, to check the robustness of our results we will also estimate a second stage linear regression model using all the other models proposed in the literature: OLS, TR, the BN (2008) approach, and the bootstrapped truncated regression following SW (2007).

2.3 Brief review of the two-stage DEA port literature

An overview of the papers using DEA-second stage to explain the influence of certain contextual variables on port efficiency[5] is provided by Table 1. With regard to the DMUs analyzed, most articles have analyzed the efficiency of port terminals, while, on the other hand, just a few studies have analyzed the efficiency of port authorities; only two out of the fourteen. Ten out of the fourteen studies have used panel dataFinally, some papers have included the DMUs of different countries (Turner et al. 2004; Yip et al. 2010; Bergantino and Musso 2011; Niavis and Tsekeris 2012; Yuen et al. 2013; and Figueiredo and Cariou 2015). Nevertheless, these latter studies have not evaluated the potential technological differences between the DMUs.

Regarding the variables used in the first stage, an increasing amount of studies have used physical variables to measure the inputs and outputs. Most of papers have used an aggregate output such as cargo throughput (Turner and Dresner 2004; Yip et al. 2010; Bergantino and Musso 2011; Niavis and Tsekeris 2012; Yuen et al. 2013; Wan et al. 2014; Figueiredo and Cariou 2015) whereas others have considered more than one output such as cargo throughput by type of cargo and/or number of

[5] A systematic overview of contextual variables influencing on terminals' efficiency is out of the scope of the present paper but could be find in Bichou (2009).

Table 1 DEA second stage papers on the port sector

Author (year)	Data	Methodological Approach	Variables employed for DEA estimation	Contextual variables
Turner, Windle and Dresner (2004)	26 containers ports in USA and Canada. 1984 to 1997	First stage: DEA VRS model Second stage: TR Dependent variable: TE VRS scores	Inputs: Quay length (m), Terminal land dedicated to container operations (ha), number of container cranes. Output: Cargo throughput (TEU)	Container port size (millions of TEU)Terminal size (millions of TEU)Dedicated container port quay/total quayOndock rail (hectares with access/total hectares) Vessel size (thousands of TEU slots) Vessel size squared (millions of TEU slots)Doublestack clearanceClass I railroads (number)Draft (mean of vessel at or above 90th percentile in feet)Labour strikes (duration in days)Feeder services (container carrying barges/total arrivals) Ro/ro service arrivals/total arrivalsMean container crane reach (m)
Pestana, and Managi, (2008)	39 Japanese portauthorities. Panel data from 2003 to 2005	First stage: DEA CRS and VRS models, SuperEfficiency DEA model, Crossefficiency DEA model Second stage: A BTR Dependent variable: TE CRS scores	Input: Employees (number), cranes (number).Output: Ship arrivals and departures (number), Liquid and dry bulk loaded and unloaded (kt) and containers (TEUs)	GDP (US$)Hub (1=yes/0=no) PopulationTrend Trend squared

Table 1 (continued)

Author (year)	Data	Methodological Approach	Variables employed for DEA estimation	Contextual variables
Yip, Sun and Liu(2010)	141 global container terminal operators1997 to 2005	First stage: DEA CRS model Second stage: Linear regression by OLS Dependent variable: TE CRS scores	Input: Cargo handling capacity at quay (kt), cargo handling capacity at yard (kt), number of berth, length of quay line (m), terminal area (m^2), storage capacity (TEU) and number of electric reefer pointsOutput: Cargo throughput (TEU)	EDI (in fraction of total sample) Depth (m)Number of liners calling the terminalNumber of operators in portNumber of terminals in portGlobal CarrierGlobal StevedoreOther: not belong to any of above groupsGDP (US$)Goods exports (US$)Goods imports (US$)Continental Distribution (in fraction of total sample) Trend
Bergantino and Musso (2011)	18 Southern European ports, 1995, 1997, 2000, 2002, 2005 and 2007	First stage: DEA VRS model Second stage: SFA model Dependent variable: input slacks Third stage: DEA with adjusted data.	Inputs: Dimension of quay (sqm), number of terminals (units), area of the port for handling (sqm) and handling equipment (units) Outputs: Total movements (kt)	GDP per person in PPS (EU27=100) Population density (Inhabitants/ km^2) Employment rate (employed/ active population)Accessibility Port size Involvement in container traffic Trend
Wanke, Barbastefano and Hijar(2011)	25 Brazilian port terminals.2008.	First stage: DEA CRS and VRS models Second stage: TR Dependent variable: TE VRS scores	Input: Terminal area (sq. m), size of parking lot (number of trucks), and number of berths. Outputs: Cargo throughput (kt) and number of loaded shipments.	Type of cargo handled by the terminal (solid bulk, liquid bulk, or container)Railroad connectivity (1 = yes/0 = no) Control (1 = private/ 0 = state) Percentage of trucks scheduled Qualified labour force (1 = yes/0 = no)

Table 1 (continued)

Author (year)	Data	Methodological Approach	Variables employed for DEA estimation	Contextual variables
Niavis, and Tsekeris(2012)	30 containers ports in South-Eastern Europe.2008.	First stage: DEA CRS and VRS models, DEA CRS SuperEfficient model Second stage: TR and BTR Dependent variable: TE DEA CRS and SuperEfficiency scores	Inputs: Number of berths, length of quays (m) and number of cranes used for container handling.Output: Cargo throughput (TEU)	Port area (km^2 in logarithm) Population (in 000s in logarithm)GDP per capita (€ 000s) Distance from Suez (km) Private
Polyzos and Niavis (2013)	30 Mediterranean ports	First stage: DEA CRS and SuperEfficiency DEA model Second stage: TR Dependent variable: TE CRS scores	Inputs: The length of quays and the number of ship to shore cranes Outputs: Cargo throughput (TEU)	Distance to the main route Suez-Gibraltar Area of port (m^2) Population
Wanke(2013)	27 Brazilian ports. 2011	First stage: NetworkDEA VRS model Second stage: BTR Dependent variable: TE VRS scores	Inputs: Number of berths, warehousing area (m^2) and yard area (m^2)Intermediate input/output: Solid bulk frequency (shipments/year) and Container frequency (shipments/year)Outputs: Solid bulk throughput (tons/year) and Container throughput (containers/year)	Three factors represent the original set of contextual variables: Factor 1: Hinterland size and cargo diversity (Hinterland km^2 and both container and solid bulk 1=yes/0=no) Factor 2: Highway connectivity (Number of high way accesses) Factor 3: Private administration (1=yes/0=no)

Table 1 (continued)

Author (year)	Data	Methodological Approach	Variables employed for DEA estimation	Contextual variables
Yuen, Zhang and Cheung (2013)	21 China and other Asian cities' major containers terminals 2003 to 2007	First stage: DEA CRS model Second stage: TR and BTR Dependent variable: TE CRS scores	Inputs: Number of berths, total berth length (m), port land area (m^2), number ofquay cranes and number of yard gantries.Output: Cargo throughput (TEU)	Chinese ownership (%) Hinterland size (population and GDP) Interport competition (log(distance)) Intraport competition intensity (N° container port terminal operators) Average monthly wage (US$)
Wan, Yuen and Zhang. (2014)	12 US container ports 2000 2009	First stage: DEA CRS and VRS models Second stage: TR Dependent variable: TE VRS scores	Inputs: container terminal size, total length of berths and total number of cranes and gantries Outputs: Cargo throughput (TEU)	Population Intraport competition: number of container terminal operators in the port and number of operators / number of container terminals Rail service Ondock rail facility (1 = yes/0 = no) Road congestion index Port operational scale (1=annual container throughput over three million/0=no)

Table 1 (continued)

Author (year)	Data	Methodological Approach	Variables employed for DEA estimation	Contextual variables
Figueiredo and Cariou (2015)	200 containers ports around the world.2007 and 2010	First stage: FDH model Second stage: BTR Dependent variable: Inefficiency scores	Input: Port area (m^2), storage area (m^2), length of berth (m), number of yard crane and number of quay crane.Output: Cargo throughput (TEU)	Port city population (million) Gateway or Hub (1=yes/0=no) Liner Shipping Connectivity Index (LSCI)Herfindhal-Hirschman Index (HHI)Market share (100, 200, .., 1000 km) Changes in number of cranes (1=yes/0=no)
Ju and Liu (2015)	14 Chinese port 20012011	First stage: DEA CRS and VRS models Second stage: Pooled OLS and dynamic OLS Dependent variable: TE VRS scores	Inputs: Total assets (mil. yuan), number of employees and prime operating costs (mil. yuan), Outputs: The earnings per share (yuan/share) and prime operating revenues (mil. yuan).	The ratio of stateowned shares log net fixed assets Debt asset ratio Operating costs ratio Ratio of outside Proportion of employees who have a college degree

Table 1 (continued)

Author (year)	Data	Methodological Approach	Variables employed for DEA estimation	Contextual variables
Wanke, and Pestana (2015)	27 Brazilian ports2012	First stage: PCADEA CRS and VRS models Second stage: BTR Dependent variable: SE scores	Factors represent the original set of variables: Inputs: Port infrastructure index (Factor 1): Quay length (m), number of berths, warehousing area (m^2), yard area (m^2) Depth accessibility index (Factor 2): maximal quay depth (m), channel depth (m) Width accessibility index (Factor 3): channel width (m) Outputs: Container output (Factor 1): Container loading hours (per year), container throughput (containers/year), and container frequency (shipments per year) Solid buck output (Factor 2): Solid bulk loading hours (per year), solid bulk throughput (tons/year), solid bulk frequency (shipments/year)	Public Private Partnerships PPP (1=yes/0=no)Both container and solid bulk (1=yes/0=no) Hinterland (km^2) Number of highway accessesRiverine access? (1=yes/0=no)Railroad access? (1=yes/0=no)Number of accessing channels
Wanke and Pestana(2016)	27 Brazilian ports. 2007 to 2011	First stage: PCADEA CRS and VRS models in a cluster analysis context Second stage: BTR and TR using the fixed effects model. Dependent variable: TE CRS, TE VRS and SE scores		

Table 1 (continued)

Author (year)	Data	Methodological Approach	Variables employed for DEA estimation	Contextual variables
Tovar and Wall (2017)	26 Spanish port authorsities 1993 to 2012,	First stage: DEA CRS and VRS models Second stage: BTR Dependent variable: TE CRS and TE VRS scores	Inputs: labour (number); intermediate consumption expenditures (€); capital assets (€); and deposit surface area (m^2). Outputs: Liquid bulk (kt)y1, solid bulk (kt) –y2, container (kt) –y3, general noncontainer merchandise (kt) –y4, and passengers (number).	Normalised HerfindahlHirschman Index Output y1 of port i/Output y1 of all ports Output y2 of port i/Output y2 of all ports Output y3 of port i/Output y3 of all ports Output y4 of port i/Output y4 of all ports Relative specialisation in output y1 Relative specialisation in output y2 Relative specialisation in output y3 Relative specialisation in output y4 Total cargo of port i/Total cargo of all ports Dummy if port has passenger traffic

Table 1 (continued)

Author (year)	Data	Methodological Approach	Variables employed for DEA estimation	Contextual variables
Present Study	14 Peruvian and Chilean ports terminals 20022014	First stage: (TE_i^*, TE_i^k) and TGR_i from a PCADEA VRS model in a nonconvex metafrontier framework Second stage: Linear regression by OLS, TR, BTR, BN and several FRMs Dependent variable: (TE_i^*, TE_i^k) and TGR_i scores	Inputs: labour (number) and net stock of fixed assets (US$ year 2000=100) Output: Aggregate output (Factor 1): represents the original set of variables: Containerized cargo (kt) General and rolling freight (kt) Bulk cargo (kt)	Container index Bulk ratio Type of management (public or private) Capital intensity (CapitalLabour Ratio) Number of berths Interport competition (log(distance)) Occupancy rate Trend

TE Technical efficiency *SE* Scale efficiency, *CRS* Constant Return to Scale, *VRS* Variable Return to Scale, *TGR* Technological Gap Ratio, *OLS* Ordinary least square, *TR* Tobit regression *BTR* Bootstrapped truncated regression, *BN* Banker and Natarajan approach, *FRMs* Fractional Regression Models ships, and so on (Pestana and Managi 2008; Wanke et al. 2011; Wanke 2013; Wanke and Pestana 2015, 2016; and Tovar and Wall 2017).

With respect to inputs variables, the majority of the studies have used only capital variables; eleven out of the fourteen4 (Turner, et al. 2004; Yip et al. 2010; Bergantino and Musso 2011; Wanke et al. 2011; Niavis and Tsekeris 2012; Wanke 2013; Yuen et al. 2013; Wan et al. 2014; Figueiredo and Cariou 2015; Wanke and Pestana 2015, 2016). The main variables used are quay length, number of cranes, number of yard gantries, number of berth, yard area, and so on. Relatively, few studies have used both capital and labour variables (Pestana and Managi 2008; Ju and Liu 2015; and Tovar and Wall, 2017). On the other hand, only one paper has used a monetary measurement to outputs and inputs variables (Ju and Liu 2015).

Although the specification of inputs and outputs are essentially ad hoc, the choice of these variables in the case of a DEA model is not a trivial matter. This is due to the fact that this method does not allow us to carry out statistical hypotheses tests, and the omission of variables might have an adverse effect on the efficiency.[6] Therefore, when a DEA approach is considered, the choice of input and output variables should represent the productive processes of port/terminals. In that sense, variables linked to capital and labour should be included.[7] With this in mind, the present paper will consider information linked to outputs, such as general cargo (distinguishing between containerized cargo,and non containerized) and bulk cargo. With regard to the input variables, capital variable will be approximated by using the stock of net fixed assets and the labour variable by using the number of workers.

Regarding the model followed in the second stage, we found articles that use a regression model estimated by OLS (Yip et al. 2010; and Ju and Liu 2015); a TR (Turner et al. 2004; Wanke et al. 2011; and Wan et al. 2014); a bootstrapped truncated regression following SW (2007) approach (Pestana and Managi 2008; Wanke 2013; Figueiredo and Cariou 2015; Wanke and Pestana 2015; and Tovar and Wall 2017) and both the TR method and bootstrapped truncated regression following SW (2007) approach (Niavis and Tsekeris 2012; Yuen et al. 2013; and Wanke and Pestana 2016). This paper contributes to the literature because it is the first one that applies the different fractional models such as log, probit, loglog and complementary loglog suggested by Ramalho et al. (2010).

The dependent variables used are TE with CRS, and/or VRS and/or scale efficiency scores. In our case, we use as the dependent variable the technical efficiency with variable returns to scale. When it comes to contextual variables, we found the following: *public vs. private management* (Wanke et al., 2011; Niavis and Tsekeris 2012; Yuen et al. 2013; Wanke 2013; Wanke and Pestana 2015, 2016), *any relationship between the types of cargoes* (Yip et al. 2010; Wanke et al. 2011; Wanke 2013; Wanke and Pestana 2015; 2016; and Tovar and Wall 2017), *hinterland size* (Pestana

[6] Data accuracy, imprecision and missing values are common problems. To the previously mentioned problems, a useful approach could be Imprecise DEA (Zahran et al. 2020).

[7] However, there are a lot of papers that, due to the difficulties in accessing that data, ignore this variable or try to approximate it through another capital variable; for example, the number of cranes. It should be noticed that both capital and labour variables should be included in the estimation, unless it is demonstrated that there is a perfect complementarity between them. To the best of our knowledge this relationship has never been demonstrated.

and Managi 2008; Bergantino and Musso 2011; Niavis and Tsekeris 2012; Polyzos and Niavis 2013; Wanke 2013; Yuen et al. 2013; Wan et al. 2014; Figueiredo and Cariou 2015; Wanke and Pestana 2015; 2016), *any variable that measures port size* (Turner, et al., 2004; Pestana and Managi 2008; Yip et al., 2010; Bergantino and Musso 2011; Niavis and Tsekeris 2012; Polyzos and Niavis 2013; Wan et al. 2014; Figueiredo and Cariou 2015; and Ju and Liu 2015); *connectivity* (Wanke et al. 2011; Niavis and Tsekeris 2012; Polyzos and Niavis 2013; Wanke 2013; Wan et al. 2014; Wanke and Pestana 2015; 2016), *the level of competition* (Yip et al. 2010;Yuen et al. 2013; Wan et al. 2014; Figueiredo and Cariou 2015; Wanke and Pestana 2015; 2016; and Tovar and Wall 2017) *time trend* (Pestana and Managi 2008; Yip et al. 2010; Bergantino and Musso 2011) and *time trend squared* (Pestana and Managi 2008).

With this in mind, contextual variables related to *type of management* (dummy variable: 1 private and 0 public), *type of cargoes* (containerization index, bulk rate), *hinterland size* (population, area of region, density and regional gross domestic product), *terminal port size* (maximum draft, maximum length, number of berth), *connectivity* (road access, kilometres of asphalted road and railway access) and *level of competition* (number of terminals, distance to the nearest port) are obtained from each terminal, and they will be tested in second stage models. Moreover, and following Pestana and Managi (2008) a time trend and time trend squared will be tested to analise the port terminals' TE and TGR levels over time.[8]

3 Data

To estimate the DEA (VRS) efficiencies scores (TE_i^*, TE_i^k) and TGR_i scores in the first stage, we consider the principal public use marine terminals in Peru and Chile. We gathered information related to fourteen terminals[9] from 2004 to 2014, seven in each country (see Table 2).

Recently and applying a Latent Class Stochastic Frontier Model[10] to the same dataset (to take into account for possible technological differences among terminals) Chang and Tovar (2017a) have shown that two groups (classes) can be distinguished. These two classes of terminals differ not only in size but also in the degree of mechanisation, as pointed out by Chang and Tovar (2017a): *Class 2 groups mainly large terminals with more employees, more equipment, and more infrastructure. Also, Class 2 has other superior physical variables, such as machinery, draughts, berths, and length of berths.*

[8] The time trend shows the efficiency evolving in a period. If firms improved their efficiency the coefficient linked to this variable would be positive. The time trend squared variable is included to allow more flexibility when modelling the temporary pattern of TE. We included both in our model because we believe that, due to the effect of learning by doing, when time pass leads to a more efficient situation although to a diminishing rate. Therefore, we expect that the coefficient linked to time squared variable ends up being negative.

[9] The data used was obtained from various sources and is the same that the one used in Chang and Tovar, (2017a). The reader interested in more details about the dataset, can find it there.

[10] Chang and Tovar (2017a) found that Latent Class Stochastic Frontier Model, with two classes, fits the unobserved heterogeneity of the Peruvian and Chilean port terminals better than the other Standard Stochastic Frontier Models.

Table 2 Peru and Chile: public use port terminals analysed. *Source*: Adapted from Chang and Tovar (2017a)

Country	Class	Terminal	Located in port…	Main type of cargo handled	Management
Peru	2	Paita	Paita	Containers	Private. Concession agreement: 2009
	1	Salaverry	Salverry	Bulk	Public
	1	Chimbote	Chimbote	General	Public
	2	Callao North	Callao	Containers and Bulk	Private. Concession agreement: 2011
	2	San Martin	San Martín	Bulk	Public
	1	Matarani	Matarani	Bulk	Private. Concession agreement: 1999
	2	Ilo	Ilo	General and bulk	Public
Chile	1	Arica	Arica	Containers	Private. Concession agreement: 2004
	1	Iquique	Iquique	Containers	Private. Concession agreement: 2000
	2	Mejillones	Mejillones	Bulk	Private. Concession agreement: 2000
	2	Antofagasta	Antofagasta	Containers and Bulk	Private. Concession agreement: 2000
	2	Valparaiso	Valparaiso	Containers	Private. Concession agreement: 1999
	2	San Antonio	San Antonio	Containers	Private. Concession agreement: 1999
	1	San Vicente	San Vicente	Containers	Private. Concession agreement: 1999

Regarding the degree of mechanisation, Class 2 terminals have a high container/bulk ratio, containerisation index, and a bulk rate, in comparison with Class 1 terminals.

Chang and Tovar (2017a) provided evidence that there is different technology by class. Therefore, this fact has to be taken into account when estimating technical efficiency in the first stage to obtain accurate results. Thus, we borrow their classification of terminals (see Table 2) to estimate the DEA model in a metafrontier framework. This choice let us avoid the biased results obtained if a standard DEA is chosen when, as occur in this case, there are technological differences among terminals.

Table 3 shows the variables used in the estimation.

Idyllically, the three output[11] variables should be included, but to avoid "the curse of dimensionality" and, at the same time, to take into account the multi-output nature of the port terminals, an aggregate output variable, using Principal Component Analysis (PCA), was built (Chang and Tovar 2017b). Therefore, and as Table 3 shows, one output and two inputs (labor and capital) were used in the first stage.

[11] Peruvian terminals analysed in this paper manage three type of cargo: containerized cargo, general & rolling freight and bulk cargo.

Table 3 Descriptive statistics: first stage and second stage

	Variables		Class1		Class 2	
			Mean	Standard error	Mean	Standard error
First stage	Output	Aggregate output by PCA	1,260,977	881,260	2,753,578	2,823,008
	Input	Labour (Number of workers)	203	175.231	207	221.0708
		Capital (Net stock of fixed assets)	12,672	10,278	19,663	18,911
Second stage	Container index	0.58	0.38	0.68	0.34	
	Bulk ratio	0.38	0.36	0.4	0.27	
	Capital ratio	82.35	46.49	118.34	76.69	
	Dgest (Private = 1, public = 0)	0.67	0.48	0.6	0.49	
	Berth (Number)	3.74	1.47	5.6	4.37	
	Distance to the nearest port	418.17	127.36	334.13	254.43	
	Occupancy rate	0.32	0.11	0.33	0.17	

PCA= Principal Component Analysis; Net stock of fixed assets = basic infrastructure, superstructure, machines and mobile equipment were grouped into a capital variable approximated by the stock of net fixed assets, obtained from each terminal. This data was then converted into MUS$ constant values (the year 2000 =100); Container index = Containerized cargo/Total general cargo; Bulk ratio = Bulk cargo/Total cargo; Capital ratio = Capital/Labour; Dgest = Type of management (private or public); Distance to the nearest port = The natural logarithm of distance to the nearest port (Km); Occupancy rate = The effective hours of berth occupancy/The potential hours of berth occupancy

The second stage allows us to model the TE_i^*, the TE_i^k and the TGR_i scores as a function of the firm-specific variables that we consider may influence a port terminal's efficiency. As Table 3 shows, we consider several variables following our literature review (see last paragraph in Sect. 2.2). The best models for each dependent variable were obtained with the variables shown in the following equations:

$$TE_{it}^{*} = f\begin{pmatrix} containerindex_{i,t}, bulkrate_{i,t}, dgest_{i,t}, \\ berth_{i,t}, distance_{i,t}, occupancyrate_{i,t}, class_{i}, \boldsymbol{\beta} \end{pmatrix} + \epsilon_{i,t} \tag{14}$$

$$TGR_{it} = f\left(bulkrate_{i,t}, dgest_{i,t}, berth_{i,t}, distance_{i,t}, class_{i}, trend_{t}, \boldsymbol{\gamma}\right) + \varepsilon_{i,t} \tag{15}$$

$$TE_{it}^{k=1} = f\left(\text{bulk}rate_{i,t}, \text{capital}ratio_{i,t}, berth_{i,t}, \text{distance}_{i,t}, \boldsymbol{\delta}\right) + \mu_{i,t} \tag{16}$$

$$TE_{it}^{k=2} = f\left(bulkrate_{i,t}, dgest_{i,t}, distance_{i,t}, occupancyrate_{i,t}, \boldsymbol{\varphi}\right) + \omega_{i,t} \tag{17}$$

where the containerization index is defined by dividing containerized merchandise by the total general cargo; bulk rate is defined by dividing bulk cargo by the total cargo; capital ratio variable is defined by dividing capital by labour; berth variable represents the number of berths in each terminal; distance variable is the natural logarithm of distance to the nearest port and occupancy rate is defined by dividing the effective hours of berth occupancy by the potential hours of berth occupancy, dgest is a dummy variable that accounts for the type of management (public or private), class is a dichotomous variable that takes a value of 1 or 2 depending on whether the terminal belongs to Class 1 or Class 2 respectively, trend represents time and takes values from 1 to 11 for each year, $\boldsymbol{\beta}, \boldsymbol{\gamma}, \boldsymbol{\delta}, \boldsymbol{\varphi}$ are the parameters vectors to be estimated, and $\varepsilon_{i,t}$,$\varepsilon_{i,t}$,$\mu_{i,t}$,$\omega_{i,t}$, $\mu_{i,t}$, $\omega_{i,t}$ are random variables.

The bulk rate and containerization index are variables that account for the degree of mechanization at the terminals an it is presumed that the higher the level of mechanization (either in bulk or container), the higher efficiency.[12] On the other hand, we expect that private mamagement leads to a more efficient situation.

Capital ratio variable represents the capital intensity; i.e. the amount of capital present in relation to labour. We expect that higher capital intensity at port terminals permits higher efficiency. Berth is a proxy variable of the size of a port terminal. It is expected that larger terminals will be more efficient.

The distance to the nearest port is a variable that accounts for the influence of the degree of inter-port competition on technical efficiency.[13] This variable has been

[12] Container index, bulk ratio, occupancy rate and dgest variables have been identified by Chang and Tovar (2014b) as specific explanatory variables that contribute to reducing the inefficiency of Peruvian and Chilean port terminals.

[13] Another commonly used proxy for inter-port competition is the Herfindahl–Hirschman Index (Figueiredo De Oliveira and Cariou 2015). Nevertheless, the construction of this variable requires very comprehensive data to appropriately define the relevant market of each kind of cargo. This data is not available for each terminal for the whole period.

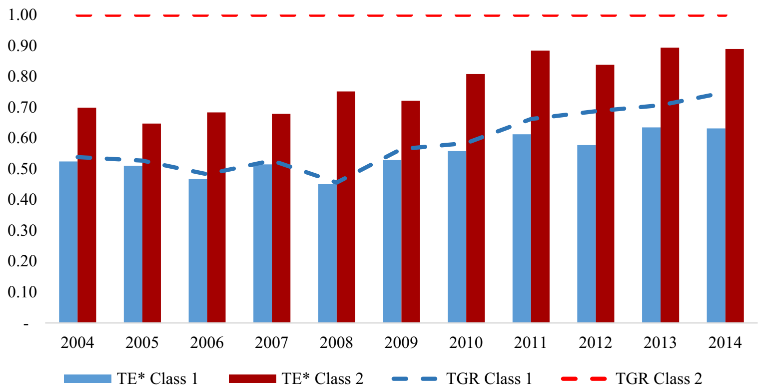

Fig. 2 Average Technical efficiency (TE*) and Technological Gap Ratio (TGR), by class, 2004–2014

used by Yuen et al. (2013) who concluded that inter-port competition has a positive impact on container terminal efficiency, but it is negatively correlated with the growth of efficiency. As Figueiredo De Oliveira and Cariou (2015) have recently stated the impact of inter-port competition on port efficiency remains ambiguous and deserves further investigation. Thus, increasing inter-port competition could impact positively on port efficiency, but it may also have the opposite result.

Occupancy rate is included to consider the idle capacity. Because this indicator was below 70% for all terminals during the period analysed (when it is above 70% there is congestion -APN, 2010-) we expect that the higher the occupancy rate the higher the efficiency level. Finally, with respect to the trend variable, we expect a positive effect over time.

As Table 3 shows, Class 2 groups mainly large terminals which are also more capital-intensive than Class 1 terminals.

4 Results

Figure 2[14] shows the evolution of the average TE_i^* and the average TGR_i. The Class 2 terminals show always higher levels of TE than the other Class. The average TE_i^* with VRS were 54.6% and 77.2% for Classes 1 and 2, respectively implying that the average output of Class 1 and Class 2 terminals could be a 45.4% and 22.8% higher using the same input levels and the production technology available at the

[14] Remember that TE_i^*, TE_i^k and TGR_i scores are calculated following the yearly model because in the second stage, as we explained in footnote 3, we are interested in analysing the drivers of the variable *levels* each year and not in analysing the drivers of the *changes* in variables between the years. (The latter could be done by computing Malmquist productivity indices using metafrontiers, as Chang and Tovar (2017b) have recently shown). Therefore, Fig. 2 should be understood as reflecting how the levels of those variables change regarding the frontier of each year.

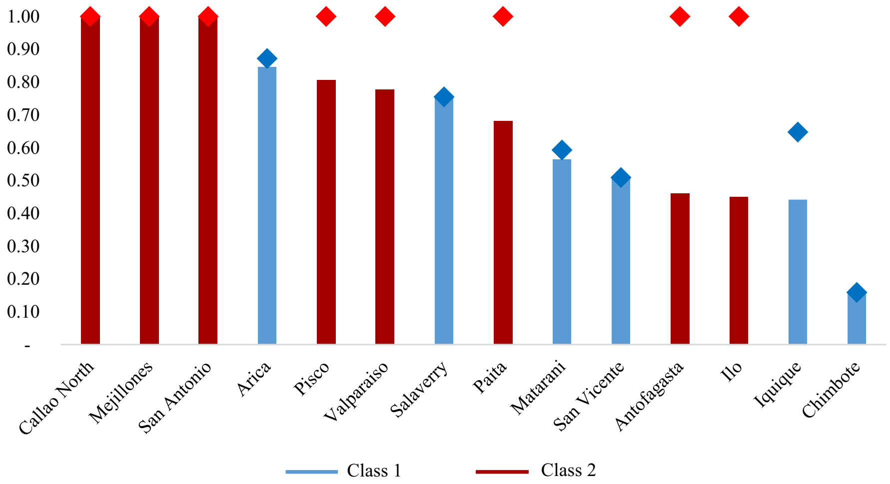

Fig. 3 Average Technical efficiency (TE*) and Technological Gap Ratio (TGR), by terminal, 2004–2014

metafrontier. Furthermore, the TGR of Class 2 terminals was higher than the TGR of Class 1 terminals in a yearly base for the whole period; that is to say Class 2 terminals produce under better technological conditions. Nevertheless, the TGR of Class 1 terminals has evolved positively since 2008 in a yearly base; i.e., the terminals of this class have been catching up with the best available technology.

The average TE_i^*[15] and the average TGR_i^*[16] by terminal during the whole period are shown in Fig. 3. The terminals of Callao North, San Antonio, Mejillones and Arica were found to be the most efficient; and the least efficient were Ilo, Iquique and Chimbote. Our results also show that chilean port terminals are more efficient than the peruvian ones. On average, the technical efficiency of chilean terminals and peruvian terminals were 72.0% and 63.0%, respectively. These results were expected and associated, as shown by Chang and Tovar (2014a,2014b) primarily with the speed in the process of reforms in Chile which fostered a greater investment in infrastructure and technology.

The blue and red diamonds (Fig. 3) represent the average TGR of Class 1 and Class 2 terminals, respectively. Thus, all the Class 2 terminals have a value of one for the TGR, therefore these terminals produce with the best available technology. Conversely, no Class 1 terminal has a value of one for the TGR. Then again, when the TGR of a terminal is equal to the TE_i^*, it indicates that this terminal is at the frontier of its class. Thus, Salaverry, San Vicente and Chimbote make up the frontier

[15] This is the average technical efficiency with respect to the metafrontier and its value varies between 0 and 1.

[16] This is the average relationship between the technical efficiency with respect to k-th group $[TE_i^k\left(x^k, y^k\right)]$ andthe technical efficiency with respect to the metafrontier $[TE_i^*(x^*, y^*)]$.

Table 4 Regression models of TE*

Variables	OLS	Tobit regression	Simar and Wilson (2007)	Banker and Natarajan (2008)	Ramalho et. al (2010)			
					Fractional Models			
					Log	Probit	Loglog	cloglog
Container index	0.0217	−0.043	0.0907	0.3882**	0.4878**	0.2927**	0.3018*	0.3949**
	(0.0772)	(0.0978)	(0.0552)	(0.1587)	(0.2402)	(0.1494)	(0.1701)	(0.1744)
Bulk ratio	0.4420***	0.6080***	0.4331***	1.2644***	2.0631***	1.2423***	1.2672***	1.6312***
	(0.0576)	(0.0572)	(0.049)	(0.1727)	(0.1883)	(0.1085)	(0.1113)	(0.1597)
Dgest	0.2279***	0.2374***	0.1780***	0.4905***	0.8245***	0.4982***	0.5147***	0.6575***
	(0.0647)	(0.0826)	(0.0659)	(0.1328)	(0.243)	(0.1494)	(0.1664)	(0.1817)
Berth	0.0382***	0.1085***	0.0997***	0.0444*	0.4198***	0.2598***	0.3066***	0.2876***
	(0.0128)	(0.018)	(0.0127)	(0.0263)	(0.0527)	(0.0312)	(0.0378)	(0.0347)
Distance	0.0770*	0.1256**	0.1189***	0.1865**	0.5846***	0.3492***	0.3307***	0.4815***
	(0.0446)	(0.0532)	(0.0274)	(0.0767)	(0.1359)	(0.0845)	(0.1019)	(0.0981)
Occupancy rate	0.4318**	1.2296***	0.7457***	1.0069***	3.2921***	2.0272***	2.3018***	2.2611***
	(0.1735)	(0.2512)	(0.1671)	(0.3409)	(0.824)	(0.492)	(0.5393)	(0.5696)
Class	0.2282***	0.3453***	0.0755**	0.3848***	0.4168**	0.2439**	0.1707	0.3947***
	(0.0551)	(0.0651)	(0.0347)	(0.0962)	(0.1705)	(0.105)	(0.1237)	(0.1179)
Constant	−0.5274*	−1.3476***	−1.1447***	−3.3924***	−7.7211***	−4.6679***	−4.4089***	−6.3895***
	(0.2875)	(0.3157)	(0.1859)	(0.552)	(0.807)	(0.4871)	(0.5905)	(0.5967)

p-value (p): *$p<0.10$, **$p<0.05$, ***$p<0.01$

Standard errors in parentheses

Table 5 Regression models of TGR

Variables	OLS	Tobit regression	Simar and Wilson (2007)	Banker and Natarajan (2008)	Ramalho et. al (2010)			
					Fractional Models			
					Log	Probit	Loglog	cloglog
Bulk ratio	0.3019***	0.5079***	0.4214***	0.8963***	2.5011***	1.5008***	1.5636***	1.8719***
	(0.0659)	(0.0697)	(0.0479)	(0.1627)	(0.3372)	(0.2428)	(0.2174)	(0.2361)
Dgest	0.2071***	0.3972***	0.3556***	0.6603***	1.9941***	1.1789***	1.2883***	1.4303***
	(0.0494)	(0.0518)	(0.0387)	(0.1186)	(0.2839)	(0.1901)	(0.2318)	(0.1893)
Berth	0.0099	0.0662***	0.0303***	0.0023	0.3189***	0.1959***	0.2568***	0.1989***
	(0.0092)	(0.0161)	(0.0112)	(0.0215)	(0.081)	(0.0403)	(0.0853)	(0.0449)
Distance	0.1043***	0.2439***	0.2461***	0.3301***	1.6564***	0.9822***	1.0697***	1.1668***
	(0.0282)	(0.0439)	(0.045)	(0.0633)	(0.2544)	(0.1751)	(0.1649)	(0.1506)
Class	0.4624***	0.7939***	4.4172***	0.8784***	9.1182***	4.1182***	8.2146***	3.5003***
	(0.0403)	(0.0534)	(0.6374)	(0.0885)	(0.438)	(0.2053)	(0.3718)	(0.1848)
Trend	0.0065	0.0226***	0.0148***	0.0001	0.1237***	0.0726***	0.0716**	0.0836***
	(0.0041)	(0.0073)	(0.0054)	(0.0092)	(0.0368)	(0.0212)	(0.0279)	(0.0209)
Constant	− 0.3624	−1.6924***	− 1.5298***	− 3.4455***	− 13.7002***	− 8.1341***	− 8.4890***	− 10.0382***
	(0.2268)	(0.3167)	(0.3002)	(0.5229)	(1.8523)	(1.2416)	(1.2658)	(1.1013)

p-value (p): *$p<0.10$, **$p<0.05$, ***$p<0.01$

Standard errors in parentheses

Table 6 Regression models of TE^k. Class 1

Variables	OLS	Tobit regression	Simar and Wilson (2007)	Banker and Natarajan (2008)	Ramalho et. al (2010)			
					Fractional Models			
					Log	Probit	Loglog	cloglog
Bulk ratio	0.0388	1.7900***	1.0719***	0.0548	11.6664***	5.7350***	10.9364***	4.1336***
	(0.0258)	(0.548)	(0.3826)	(0.0443)	(2.4035)	(1.3046)	(2.1024)	(1.0794)
Capital ratio	0.0008***	0.0109***	0.0066*	0.0010***	0.0606***	0.0314***	0.0559***	0.0233***
	(0.0001)	(0.0039)	(0.0037)	(0.0002)	(0.014)	(0.0069)	(0.0133)	(0.0056)
Berth	0.0432***	0.1611	− 0.0232	0.0537***	1.1658***	0.5179***	1.1101***	0.3493***
	(0.0115)	(0.1701)	(0.0296)	(0.0151)	(0.3226)	(0.1281)	(0.3012)	(0.0855)
Distance	0.0063	1.4899***	0.4371	0.0041	9.4720***	4.6437***	8.8748***	3.3354***
	(0.0202)	(0.4594)	(0.3145)	(0.0262)	(1.952)	(1.0332)	(1.7489)	(0.8371)
Constant	0.6584***	-9.4526***	− 1.6547	− 0.3983**	− 63.8908***	− 31.1390***	− 59.6335***	− 22.4646***
	(0.1164)	(3.1503)	(2.1681)	(0.1713)	(13.0079)	(6.9295)	(11.6321)	(5.6476)

p-value (p): *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

Standard errors in parentheses

Table 7 Regression models of TE^k. Class 2

Variables	OLS	Tobit regression	Simar and Wilson (2007)	Banker and Natarajan (2008)	Ramalho et. al (2010)			
					Fractional Models			
					Log	Probit	Loglog	cloglog
Bulk ratio	0.5189***	1.5668***	0.7286***	1.0297***	5.9260***	3.4648***	4.7441***	3.3704***
	(0.1333)	(0.2705)	(0.1556)	(0.3085)	(1.0922)	(0.6334)	(0.9898)	(0.5431)
Dgest	0.2105**	0.4777***	0.1970*	0.4387**	1.9432***	1.1626***	1.4751***	1.2005***
	(0.096)	(0.1388)	(0.1061)	(0.1767)	(0.6186)	(0.386)	(0.4147)	(0.3428)
Distance	0.1034*	0.4058***	0.2378***	0.1445	1.7764***	0.9976***	1.4641***	0.9137***
	(0.0528)	(0.1114)	(0.0598)	(0.1268)	(0.4245)	(0.2506)	(0.3238)	(0.179)
Occupancy rate	0.9261***	2.8419***	2.2176***	1.7397***	12.3196***	6.7396***	10.3132***	5.8481***
	(0.1807)	(0.458)	(0.4197)	(0.4181)	(2.4191)	(1.0469)	(1.7257)	(1.0681)
Constant	− 0.432	− 3.0378***	− 1.7294***	− 2.4228***	− 15.3033***	− 8.6196***	− 12.1168***	− 8.3226***
	(0.3974)	(0.8126)	(0.4279)	(0.9039)	(3.1781)	(1.8174)	(2.3601)	(1.328)

p-value (p): $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$

Standard errors in parentheses

of Class 1, and Callao North, Mejillones and San Antonio form the frontier of Class 2, for all the period.

The following tables show the second stage analysis. Table 4 shows the regression models in a non-convex metafrontier context; i.e., it takes into account the TE_i^* of the fourteen terminals as a dependent variable. Table 5 presents the regression models where TGR is the dependent variable, while Table 6 and Table 7 present the regression models linked to Class 1 and Class 2 terminals, respectively. That is to say, they take as dependent variables the technical efficiency score of the terminals belonging to each class measured with their own group frontier: TE_i^1 and TE_i^2. In all cases, the main second stage models available in the empirical literature have been estimated.

Regarding the regression models that are related to the metafrontier, Table 4 shows that the coefficients of the container index variable have the expected sign and were significant at the usual level for all models, except for the models estimated by OLS, TR and SW (2007) approach. Moreover, the coefficients of the bulk ratio have the expected sign and were significant at the usual level in all models. It means that the greater the degree of mechanization, the higher the level of efficiency.

The coefficients of dgest are positive and also significant in all regression models, which indicates that private management contributes positively to technical efficiency. As shown by Chang and Tovar, (2014b) this result could be related to the institutional rather than the type of ownership.

The coefficients of the distance variable are positive and significant at usual levels in all the regression models. Therefore, it seems that a greater distance to the nearest port contributes to increasing the TE at port terminals. Thus, as Figueiredo De Oliveira and Cariou (2015) concluded, we found that efficiency does not always go hand in hand with competition. This could be explained by the technological characteristics of this industry, such as the presence of high sunk costs and the reduced market size in the region.

The positive coefficient of occupancy rate means that the lesser the idle capacity of terminals the higher the levels of TE. The parameters are significant at the usual level in all models. Moreover, the coefficients of the berth variable are positive and significant, at the usual level in all models; thus, it seems that the levels of TE changes directly in accordance with the size of the port terminal.

Finally, the coefficients of the class variable are positive and significant at the usual level in all models, except for loglog specification of the fractional model suggested by Ramalho et al. (2010). Therefore, our results show that terminals which belong to Class 2, i.e., that operate using the Class 2 production technology, have a higher TE level than Class 1 terminals.[17]

It should be noted that the results linked to those variables in common with Chang and Tovar (2014b), the container index, bulk ratio, occupancy rate and dgest variables, are similar to those obtained by the aforementioned authors. This fact confirms that these results are robust, no matter whether the SFA or DEA approaches are followed.

[17] Remember that this variable is equal to 1 when terminal belongs to class 2 and zero otherwise.

Table 5 presents the regression models where TGR is the dependent variable. It shows that the coefficients of bulk ratio have the expected sign and are significants at the usual level in all models. It means that the greater the degree of mechanization available to move bulk, then the higher the TGR; i.e., the higher degree of mechanization linked to moving bulk, then the higher the catching up effect.

When it comes to the coefficients of dgest (type of management), they are positives and significants in all the regression models. Therefore, they indicate that private management enables terminals to advance towards the best available technology.

Additionally, the coefficients of the berth variable are significants, at the usual level in all models, except for the coefficient linked to the linear regression estimated by OLS and the coefficient linked to the Banker and Natarajan (2008) method. Thus, as coefficients are positives and significants, it seems that the TGR changes directly in accordance with the size of the port terminal.

The coefficients of the distance variable are positives and significants at usual levels in all the regression models. Therefore, it seems that the TGR changes inversely in accordance with the inter-port competition.

The coefficients of the class variable are positives and significants at the usual level in all models. Therefore, again our results show that terminals which belong to Class 2, have a higher TGR in comparison with Class 1 terminals. That is to say Class 2 terminals have a technological advantage when compared with the other class terminals.

Finally, the coefficients of the trend variable are positives and significants at the usual level in all models, except for linear regression estimated by OLS and the coefficient linked to the BN (2008) method. Therefore, our results show that the terminals have increased their TGR over time and that they are converging with the best available technology.

As expected, there are differences between the results of the models linked to contextual variables in Class 1 and Class 2 (Tables 6 and 7, respectively) and those obtained for the metafrontier (Table 4). It seems that the container index variable is no longer a driver that explains TE. Furthermore, neither dgest nor occupancy rate variables in Class 1, nor the berth variable in Class 2 explain the TE levels. However, the bulk ratio result does not change; i.e., the higher degree of mechanization for moving bulk cargoes positively influences the TE in both classes, and it seems that the capital ratio variable explains the TE in Class 1.

The dgest variable is positive and significant at the usual level in all models in Class 2 but it is not significant in Class 1. It indicates that private management contributes positively to the TE levels, but only in the Class 2 terminals.

The coefficients of the capital ratio variable are positives and significants at the usual levels in all models in Class 1, in contrast to the regression models which are related to the metafrontier. In this way, a greater intensity of capital leads to greater TE in Class 1 terminals. However, the coefficients of the capital ratio variable are not significants in all Class 2 models; this could be due to the fact that the capital ratio in Class 2 terminals is more or less appropriate.

The coefficients of berth variable are positives and significants at usual levels in all Class 1 models, except in the TR and the SW (2007) model, but they are not significants for Class 2. Therefore, it suggests that for Class 1 terminals, the bigger the terminal the higher the TE level, whereas this variable is not relevant for Class 2 terminals.

The coefficients of the distance variable are positives and significants at the usual levels in all Class 1 and Class 2 models, except for the linear regression estimated by OLS and SW (2007) model in Class 1 and the BN (2008) method for both classes. Thus, the results suggest that a higher level of inter-port competition reduces the TE level.

Finally, the coefficients of occupancy rate are positives and significants for all models in the case of Class 2 terminals, but they are never significants for Class 1 terminals. Therefore, it seems that this variable is only relevant for explaining the efficiency in the case of Class 2 terminals.

5 Conclusions

DEA is the most popular method used for measuring efficiency/productivity in the port sector. To analyse efficiency drivers, DEA has to follow a two-stage process. As it has been shown in this paper, it is key how these two stages are performed in order to obtain accurate estimates.

The influence of certain contextual variables in the efficiency levels of peruvian and chilean port terminals was evaluated through a two-stage non-convex metafrontier DEA approach. In the first stage, and due to the existence of technological differences among the terminals, this paper estimates technical efficiencies using a non-convex metafrontier DEA approach. Moreover, in the second stage, we consider all the different regression models found in the literature that try to explain the TE levels with respect to the metafrontier (TE^*), with respect to the group-specific frontier (TE^k) and TGR obtained in the first stage.

The first-stage results show that, on average, between 2004 and 2014 the TE* were 54.6% and 77.2% for Classes 1 and 2 respectively. The terminals of Callao North, San Antonio, Mejillones and Arica were the most efficient, followed by Pisco, Valparaiso, Salaverry, Paita, Matarani, San Vicente and Antofagasta; and finally were Ilo, Iquique and Chimbote.

The literature review shows that the contextual variables usually tested as port terminals' TE drivers were the type of management, type of cargoes, hinterland size, port size, connectivity, level of competition, time trend and time trend squared. These variables were obtained from each terminal and they were tested in second stage models.

Regarding the regression models related to the metafrontier, the results show that the degree of mechanization to move container cargo and bulk cargo (container index and bulk ratio variables), private management, size and the occupancy of berths all positively affect the TE of port terminals; however, the inter-port competition negatively affects the TE. Moreover, there are some differences between Class 1 terminals and Class 2 terminals, as terminals belonging to Class 2 show a higher TE level. Therefore, these results provide evidence that there are differences by class, which the proposed approach (a non-convex metafrontier framework) captures properly. What is more, it should be noted that four of the previous variables (container index, bulk ratio, private management and occupancy of berths) were also identified as efficiency drivers by Chang and Tovar (2014b), with similar results to the ones obtained here; thus, we can confirm that these results are robust no matter the approach (SFA vs. DEA) used.

With respect to second stage models related to TGR the results show that the degree of mechanization to move bulk, private management, size, the fact of belonging to Class 2 and the time trend all affect the TGR positively. That is to say they are all variables which contribute to converging on the best available technology, whereas the inter-port competition affects the TGR negatively.

However, when the sample is divided by class, to take into account how close a firm is to operating on the group-specific frontier, some results change. It seems that the container index variable is not a driver that explains the TE in both classes. Likewise, the type of management and the occupancy rate variables in the case of Class 1, and the size of port terminals in the case of Class 2 are not variables that explain the TE levels anymore. In contrast to the regression models related to the metafrontier, a greater intensity of capital in Class 1 terminals increases their TE. Last but not least, it should be noted that the results obtained are robust across all the estimated models.

Therefore, it is suggested that the policy makers for the South Pacific West Coast terminals take into account the determinants of TE and TGR found in this paper, in order to guide their public policies. These determinants are the degree of mechanization to mobilize containers and bulk cargoes, the private management, the capital intensity, the size, the inter-port competition, the occupancy of berths and the time trend.

The empirical evidence shows that private management increases the TE of all terminals with regard to the metafrontier and the efficiency of Class 2 terminals related to their own frontier; this suggests that both Peruvian and Chilean governments should promote more private participation in the management of other terminals, and that the Peruvian government should continue with the concession process of the Ilo and Chimbote terminals.

Furthermore, the results show that policy measures should be oriented towards improvements in the degree of mechanization in both classes and to increasing the size of terminals, mainly Class 1 terminals. Moreover, the occupation rate variable shows that it is necessary to increase the volume of cargoes managed by the terminals. This could be done through marketing policies design to attract more and/or new cargoes. This is mainly the case for Class 2 terminals. Likewise, the capital intensity in Class 1 terminals should be increased. It should be noted that Class 1 terminals are less capital intensive and smaller than their Class 2 counterparts. Thus, the investments in Class 1 terminals should be oriented mainly to increase their infrastructure and equipment, so that they increase their size and become more capital intensive.

Finally, our results suggest that inter-port competition negatively affects terminal efficiency scores for both classes. Indeed, although this result could be explained by the technological characteristics of this industry, such as the presence of high sunk costs and the reduced market size in the region, we consider that the impact of inter-port competition on port TE is unclear and requires additional investigation.

To conclude, both countries' regulatory agencies should take into consideration the extremely important issue of the treatment of heterogeneity in order to introduce an asymmetric incentive mechanism, according to each class's technology of production. This would avoid, the estimated efficiency being erroneous (and, a as a consequence, a terminal being considered erroneously not efficient) and it would avoid identifying untruthful drivers that generate erroneous public policies. This fact opens the door to the necessary cooperation among the regulatory agencies in the region to evaluate port efficiency using a dataset which contains all the relevant homogeneous classes of ports in the region. This is especially true when the number of ports in a country is not enough to get reliable results.

Acknowledgements This research was partially funded with Grant ECO2015-68345-R (MINECO/FEDER) from Ministerio de Economía y Competitividad and Fondo Europeo de Desarrollo Regional (FEDER).

Author contributions Authors contributed equally to the development of the present paper.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

References

Autoridad Portuaria Nacional del Perú-APN (2010). Reporte mensual 2010, Ocupabilidad de muelles en los TP de ENAPU Callao y DP World

Banker RD, Natarajan R (2008) Evaluating contextual variables affecting productivity using data envelopment analysis. Operations Res 56(1):48–58

Battese GE, Rao DSP (2002) Technology Potential, Efficiency and a Stochastic Metafrontier Function. Int J Bus Econ 1(2):1–7

Bergantino AS, Musso E (2011) The role of external factors versus managerial ability in determining seaports' relative efficiency: An input-by-input analysis through a multi-step approach on a panel of Southern European ports. Marit Econ Logist 13(2):121–141

Bichou K (2009) Port Operations Planning and Logistics (Lloyd's Practical Shipping Guides) 2nd Edition. Routledge, Informa Law

Chang V, Tovar B (2014a) Efficiency and productivity changes for Peruvian and Chilean ports terminals: a parametric distance functions approach. Transp Policy 31:83–94

Chang V, Tovar B (2014b) Drivers explaining the inefficiency of peruvian and chilean ports terminals. Transp Res Part E 67:190–203

Chang V, Tovar B (2017a) Heterogeneity unobserved and efficiency: a latent class model for west coast of south pacific port terminals. J Transp Econ Policy 51(2):139–156

Chang V, Tovar B (2017b) Metafrontier analysis on efficiency and productivity for west coast of south pacific terminals. Transp Res Part A: Policy Practice 103:118–134

Charnes A, Cooper WW, Rhodes E (1978) Measuring the inefficiency of decision making units. Eur J Oper Res 2(6):429–444

Charnes A, Cooper WW, Rhodes E (1979) Short communication: measuring efficiency of decision making units. Eur J Operations Res 3:339

Coelli TJ, Rao DSP, O'Donnell CJ, Battese GE (2005) An introduction to efficiency and productivity analysis, 2nd edn. Springer, New York

Cooper WW, Seiford L, Zhu J (2004) Handbook on Data Envelopment Analysis. Volumen 71 de International Series in Operations Research & Management Science, ISSN 0884-8289EA. Taylor & Francis. ISBN:1402077971, 9781402077975

Cullinane KW, Wat T (2010) The efficiency analysis of container port production using DEA panel data approaches. OR Spectrum 32:717–738

Färe R, Grosskopf S, Lovell CAK (1985) The Measurement of efficiency of production. Kluwer Academic Publishers, Boston

Figueiredo G, Cariou P (2015) The impact of competition on container port in efficiency. Transp Res Part A 48:124–133

Fried HO, Lovell CAK, Schmidt SS (2008) The measurement of productive efficiency and productivity growth. OUP, New York

Jin Q, Kerstens K, Van de Woestyne I (2019) Metafrontier productivity indices: questioning the common convexification strategy. Eur J Oper Res. https://doi.org/10.1016/j.ejor.2019.11.019

Ju S, Liu N (2015) Efficiency and its influencing factors in port enterprises: empirical evidence from Chinese port listed companies. Marit Policy Manag 42(6):571–590

Kerstens K, O'Donnell CJ, Van de Woestyne I (2015) Frontier metatechnologies and convexity: a restatement. IESEG School of Management Discussion paper LEM, France, pp 2015–2108

Kerstens K, O'Donnell CJ, Van de Woestyne I (2019) Metatechnology frontier and convexity: a restatement. Eur J Oper Res. https://doi.org/10.1016/j.ejor.2018.11.064

McDonald J (2009) Using least squares and Tobit in second stage DEA efficiency analyses. Eur J Oper Res 197:792–798

Niavis S, Tsekeris T (2012) Ranking and causes of inefficiency of container seaports in South-Eastern Europe. Eur Transp Res Rev 4:235–244

O'Donnell C (2008) An aggregate quantity-price framework for measuring and decomposing productivity and profitability change, Centre for Efficiency and Productivity Analysis Working Papers: WP07/2008, University of Queensland

Panayides P, Maxoulis C, Wang T-F, Koi Yu (2009) A critical analysis of DEA application to seaport economic efficiency measurement. Transp Rev 29(2):183–206

Papke LE, Wooldridge JM (1996) Econometric methods for fractional response variables with an application to 401 (K) plan participation rates. J Appl Econometrics 11:619–632

Pestana C and Managi S (2008) Productivity drivers in Japanese seaports, technical University of Lisbon, Department of Economics, Working Paper

Polyzos S, Niavis S (2013) Evaluating port efficiency in the Mediterranean. Int J Data Anal Techniques Strategies 5(1):84–100

Ramalho EA, Ramalho JS, Henriques PD (2010) Fractional regression models for second stage DEA efficiency analyses. J Prod Anal 34:239–255

Rao DSP, O'Donnell CJ and Battese G (2004) Metafrontier functions for the study of inter-regional productivity differences. CEPA Working Paper, No.1/2003, School of Economics, University of Queensland, Brisbane

Simar L, Wilson PW (2007) Estimation and inference in two-stage, semi-parametric models of production processes. J Econometrics 136:31–64

Simar L, Wilson PW (2011) Two-stage DEA: caveat emptor. J Prod Anal 36:205–218

Tovar B, Rodríguez-Déniz H (2015) Classifying ports for efficiency benchmarking: a review and a frontier-based clustering approach. Transp Rev 35(3):378–400

Tovar B, Wall A (2017) Specialization, diversification, size and technical efficiency in ports: an empirical analysis using frontier techniques. Eur J Transp Infrastructure Res 17(2):279–303

Tovar B, Wall A (2019) Are larger and more complex port more productive? an analysis of Spanish port authorities. Transp Res Part A: policy and practice 121:265–276

Turner H, Windle R, Dresner M (2004) North American container port productivity: 1984–1997. Transp Res Part E 40:339–356

Wan Y, Yuen ACL, Zhang A (2014) Effects of hinterland accessibility on US container port efficiency. Int J Shipp Transp Logist 6(4):422–440

Wanke PF, Barbastefano R, Hijjar MF (2011) Determinants of efficiency at major Brazilian port terminals. Transp Rev 31(5):653–677

Wanke PF (2013) Physical infrastructure and shipment consolidation efficiency drivers in Brazilian ports: a two-stage network-DEA approach. Transp Policy 29:145–153

Wanke PF, Pestana C (2015) Public-private partnerships and scale efficiency in Brazilian ports: Evidence from two-stage DEA analysis. Socio-Econ Plan Sci 51:13–22

Wanke PF, Pestana C (2016) New evidence on the determinants of efficiency at Brazilian ports: a bootstrapped DEA analysis. Shipp Transp Logist 8(3):250–272

Woo S-H, Pettit SJ, Kwak D-W, Beresford AKC (2011) Seaport research: a structured literature review on methodological issues since the 1980s. Transp Res Part A 45:667–685

Yip TL, Sun X, Liu J (2010) Evolution of global container operator efficiency: a DEA approach. The Hong Kong Polytechnic University, Department of Logistics and Maritime Studies

Yuen A, Zhang A, Cheung W (2013) Foreign participation and competition: a way to improve the container port efficiency in China? Transp Res Part A 49:220–231

Zahran SZ, Alam JB, Al-Zahrani AH, Smirlis Y, Papadimitriou S, Tsioumas V (2020) Analysis of port efficiency using imprecise and incomplete data. Oper Res Int J 20:219–246. https://doi.org/10.1007/s12351-017-0322-9