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Examining the influence of corruption on port efficiency in West Africa and the Mid-Atlantic: A bootstrapped DEA analysis

Andrea Rodríguez [a,*], Antonio Gil Ropero [b], M. Mar Cerban [b], Lourdes Trujillo [a]

[a] Department of Applied Economic Analysis of the University of Las Palmas de Gran Canaria. Campus de Tafira. C/ Saulo Torón, 4, 35017, Las Palmas de Gran Canaria, Las Palmas, Spain

[b] Faculty of Economics and Business Studies, Avda. Duque de Nájera s/n, 11002, Cádiz, Spain

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1. Introduction

In recent years, Africa has demonstrated considerable progress both economically and demographically, inspiring growing scholarly interest in domains such as trade and infrastructure (Schwab, 2018). Within this context, maritime transport—responsible for more than 90 % of global trade—plays a pivotal role in fostering commerce, driving economic expansion, and connecting African economies to worldwide markets (Fugazza and Hoffmann, 2017; Ducruet, 2020). Nonetheless, the continent's economic landscape remains complex, marked by significant disparities across countries, sectors, and social groups (Robinson, 2002; Cramer et al., 2020).

Against this backdrop, governance quality—and the issue of corruption—has drawn increasing scrutiny, given its far-reaching implications for port performance. Several authors have highlighted how corruption index levels significantly affect port quality, productivity, investment decisions and efficiency scores (Sequeira and Djankov, 2010; Suárez-Alemán et al., 2016; Serebrisky et al., 2016). Comparable studies in Latin America emphasize that systemic corruption inflates shipping costs, undermines competitiveness, and curtails container throughput (Seabra et al., 2016). While these findings illustrate the adverse consequences of corruption on maritime logistics, few investigations explicitly integrate corruption measures into multi-country frameworks encompassing both shared geography and varied governance regimes.

Building on these insights, the present research contributes to the literature by systematically incorporating Transparency International's (1995) Corruption Perceptions Index (CPI)[1] into an efficiency analysis. Although previous work has explored the role of corruption in Africa's port (Trujillo et al., 2013), limited attention has been paid to its direct impact on efficiency rankings within a single, heterogeneous sample of ports. Specifically, this study considers two main ports from the Canary Islands (Spain)—which, despite their proximity to Africa, benefit from European Union (EU) regulatory stability—and 14 main seaports across West Africa, where operational and bureaucratic conditions often diverge substantially.

Intense competition among these ports for transhipment traffic and maritime trade destinations underscores the need for a unified analytical framework. According to Rodríguez et al. (2025), while some African ports are steadily enhancing their infrastructure and cargo-handling capabilities, Canary Island ports often maintain a competitive edge

* Corresponding author.
E-mail addresses: andrea.rodriguez@ulpgc.es (A. Rodríguez), antonio.gilropero@uca.es (A. Gil Ropero), mariadelmar.cerban@uca.es (M.M. Cerban), lourdes.trujillo@ulpgc.es (L. Trujillo).

[1] Further information on the data and methodology is available on Transparency International's official website: http://www.transparency.org. The CPI calculation incorporates alternative approaches developed by Professor Andrew Gelman (Department of Statistics and Department of Political Science, Columbia University) and Dr Piero Stanig (Fellow, Methodology Institute, London School of Economics and Political Science). It is worth noting that Transparency International has revised both the sample and the methodology for the CPI multiple times since the index was first introduced in 1995. The present study comprise data from 2011 to 2020, downloaded in 2024.

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due to more stringent security standards and stricter regulatory oversight. Building on this contrast, recent studies highlight the importance of addressing governance and political factors in port efficiency. In this regard, Mlambo (2021) found that higher operational efficiency strongly supports national trade relations, reinforcing the connection between governance, efficiency, and trade competitiveness. Similarly, Buor (2024) identified nationalism and political considerations as major drivers of efficiency outcomes, confirming that regulatory and political issues are critical to a unified analytical approach.

In practical terms, we examine how incorporating the CPI—using as proxy of legacy environment and for instance time-congestion problems—reshapes efficiency rankings among ports that, although geographically proximate and linked by similar shipping routes, operate under distinct legal, regulatory, and bureaucratic conditions. Such a comparative analysis is particularly relevant for West African ports, which compete directly with Atlantic and Mediterranean gateways. In contrast to studies confined to a single region or reliant on broad structural indicators, our approach illuminates the specific mechanisms through which corruption influences port performance and produces flexible results, thus enabling the construction of a realistic comparative framework for this sample.

By employing a Bootstrap Data Envelopment Analysis (DEA) methodology, we mitigate bias in efficiency estimates and provide robust, data-driven insights into how governance capacity, infrastructure development, and maritime logistics intersect. Moreover, by capturing political and legislative heterogeneity within a single framework, this work refines our understanding of how differing institutional environments shape operational effectiveness. To our knowledge, no previous research has explicitly integrated the CPI as a contextual factor in a consolidated dataset of multiple ports—European and African—competing along similar trade routes.

In order to frame the comparative analysis presented in this study, we introduce two key governance-related concepts already establish in the literature: *regulatory asymmetry* and *institutional edge*. The former refers to situations in which institutions or stakeholders operating within the same geographical area are subject to unequal norms, conditions, or rules. These disparities may stem from legal requirements, differential access to information or resources, or the application of overlapping regulations from various jurisdictions—national, supranational, regional, or local (Laffont and Tirole, 1993). In the port sector, *regulatory asymmetry* arises when ports competing within the same maritime corridor operate under divergent legal, fiscal, or administrative frameworks, which may alter their competitive conditions. Additionally, varying degrees of autonomy in port authority governance and stakeholder coordination can further reinforce these asymmetries (Brooks and Cullinane, 2006).

The concept of *institutional edge* refers to the competitive advantage that a port authority—or other actors within the port community—may enjoy due to specific institutional features. These include the governance structure, the level of integration within national or supranational legal frameworks, and the predictability or stability of the regulatory environment (Notteboom et al., 2022). Together, these concepts provide the analytical lens through which we interpret how governance factors influence technical efficiency, particularly in port systems characterized by overlapping jurisdictions and uneven institutional quality.

The structure of this paper is as follows. Section 2 reviews the existing literature on port efficiency in line with the study's objectives. Section 3 outlines the methodological rationale behind the Bootstrap DEA approach. Section 4 describes the dataset and highlights legislative disparities between the EU-regulated Canary Islands and West African ports. Section 5 presents and discusses the empirical findings, focusing on implications for port administrators and policymakers. Section 6 synthesizes the main conclusions, while Section 7 addresses the study's proposed avenues for future research.

2. State of the art

2.1. Bootstraps efficiency analysis

In recent decades, efficiency estimation has evolved significantly, driven by the development of non-parametric methodologies. Among these, the Bootstrap method has emerged as a fundamental tool, enabling robust statistical inferences without the need to assume specific parametric distributions. This approach has been widely adopted across various fields, including economics, management, and the social sciences, where the goal is to evaluate the relative efficiency of productive units or firms. Through a series of key studies, the advantages of Bootstrap in estimating standard errors, confidence intervals, and other accuracy measures have been demonstrated, expanding the analytical possibilities in complex contexts.

The evolution of this methodology has been shaped by foundational works. Efron and Tibshirani (1986) introduced the Bootstrap as a key technique for estimating standard errors and confidence intervals, while Manski (1988) brought new perspectives by incorporating analogue estimation methods in econometrics. Simar (1992) adapted these concepts to the analysis of panel data, proposing a semi-parametric approach that improved the statistical significance assessment of efficiency estimators. Later, Simar & Wilson (1998) advanced the field by introducing non-parametric tests for returns to scale, utilizing Bootstrap procedures to reinforce statistical inference.

In 1999, Lothgren and Tambour applied the Bootstrap to calculate confidence intervals for Malmquist productivity indices, revealing significant productivity changes. Simar and Wilson (1999a) refined this approach with an iterative Bootstrap procedure, enhancing confidence interval estimates in DEA models. In their 2007 study, Simar and Wilson integrated several preceding approaches, developing novel bias corrections and interpolation techniques to enhance the reliability of non-parametric estimators (Simar and Wilson, 2007).

In the port-maritime sector, non-parametric approaches can be found in a wide range of studies, demonstrating its versatility and applicability. In terms of a more global unit of analysis, studies such as Gutiérrez et al. (2014) evaluated the efficiency of major international container shipping lines using a Bootstrap DEA approach. Their study highlighted the presence of oversized operations and inefficiencies within strategic alliances. Following this, Chang et al. (2017) shifted focus to the cruise industry, using a network DEA model to reveal operational efficiency among major cruise lines, but also identified significant inefficiencies in non-operational aspects due to high debt and poor financial risk hedging.

Moving to cargo activities, Gil Ropero et al. (2019) analysed the efficiency of the main container ports in Spain and Portugal using a DEA Bootstrap-based approach. Their findings indicated that inefficiencies were present, but they were not necessarily due to a lack of infrastructure, as the Bootstrapped results suggested that future investments in port expansion were not required. More recently, Danladi et al. (2024) extended the methodology to container ports in lower-middle-income countries, identifying that poor efficiency was mainly due to pure technical inefficiency rather than scale inefficiencies.

Following geographical criteria, Barros and Managi (2008) analysed the drivers of efficiency in Japanese seaports using a DEA Bootstrapped two-stage approach. Their study highlighted the importance of identifying key efficiency drivers, offering valuable insights for policy strategies aimed at improving port productivity. Similarly, Hung et al. (2010) investigated the operational efficiency of Asian container ports by integrating a comprehensive DEA framework with Bootstrap methods. Their research focused on determining scale efficiency targets and assessing the variability of efficiency estimates, providing crucial guidance for port managers to optimize resource allocation and improve operational performance. Nguyen et al. (2016) further extended this approach by applying Bootstrapped DEA to assess the efficiency of 43 major Vietnamese ports, stressing that standard DEA tends to produce biased results—particularly sensitive to sample size—while Bootstrapped DEA yields more consistent and unbiased efficiency scores.

Relevant studies have also expanded these approaches to other regions. In Europe, Carvalho et al. (2010) analysed the governance and performance of 33 seaports in the Iberian Peninsula, revealing significant inefficiencies due to mismanagement, political interference, and labour challenges, and highlighting the importance of governance models in improving port efficiency. In the Americas, Wanke and Barros (2015)investigated the role of public-private partnerships in enhancing scale efficiency in Brazilian ports. Their two-stage DEA analysis demonstrated that partnerships with private terminal operators significantly improved coordination, technology use, and connectivity, leading to greater efficiency. In a subsequent study, Wanke and Barros (2016) used Bootstrapped DEA to confirm these findings, emphasizing the positive impact of connectivity infrastructure and private management on port performance, particularly in reducing costs and queuing times.

2.2. African efficiency analysis

Studies estimating the efficiency of African ports have increased since the early 21st century, predominantly utilizing non-parametric methods. Nonetheless, Zhang et al. (2024) notes in a recent literature review that Middle Eastern and African ports collectively accounted for only 6.6 % of all port-efficiency research as of 2024. This discrepancy underscores the relative scarcity of in-depth analyses focused on African contexts, even as scholars acknowledge the region's growing economic and infrastructural significance.

One of the pioneering works in this area is by Al-Eraqi et al. (2008), which evaluates the efficiency of 22 cargo seaports across East Africa and the Middle East. The study employs DEA with a Window Analysis to assess both standard and super efficiency scores, drawing on panel data from 2000 to 2005. The findings indicate that the number of efficient decision-making units (DMUs) under the super-efficiency model exceeds those identified under the standard efficiency model. A follow-up study further applied both Standard DEA and Window Analysis to the same dataset, offering deeper insights into port efficiency and revealing the distinct advantages and disadvantages of each approach over time (Al-Eraqi et al., 2010).

Subsequent research has continued to apply DEA Window Analysis to evaluate port efficiency across Africa. Gamassa and Chen (2017) used this method to compare major ports in East and West Africa, finding that West African ports, despite their larger size and higher throughput, were generally less efficient than their East African counterparts. Tema in Ghana was identified as the most efficient, while Dar es Salaam ranked the least efficient over seven years. The study recommended port development strategies based on these efficiency rankings. Kalgora et al. (2019) assessed the efficiency of five major commercial ports in West Africa, reporting a scale efficiency score of 89.53 %. Ports like Abidjan and Cotonou were found to require adjustments in operational scale, and the study highlighted the impact of external factors such as pandemics and security threats on port efficiency. Most recently, Mwendapole et al. (2022) provided a recent example of this methodology, evaluating the operational efficiency of seaports in Southern and Eastern Africa over 10 years (2010–2019). They concluded that East African ports, despite being smaller, were generally more efficient than their South African counterparts.

By contrast, Barros et al. (2010) introduced a Bootstrapped DEA approach to analyze the technical efficiency of 25 African seaports. Their findings revealed that the original efficiency scores were biased, making Bootstrap methods essential for providing more reliable estimates. The results indicated that Nigerian seaports exhibited the greatest efficiency, followed by those in Mozambique and Angola. Diallo et al. (2022) likewise employed DEA Bootstraps at the Autonomous Port of Dakar, identifying inefficiencies and offering insights for improved decision-making.

Regarding standard DEA applications, Okeudo (2013) analysed the impact of reforms on the ports of Onne and Rivers, finding a continuous improvement in efficiency since 2006, with faster cargo handling, increased ship traffic, and higher berth occupancy. Carine (2015) extended the approach to 16 container ports in Sub-Saharan Africa, concluding that inefficiencies were primarily scale-related rather than technical. Van Dyck (2015) similarly assessed six major West African ports, reporting average efficiency scores above 76 % for most. Building on this context, Wanke et al. (2018) applied a two-stage fuzzy DEA model to six major ports in Nigeria from 2007 to 2013. Their study addressed the imprecision of port data by integrating fuzzy set theory into both efficiency measurement and the regression of contextual variables, such as operator type and cargo specialization Focusing on East Africa, Ngangaji (2019) found comparable technical efficiency for Dar es Salaam and Mombasa, suggesting that "coopetition" strategies could further enhance overall port performance. Moreover, Birafane & Abdi (2019) focused on Moroccan seaports through the application of two DEA models (Standard with Charnes-Cooper-Rhodes (CCR) and Banker-Charnes-Cooper (BCC); and scale of efficiency analysis), demonstrating that port expansions do not necessarily yield proportional gains in operational performance.

Other non-parametric productivity methodologies have also been explored. Barros and Peypoch (2012) used the Luenberger productivity indicator, concluding that Nigerian ports were the most efficient, followed by Angola and Mozambique. Nwanosike et al. (2016) employed the Malmquist Productivity Index on six Nigerian seaports, revealing post-reform gains in technical efficiency but a decline in technological progress. Adeola Osundiran et al. (2020) further examined 19 Sub-Saharan African ports (from 2008 to 2015), identifying technical efficiency as the main driver of productivity and recommending a continuous port improvement framework.

In contrast, parametric analyses are relatively scarce. Trujillo et al. (2013) employed a Stochastic Production Frontier (SPF) to examine reforms in 37 African ports, finding moderate yet consistent efficiency improvements. The study identified corruption, port size, Gross Domestic Product (GDP), and the landlord port model as influential determinants. Similarly, Akinyemi (2016) focused on Nigeria's port reforms using a SPF approach, reporting notable gains in cargo throughput and berth occupancy. More recently, Ayesu et al. (2023) used a System-Generalized Method of Moments to assess seaport efficiency for 28 African countries, concluding that higher performance in these dimensions strongly correlates with economic growth. Subsequently, Ayesu et al. (2024) took a gravity-based approach to 33 African countries, demonstrating that improved seaport efficiency significantly boosts trade performance.

Table 1 summarizes the principal studies on African port efficiency. Notably, none of these works combines African ports with those operating under distinct political and legislative frameworks, such as European-administered ports. Moreover, Table 2 presents the studies most closely aligned with the current research in terms of methodology, regional scope, and the integration of governance-related variables.

From a methodological standpoint, Barros et al. (2010) and Diallo et al. (2022) apply Bootstrap DEA to evaluate technical efficiency in African ports. The former, uses inputs such as labour, capital, and operating costs, and outputs including total cargo throughput and vessel calls. Similarly, Diallo et al. (2022) use physical infrastructure inputs—such as the number of berths, quay length, and cranes—and outputs like container throughput and general cargo. Although these studies demonstrate the value of Bootstrapped DEA, they have no integrated external governance variables—such as corruption—into their models (see Table 2).

Although some efficiency studies conducted outside the African context have used indicators such as the CPI as a proxy for institutional quality (e.g., Suárez-Alemán et al., 2016; Serebrisky et al., 2016), no existing research has jointly analysed ports from heterogeneous institutional environments in a single framework. Among the studies reviewed, only Trujillo et al. (2013) explicitly incorporate CPI in the

Table 1
Summary of the literature review on efficiency studies in africa.

Year	Authors	Unit of analysis	Methodology
2008–2010	Al-Eraqi *et al.*	22 cargo seaports across East Africa and the Middle East	Standard DEA and DEA Window Analysis
2010	Barros et al.	25 African seaports 2004–2006	DEA bootstraps
2013	Okeudo	Onne and its river ports from 2001 to 2010	Standard DEA
2013	Trujillo et al.	1998 and 2007 across 37 African ports.	SPF
2015	Carine	16 container port of Sub-Saharan Africa over the year 2012	Three DEA models: CCR, BCC, and Super-Efficiency
2015	Van Dyck	Six major West African ports for the period 2006–2012	Standard DEA
2016	Akinyemi	Nigerian seaports from 2000 to 2011	SPF
2016	Nwanosike et al.	Six major Nigerian seaports from 2000 to 2011	Malmquist Productivity Index
2017	Gamassa & Chen	Eastern and Western African ports from 2008 to 2014	DEA Window
2018	Wanke et al.	Six major Nigerian ports from 2007 to 2013	Two-Stage Fuzzy-DEA models
2019	Kalgora et al.	West-Africa Ports over the years 2005–2016	DEA Window
2019	Ngangaji	Dar es Salaam and Mombasa Port from 2008 to 2018	Standard DEA
2019	Birafane & Abdi	Eight seaports in the Kingdom of Morocco from 2014 to 2017	Two DEA models (Standard with CCR and BCC, and scale of efficiency analysis)
2020	Adeola Osundiran	19 Sub-Saharan African ports from 2008 to 2015	Malmquist Production Index
2022	Diallo et al.	Autonomous port of Dakar for the year 2021	DEA bootstraps
2022	Mwendapole et al.	Six South and East African seaports from 2010 to 2019.	DEA Window
2023	Ayesu et al.	28 African countries, using data from 2010 to 2018	Generalized Method of Moments

Sources: Own Elaboration.

efficiency analysis of African ports (see Table 2 for more details).

Addressing this gap, the present article proposes an integrated analysis of major ports in West Africa and selected Atlantic ports in the Canary Islands, which operate under EU environmental and institutional frameworks. By incorporating the CPI into a Bootstrap DEA model, this study offers new insights into how differences in governance quality affect port efficiency, thereby contributing to the broader literature on maritime performance across diverse regulatory settings.

3. Methodology

One of the significant characteristics of the standard Data Envelopment Analysis (DEA) method is its deterministic nature, which precludes the derivation of statistical properties for the efficiency scores. A more attractive solution involves the application of Bootstrap methodology, which preserves the advantages of DEA while enabling the extraction of statistical properties from a data-driven scheme. Accordingly, this analysis adopts a fully non-parametric approach, wherein an iterative bootstrapped procedure characterizes the production set. The estimation of non-parametric efficiencies using Bootstrap methodology not only yields more consistent efficiency measurements but also facilitates the detection of extreme values. Under the standard DEA method, some ports are deemed efficient (i.e., they receive an efficiency score of one); however, the Bootstrapped DEA is particularly effective in addressing this overestimation problem (Barros et al., 2010). According to Simar and Wilson (2000a), the application of Bootstrap methodology results in more robust and consistent outcomes.

Consequently, this study employs the DEA methodology to measure pure technical efficiency. In a subsequent stage, the DEA-Bootstrap-BCC model is utilized to derive more reliable efficiency rankings without bias. All calculations were performed using software developed by the authors. The methodological details are provided in Sections 3.1 and *3.2*.

To ensure full transparency and replicability, Appendix A provides a comprehensive description of the computational procedure. This includes the algorithmic assumptions underlying the simulations, and the parameter settings adopted—such as the treatment of random seed initialization and the specification of the number of Bootstrap replications. We also explain how our custom-developed software faithfully implements the Bootstrap algorithm proposed by Simar and Wilson (2000a), ensuring full methodological consistency with the established literature.

3.1. Data Envelopment Analysis (DEA) methodology

The DEA methodology is a non-parametric technique and does not assume any functional form for the relationship between inputs and outputs, or any distribution of inefficiency. Furthermore, it is capable of handling situations with multiple inputs and outputs, expressed in different units. It is precisely these advantages that have favoured the extensive use of DEA. Applying DEA methodology, the efficient frontier can be defined by either an input orientation (minimal achievable input level for a given output) or an output orientation (maximal achievable output given the input level).

In this study, an output-oriented DEA model is employed to estimate Pure Technical Efficiency (PTE) under Variable Return Scale (BCC–VRS), commonly referred to as the BCC-VRS model. Suppose that there are $\boldsymbol{n}$ Decision Making Units (DMUs)- in this context, the port under analysis-each using $\boldsymbol{m}$ inputs X_{ij} $(i = 1 \ldots, m)$ to produce $\boldsymbol{s}$ outputs Y_{rj} $(r = 1 \ldots, s)$. Let $X_{ij} > 0$ denote the amount of input i used by DMU j and Yrj >0 the amount of output r produced by DMUj.

Following Charnes et al. (1978) and Banker et al. (1984), the

Table 2
Comparative summary of key efficiency literature.

Year	Authors	Unit of analysis	Methodology	Variables	CPI
2010	Barros et al.	25 African seaports (2004–2006)	DEA bootstraps	Inputs: Labor, capital, operating costs. Outputs: Cargo throughput, vessel calls	Not included
2022	Diallo et al.	Autonomous port of Dakar (2021)	DEA bootstraps	Inputs: Number of berths, quay length, cranes. Outputs: Container throughput, general cargo	Not included
2016	Suárez-Alemán et al.	70 developing countries (2000–2010)	Stochastic Frontier	Inputs: Berth length, area, cranes. Outputs: Annual throughput (TEUs), transshipment volumes.	CPI as explanatory variable of inefficiency
2016	Serebrisky et al.	63 ports of Latin America and the Caribbean (1999–2009)	Stochastic Frontier	Inputs: Berth length, area, cranes. Outputs: Annual throughput (TEUs), transshipment volumes	CPI as explanatory variable of inefficiency
2013	Trujillo et al.	37 African ports (1998 and 2007)	Stochastic Frontier	Inputs: Berths, area, cranes. Outputs: Container throughput (TEUs)	CPI used as explanatory variable in a second-stage efficiency model

Sources: Own Elaboration.

output-oriented VRS (BCC) model can be formulated in matrix form as follows:

$$\text{Max } \theta + \varepsilon \left(\sum_{i=1}^{m} S_i^- + \sum_{r=1}^{s} S_r^+ \right) \tag{1}$$

subject to

$$\sum_{j=1}^{n} \left(\lambda_j x_{ij} \right) + S_i^- = x_{io} \quad i = 1, 2, \ldots, m;$$

$$\sum_{j=1}^{n} \left(\lambda_j y_{rj} \right) - S_r^+ = \theta y_{ro} \quad r = 1, 2, \ldots, s;$$

$$\lambda_j \geq 0 \quad j = 1, 2\ldots, n.$$

$$\sum_{j=1}^{n} \lambda_i = 1$$

where:

- Y_{ro} and X_{io} the r_{th} output and i_{th} input for a DMU_o under evaluation
- λj the decision variables that represent the weights DMU j would place on DMU_o in constructing its efficient reference set
- θ the proportional distance in inputs to the envelope and therefore the measurement of the index of technical efficiency
- ε the smallest real positive number
- S_i and S_r the potential slacks or excess factor for each input

In brief, the output-oriented BCC model thus provides a measure of how much each DMU (port) can proportionally increase its outputs, given its current input levels, before reaching the efficient frontier.

3.2. Bootstrapped DEA methodology

Simar and Wilson (1999a) proposed an algorithm to obtain Bootstrap estimates of confidence intervals, bias, and other statistical properties for the output distance function $\theta_{(x_0,y_0)}$ evaluated for a particular, arbitrary point $(x_0, y_0) \in R_+^{p+q}$, provided that the corresponding estimate $\widehat{\theta}_{(x_0,y_0)}$ exists.

The concept discussed above is illustrated in Figure A.1, which depicts the production possibility frontier under variable returns to scale, along with the standard DEA and Bootstrap DEA frontiers. Under the assumption that the smooth Bootstrap holds, it is expected that: $[\widehat{\theta^*}_{(x_0,y_0)} - \widehat{\theta}_{(x_0,y_0)}] \sim [\widehat{\theta}_{(x_0,y_0)} - \theta_{(x_0,y_0)}]$.

4. Characteristic of the sample

The dataset used to estimate efficiency scores comprises 16 seaports: two Spanish ports—Las Palmas and Santa Cruz de Tenerife, both in the Canary Islands Archipelago—and 14 seaports located across the West African mainland (see Table 3). As previously noted, including the two Spanish ports introduces a distinctive dimension to the analysis. Although these ports are geographically situated off the African coast, they operate under EU regulations, thereby creating a regulatory contrast within the sample. This contrast sheds light on the competitive advantages and governance disparities across the ports, ultimately allowing for a more realistic comparison of efficiency scores. Moreover, despite belonging to different countries, these ports share overlapping spheres of commercial influence, further underscoring the relevance of their joint assessment.

The ports (see Fig. 1) were selected based on their geographical proximity, operational capacities (movements of Twenty-Foot Equivalent Units (TEUs) by port), traditional main port of the area and competitive relevance within the Mid-Atlantic cargo traffic network (Rodríguez et al., 2025). This sample represents a diverse cross-section of West African ports, which include hubs such as Dakar, Tema, and Tanger Med. These ports exhibit varying governance structures, infrastructure capabilities, and investment levels. Ports like Tanger Med and Tema stand out for their advances in digitalization and high connectivity, as demonstrated by their strong rankings in the Port Liner Shipping Connectivity Index (PLSCI) by the United Nations Conference on Trade and Development (UNCTAD). Conversely, ports like Abidjan and Dakar serve as critical gateways for landlocked countries, connecting them to global trade networks despite operational inefficiencies.

The Spanish ports are administered under the centralized framework of *Puertos del Estado*[2] ensuring uniform operational standards and benefiting from a regulatory regime, which emphasizes security, transparency, and efficiency (European Commission, 2020). This governance model stands in marked contrast to that of many African ports, where operations are often overseen by private concessions or decentralized authorities. Such arrangements can give rise to challenges, including corruption and bureaucratic inefficiencies in port performance.

Although significant dichotomies exist between EU-compliant ports and those managed under diverse national or private regimes, numerous initiatives have been undertaken to support the African continent in various areas. For example, China's Belt and Road Initiative has driven substantial investments in ports such as Tema and Lomé, leading to notable infrastructural enhancements. Moreover, regional trade policies championed by the African Union[3] and Economic Community of West African States (ECOWAS)[4] aim to reduce reliance on external hubs, like the Canary Islands, by strengthening intra-African trade. Nevertheless, prevailing indicators—including the corruption index and other socio-economic measures—suggest that much progress remains to be made.

Covering the period from 2011 to 2020, this analysis captures a decade of evolving dynamics within this competitive maritime landscape. Data were sourced from the Transparency International, World Bank, IHS Markit SeaWeb, UNCTAD, and Shipping Guides publications, providing a robust foundation for a nuanced comparison of port efficiency.[5]

4.1. Variables of the empirical model

In this study, the analysis is confined exclusively to the container handling service—specifically, the loading and unloading operations carried out at port terminals. This focus is crucial for accurately selecting the appropriate output and input data, as ports function as multi-service entities and a clear delineation of the evaluated service ensures methodological rigor. A robust framework for defining variables in port efficiency studies has been extensively developed in the literature, with seminal contributions by Cullinane et al. (2004, 2006). Building on these foundations, the variables selected for the present analysis adhere to widely accepted inputs and outputs in the field.

4.1.1. Output variable

The output variable (Y) is defined as container throughput, measured in TEUs. This indicator is universally recognized as the most critical metric in port efficiency studies, as it encapsulates the volume of cargo

[2] Official website https://www.puertos.es/.

[3] See the official website for more details https://au.int/.

[4] See the official website for more details https://www.ecowas.int/.

[5] It is important to note that significant challenges remain in obtaining reliable data from African ports for accurate efficiency analysis. Consequently, constructing a comprehensive data panel has required direct engagement with port agents, the procurement of specialized data collections—including the purchase of data—and contributions toward developing new databases. In this study, these measures have been implemented to effectively address the inherent difficulties in data acquisition.

Fig. 1. Maps of selected Ports for the analysis.
Source: Own Elaboration.

Table 3
Ports, port authorities and countries.

Port	Port Authority	Country
Cape Town	Transnet National Port Authority	South Africa
Casablanca	Agence Nationale des Ports	Morocco
Cotonou	Port Autonome de Cotonou	Benin
dÀbidjan	Port Autonome of Abidjan	Cote d' Ivoire
Dakar	Port Autonome de Dakar	Senegal
Doula	Port Autonome de Douala	Cameroon
Durban	Transnet National Port Authority	South Africa
East London	Transnet National Port Authority	South Africa
Luanda	Empresa Portuaria de Luanda UEE	Angola
Las Palmas Port	Port Authority of Las Palmas	Spain
Onne	Nigerian Ports Authority	Nigeria
Port Elizabeth	Transnet National Port Authority	South Africa
Santa Cruz de Tenerife Port	Port Authority of Santa Cruz de Tenerife	Spain
Tanger Med	Tanger Med Port Authority	Morocco
Tema	Ghana Ports and Harbours Authority	Ghana
Walvis Bay	Namibian Ports Authority	Namibia

Source: Own Elaboration.

processed by a terminal and serves as a key proxy for productivity and operational effectiveness.

Fig. 2 illustrates the evolution of container throughput (in thousands of TEUs) across the sample (from 2011 to 2020). The data reveal notable differences in both absolute volumes and growth trajectories: while certain ports exhibit a pronounced upward trend—surpassing five million TEUs by 2020—others have more modest figures, reflecting diverse operational scales and investment levels. Such variation underscores the importance of contextual factors, including infrastructure capacity, geographic location, and trade routes, in shaping port performance and container handling efficiency.

4.1.2. *Infrastructure variable (fixed variables)*

The primary input variable (X_1) is the total length of berths designated for container handling, expressed in meters. This measure reflects a port's capacity to accommodate large vessels, particularly those with drafts exceeding 14 m, and is regarded as a crucial determinant of port infrastructure and operational efficiency.

4.1.3. *Capital variable (quasi-fixed variables)*

The secondary input variable (X_2) is the total number of quay gantry cranes at the port, recorded as a unit count. These cranes are integral to container operations, directly influencing the speed and efficiency of loading and unloading processes. Consequently, the number of quay gantry cranes serves as an indicator of the capital investment in port equipment and the terminal's capacity to handle containerized cargo.

4.1.4. *Control variable*

In the estimate, port connectivity (C) is included as a control variable. In this specific case, including a connectivity variable is indispensable. Although African ports have not yet reached the development levels of their European counterparts—due to security restrictions and other constraints—many exhibits robust connectivity in terms of trade routes and commerce. This reality underscores the need to incorporate a measure that reflects the degree to which ports are integrated into global maritime networks.

The rationale for incorporating connectivity into productivity and efficiency analyses lies in the pivotal role of ports as intermodal hubs, bridging maritime and land-based logistics while addressing increasingly complex supply chain demands (Ducruet, 2020). Despite its recognized importance, relatively few studies have integrated connectivity measures into port efficiency models.

Among the earliest contributions, Suárez-Alemán et al. (2016) employed the Liner Shipping Connectivity Index (LSCI), developed by

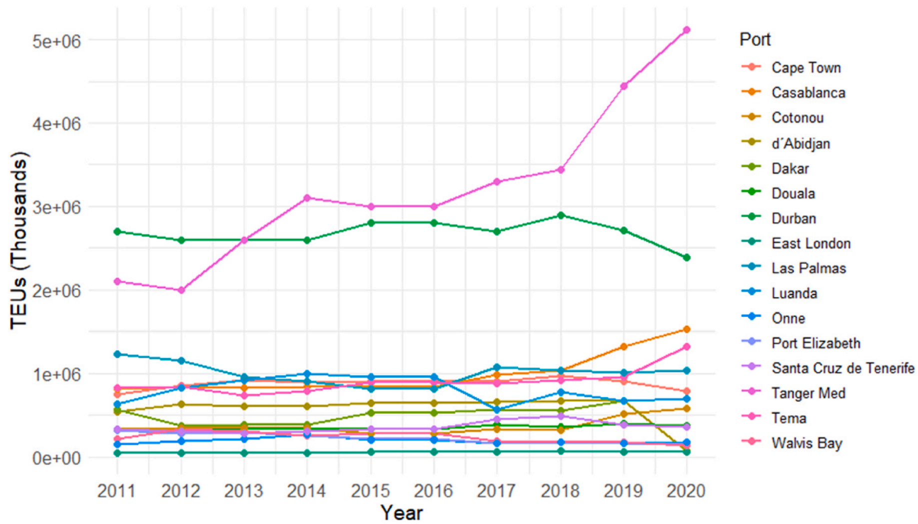

Fig. 2. TEUs (thousands) evolution by port.
Source: Own Elaboration.

UNCTAD, to evaluate how effectively ports integrate into global maritime networks. Their findings revealed a direct influence of connectivity on container throughput, particularly in developing regions. Building on this work, Serebrisky et al. (2016) applied the LSCI at a national scale in a stochastic frontier analysis, corroborating its positive impact on port productivity. In a similar vein, Schøyen et al. (2018) used the LSCI within a DEA framework to assess port efficiency in the North Sea/Baltic region.

Moreover, Tovar & Wall (2022) introduced the Port Liner Shipping Connectivity Index (PLSCI) as an explanatory variable in the inefficiency term of a stochastic output distance function. Their results indicated a direct correlation between heightened connectivity and increased efficiency, with even marginal enhancements in the PLSCI yielding substantial gains in output. Further advances include Yen et al. (2023), who investigated the influence of smart port designs on shipping efficiency using the and Nadarajan et al. (2023), who incorporated the LSCI as a dependent variable alongside GDP to examine seaport network efficiency.

Recent studies further enhance this perspective. Nguyen and Kim (2024) have provided empirical evidence that the COVID-19 pandemic significantly impacted port connectivity, operational efficiency, and resilience in major container ports in Southeast Asia. Their application of social network analysis reveals that even amidst disruptions, robust connectivity is essential for maintaining competitive performance. Similarly, Jin et al. (2024) have demonstrated that the LSCI is dynamically linked not only to port performance but also to broader economic indicators, such as energy trade and inclusive growth, thereby highlighting the multifaceted implications of connectivity in maritime economics.

For this analysis, the PLSCI—expressed as an index ranging from 0 to 100, following the UNCTAD methodology prior to 2023—is employed to capture a port's connectivity and its bearing on operational efficiency. A higher index value indicates stronger integration into global shipping networks.

4.1.5. Objective variable

As mentioned, the objective variable of this study (Z) is the Corruption Perceptions Index Score (CPI). Developed by Transparency International in 1995, the CPI measures public sector corruption at the national level by aggregating data from 13 independent sources provided by 12 institutions, including the World Bank. It captures perceptions of corruption from business executives and country experts, assessing its impact on public sector institutions. Countries are scored on a scale from 0 to 100, where 0 indicates high perceived corruption and 100 represents a corruption-free public sector.[6]

The quantitative criterion used by these entities reflects that higher values indicate better institutional quality, while lower values correspond to higher perceived corruption and weaker governance. Therefore, for the purposes of this study, the CPI value obtained from the official database has been inverted to thus adapt its value in a way that makes it possible to apply it as an input to the efficiency model. In its transformed form, higher values indicate higher perceived corruption and weaker governance, while lower values correspond to better institutional quality. This adjustment allows for a more straightforward interpretation of the CPI's influence on port performance, particularly in the context of *regulatory asymmetries* between ports operating under different governance frameworks.

Unlike previous studies that have used different methodologies (such as stochastic frontier analysis) or incorporated the CPI as part of an inefficiency term, our use of a Bootstrap DEA model—which estimates a maximization problem—requires this transformation to ensure that the direction of the effect aligns logically with the interpretation of efficiency. Specifically, in our analysis, higher levels of perceived corruption (higher inverted CPI values) are associated with lower levels of port efficiency, as expected.

In the context of this study, the CPI is used as a proxy for the national institutional and bureaucratic environment, reflecting broader administrative and security conditions that influence port operations. This approach recognizes that ports operate within national governance frameworks that shape operational environments, including regulatory efficiency, political stability, rule of law, and public sector integrity. These elements indirectly impact port performance by influencing dwell times, customs processing, security risks, and logistics reliability.

Unlike port-specific metrics, the CPI captures country-level governance dynamics, providing a comprehensive view of the environment in which ports function. It reflects the quality of public administration and security standards that affect port competitiveness and integration into global maritime networks. This influence is significant not only for public ports but also for privately operated ports, as they are equally embedded within the broader national governance context. Regardless

[6] The CPI's calculation methodology involves selecting credible sources that provide valid, comparable, and reliable data based on expert opinions. To enhance reliability and minimize biases, the CPI averages at least three different sources per country.

of ownership structure, the efficiency, security, and overall performance of ports are shaped by the regulatory and institutional climate of the host country. Therefore, the CPI is not merely a corruption measure but an indicator of the overall institutional climate.

Recent literature reinforces this broader interpretation of the CPI. Budsaratragoon and Jitmaneeroj (2020) argue that the CPI captures complex governance dimensions, including political stability, regulatory quality, and institutional trust (*regulatory asymmetries*). Their study highlights how these factors interconnect to influence the business climate and governance efficiency, validating the use of the CPI in assessing national administrative conditions affecting port operations.

When analysing the global landscape, the CPI reveals significant regional disparities. Sub-Saharan Africa continues to have the lowest average CPI score, with a regional average of 33, highlighting the persistent challenges of governance and rule of law in the region. Democracy is under pressure in many African nations, where corruption and weak institutional frameworks exacerbate the lack of accountability and hinder effective governance.

In contrast, Western Europe and the EU continue to maintain the highest regional averages, with the CPI score dropping to 65 in recent years. This decline signals a weakening of political integrity, erosion of checks and balances, and the growing threat of corruption in even traditionally strong institutions. While some countries in the region show improvements, the overall trend reflects concerns over transparency and accountability, undermining their long-held status as the global leaders in governance and anti-corruption efforts.

The rest of the world, including regions like Eastern Europe and Central Asia, faces stagnation in corruption reduction efforts. In these regions, systemic corruption, the rise of authoritarian governance, and the dysfunctional rule of law have led to limited progress in governance reforms. Similarly, the Middle East and North Africa show little improvement, with countries continuing to struggle with political corruption, conflict, and a lack of transparency in governance processes. Asia Pacific also faces long-term stagnation, although some historically top-ranking countries, such as Singapore, have seen a reversal in their progress.

In the Americas, the weak rule of law and lack of judicial independence continue to enable widespread impunity, affecting governance and contributing to corruption in public institutions. While some countries show small improvements, overall, the region struggles to make meaningful progress.

Despite the global challenges, some countries, including a few in Africa, have significantly improved their CPI scores over the last decade, showing that progress is possible even in environments with entrenched corruption. However, the overall trend indicates that most regions face substantial barriers to curb corruption, with impunity, weak judicial systems, and poor governance continuing to plague efforts to fight corruption.

Table 4 summarizes all the basic information of the panel database.

5. Results

An output-oriented DEA Bootstrap methodology, as described in Sections 3.1, and *3.2* of, has been applied to the sample of 16 ports, detailed in Section 4. The efficiency index measures the distance of each port to the nearest most efficient DMU (port) located on the frontier. This approach allows for a robust and consistent estimation of efficiency scores by addressing the potential overestimation problem inherent in the standard DEA method.

As investments in port infrastructure are typically lumpy and port expansion projects usually take several years to complete, the amounts of these inputs may remain constant over extended periods, followed by a sudden addition of port capacity. Compared to the low variation in inputs, container throughput tends to change rapidly over the years (Wan et al., 2014). Therefore, the output-oriented model is the most suitable for obtaining operating efficiency in this context.

First, the Variable Returns to Scale (VRS – BCC) model is used to estimate pure technical efficiency (PTE). At a second stage, an output-oriented Bootstrapping approach was applied to evaluate the presence of scale inefficiency (the simulations were replicated 2000 times, ensuring the robustness of the efficiency estimates).

To achieve the analytical objective, two main estimations have been developed:

- The first estimation, called the *Base Model* (BM), excludes consideration of the CPI. This estimation focuses solely on the traditional operational characteristics of each port related to cargo handling services. It evaluates operational efficiency without considering regulatory or institutional factors.
- The second estimation, named the *Adjusted Model* (AM), incorporates the CPI as an additional variable. This model considers the impact of the regulatory environment, including aspects related to corruption, on the efficiency scores of ports. By including the CPI alongside traditional operational variables, this approach provides a more comprehensive view of the factors influencing port efficiency.

5.1. Estimation analysis

Table 5 presents the values obtained for both DEA and Bootstrap DEA efficiencies for BM and AM models. The results indicate that to achieve efficiency with the same input values (i.e., maintaining the existing facilities and infrastructure), ports would require increased production. Over the entire period studied and for both approaches (DEA and DEA Bootstrap), substantial reductions in efficiency were observed.

The estimation revels that during the period 2011–2020, only five seaports—Casablanca, Durban, East London, Tanger Med, and Onne—achieved a PTE score of 1, indicating optimal operational performance under the standard BCC DEA model. However, the bootstrapped

Table 4
Statistical summary of data used (2011–2020).

Variable	Name	Description	Mean	Std. Dev.	Min	Max
Output Variable						
TEUs	Y	Number	834,630.00	895,183.80	41,957.00	5,122,630.00
Input Variables						
Length of berths	X_1	Metres	1982.69	1481.12	256.00	5336.00
Cranes	X_2	Number	11.56	11.60	0.00	37.00
Control Variable						
PLSCI	C	Index	20.79	12.00	2.30	64.98
Objective Variable						
CPI	Z	Index	0.027	0.01	0.02	0.07

Source: Own Elaboration.

efficiency scores reveal that none of the ports maintain full efficiency, demonstrating the Bootstrapped DEA's ability to provide a more conservative and reliable estimation by addressing the overestimation present in the standard approach. These scores are consistently lower than the standard DEA results, especially in ports previously deemed fully efficient, reflecting adjustments for statistical noise and bias. Despite this, the bias in inefficient ports remains minor and substantially below 1 percent, suggesting consistent inefficiencies unaffected by random variations, thereby reinforcing the robustness of the findings.

Over the period 2011–2020 (See Table B.1 and B.2 in Appendix B), the BCC DEA results indicate a relatively stable trend in efficiency scores for the most efficient ports, which consistently appear on the efficiency frontier. These ports demonstrate operational stability and optimal resource utilization. In contrast, the other ports exhibit fluctuating efficiency scores, reflecting operational inconsistencies and variations in performance over time. The Bootstrapped results, however, reveal a more dynamic pattern, with no port maintaining full efficiency throughout the decade. Ports like Durban and Tanger Med consistently achieved relatively high scores, although below 1, highlighting near-optimal performance when adjusted for statistical noise. Conversely, Port Elizabeth and Walvis Bay persistently displayed low efficiency scores, reflecting structural inefficiencies.

These differences can certainly be attributed to the fact that the estimation of efficiency scores by DEA analysis depends on the discretization in the frontier estimation. Similarly, the results are sensitive to data sampling. Consequently, the port efficiency values averaged from the DEA analysis tend to be overestimated. In contrast, the Bootstrapped DEA methodology proves to be a fundamental tool for obtaining more realistic efficiency scores by addressing this peculiarity while retaining the advantages of traditional DEA. Moreover, Bootstrapped DEA provides more robust efficiency results, enhancing the reliability of the analysis.

The efficiency gap between the estimations remained significant throughout the period, with average differences ranging from 15 % to 20 %. This discrepancy is particularly noticeable in years of economic fluctuations and trade disruptions, suggesting that the standard DEA model is more sensitive to external shocks, whereas the Bootstrapped DEA offers a more consistent evaluation.

As shown in Table 5, the two European ports included in the sample are positioned at the bottom of the efficiency rankings in BMs. However, in practice, shipping lines more commonly choose these ports over their African counterparts due to perceptions of greater safety and more predictable regulatory environments. This highlights a paradox: despite their medium-low efficiency scores, European ports in Africa may maintain an *institutional edge* linked to their robust regulatory frameworks (showed in AMs). This interpretation is supported by Rodríguez et al. (2025), who, through stakeholder interviews, identified institutional and regulatory frameworks as key perceived drivers of competitive positioning. Although our analysis does not directly test port choice behaviour, the qualitative evidence lends support to this contextual observation.

Fig. 3 provides a visual comparison of average efficiency scores across four estimation scenarios. The right-hand radar chart, based on the Bootstrap method, shows marked differences in efficiency scores for several ports when institutional quality is included in the model. For example, Las Palmas exhibits an increase in efficiency of approximately 84 % between the BM and the AM, while Santa Cruz de Tenerife improves by around 46 %. These changes, derived from Bootstrap estimates, are statistically meaningful and reflect robust improvements rather than random variation, as the method incorporates confidence intervals around the estimated scores. Although not explicitly depicted in the figure, the Bootstrap approach inherently accounts for sampling variability and corrects bias, allowing for a more reliable interpretation. Thus, the shifts observed highlight the significant impact of institutional factors on port efficiency assessments, reinforcing the importance of including governance-related variables when evaluating performance.

It is also important to note that, efficiency rankings are typically calculated based on TEUs handled relative to quay length and the number of fixed quay cranes. However, many vessels operating in African ports are equipped with their own cranes for loading and unloading containers, effectively increasing the available lifting capacity. This factor may contribute to unexpectedly high efficiency scores for some ports with limited infrastructure, potentially distorting comparisons with European ports such as Las Palmas and Santa Cruz de Tenerife.

5.2. BM and AM comparative analysis

To better understand this discrepancy, Fig. 4 shows graphically the Hierarchical ordering of the bootstrapped model. Including the CPI provides a more accurate and realistic reflection of port efficiency by considering the legal and regulatory environment influencing port operations. This approach acknowledges that the competitive edge of European ports is not solely due to operational efficiency but is also significantly influenced by their institutional and regulatory contexts.

Moreover, the results show that African ports perform similarly to European ports in terms of infrastructure and operational capacity, which reinforces the idea that the real differentiating factor lies in the regulatory and legal environment.

By incorporating the CPI, the analysis accounts for non-operational factors that shape port choice and efficiency, enhancing the relevance

Table 5
Efficiencies Average BCC DEA and BOOTSTRAP (2011–2020) for BM and AM models.

Port Name	BM				Port Name	AM			
	Rank	*BCC DEA*	*Rank*	*BOOTSTRAP*		*Rank*	*BCC DEA*	*Rank*	*BOOTSTRAP*
Tanger Med	**1**	1,00000	**1**	0,76595	Tanger Med	**1**	1,00000	**1**	0,84830
Durban	**2**	1,00000	**2**	0,75532	Durban	**2**	1,00000	**2**	0,84202
Casablanca	**3**	1,00000	**3**	0,74201	Walvis Bay	**3**	1,00000	**3**	0,84017
East London	**4**	1,00000	**4**	0,74187	Las Palmas	**4**	1,00000	**4**	0,83964
Onne	**5**	1,00000	**5**	0,74095	St Cruz Tfe.	**5**	1,00000	**5**	0,83903
Luanda	**6**	0,69989	**6**	0,60360	Onne	**6**	1,00000	**6**	0,83893
St Cruz Tfe.	**7**	0,61932	**7**	0,57665	East London	**7**	1,00000	**7**	0,83814
Tema	**8**	0,59861	**8**	0,53174	Casablanca	**8**	1,00000	**8**	0,83806
Douala	**9**	0,58486	**9**	0,48480	Port Elizabeth	**9**	0,91630	**9**	0,77283
Cape Town	**10**	0,52726	**10**	0,47443	Tema	**10**	0,70328	**11**	0,65270
Cotonou	**11**	0,51375	**11**	0,46540	Luanda	**11**	0,69989	**10**	0,65711
Las Palmas	**12**	0,49588	**12**	0,45655	Cape Town	**12**	0,62536	**12**	0,58665
d'Abidjan	**13**	0,48728	**13**	0,44609	Douala	**13**	0,58486	**13**	0,53614
Dakar	**14**	0,44677	**14**	0,42130	d'Abidjan	**14**	0,53468	**14**	0,51402
Walvis Bay	**15**	0,30940	**15**	0,28421	Cotonou	**15**	0,51375	**15**	0,49282
Port Elizabeth	**16**	0,22201	**16**	0,18514	Dakar	**16**	0,45299	**16**	0,43808

Source: Own Elaboration.

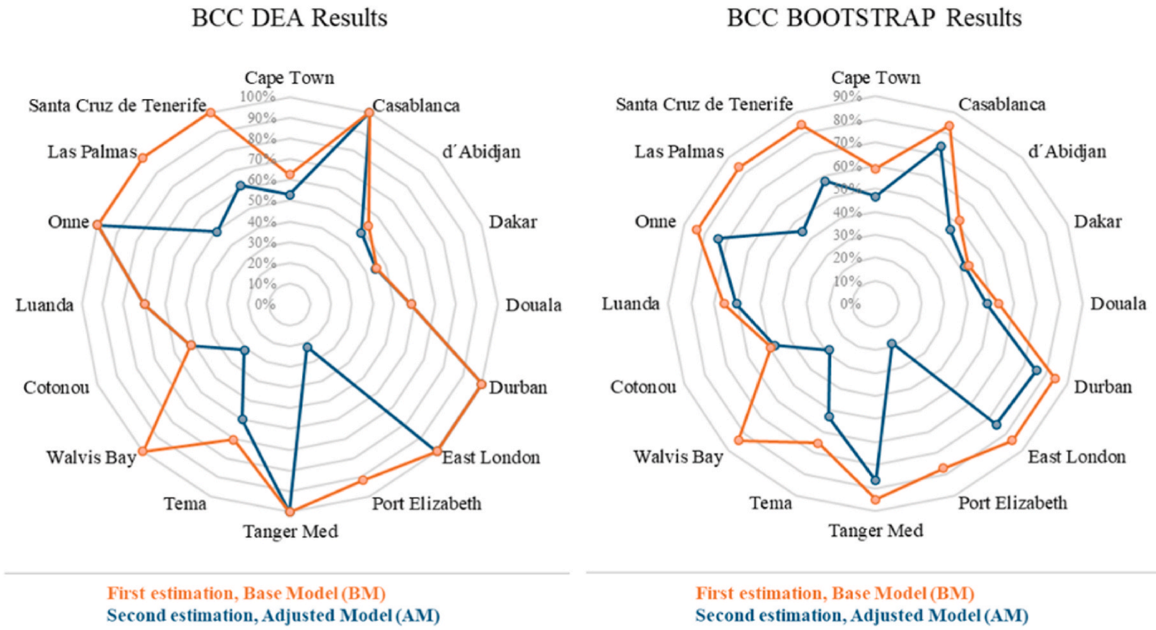

Fig. 3. Graphical Efficiencies Average BCC DEA and BOOTSTRAP (2011–2020) for BM and *AM models.*
Source: Own Elaboration.

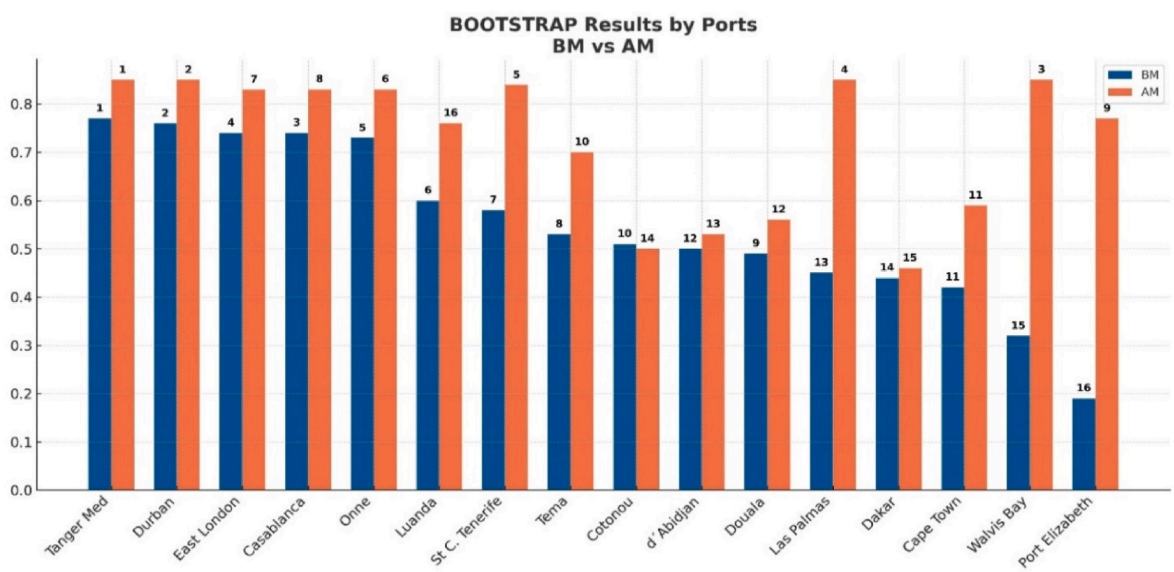

Fig. 4. Hierarchical ordering according to BOOTSTRAP Efficiency values/Average 2011–2020 for BM and AM model.
Source: Own Elaboration.

and interpretability of the results. This not only aligns efficiency scores with real-world dynamics but also quantifies the impact of the regulatory environment on port performance, bridging the gap between operational efficiency and market perception.

The most significant change in the ranking occurs with the two European ports in the sample, Las Palmas and Santa Cruz de Tenerife. These ports move from medium-low positions to high positions when the CPI is considered. In the case of the Bootstrap estimation—which provides a more robust interpretation—Santa Cruz de Tenerife advances from 7th to 5th place, while Las Palmas makes a remarkable leap from 13th to 4th place.

In the case of Las Palmas, this result is particularly revealing, as the inclusion of the CPI accounts for more than 50 % of the reason for its rise to the top of the ranking. This illustrates how these ports benefit from being part of a stronger institutional system, which—when objectively measured—proves to be their most decisive comparative advantage.

Turning to the African ports, the results indicate a structural advantage for some ports regardless of the CPI inclusion. Specifically, Tanger Med and Durban consistently maintain the top positions, underscoring their operational efficiency and strategic importance. However, it is also evident that most African ports suffer a relative decline in the adjusted model, not due to technical or logistical deficits, but because of their more fragile institutional and regulatory frameworks. This suggests that African ports do not lag behind in capacity or functionality, but in governance indicators that weigh heavily in comparative assessments.

It may appear paradoxical that the port of Tanger Med maintained its leading position in both the BM and the AM, while the port of

Casablanca experienced a significant drop—from third to eighth place—despite both being located in Morocco. This divergence can be explained by their differing governance structures. Tanger Med is considered a national strategic project, directly managed by the Tangier Med Special Agency (TMSA), a fully state-owned public company endowed with governmental powers. In contrast, Casablanca is regulated by the Agence Nationale des Ports (ANP), which oversees port safety and environmental issues and manages an additional 33 Moroccan ports. This distinction in governance highlights how institutional configuration can decisively shape performance outcomes, even within the same national context.

A noteworthy positive impact is observed for Walvis Bay, which moves from the lower end of the BM to an impressive 3rd place in the AM. This highlights the port's significant improvement when regulatory and institutional factors are considered, suggesting a competitive advantage stemming from their *institutional edge*, as reflected in more stable governance frameworks. This case exemplifies how improvements in institutional quality can dramatically shift a port's perceived efficiency and reinforce its attractiveness in international logistics networks.

This analysis is particularly relevant given the emerging trade dynamics affecting European ports, including those located in Africa, as they face increasing pressure to reduce carbon emissions in the maritime sector. The *Fit for 55-FuelEU* Maritime initiative, implemented by the EU, aims to reduce emissions by 55 % by 2030 and 90 % by 2050 (EU, 2021). In response, new trade routes are being developed to minimize the carbon footprint, potentially altering logistics patterns and influencing port choice. While necessary for climate goals, these regulatory shifts introduce asymmetric burdens that may disproportionately affect outermost regions.

These changes are likely to impact the comparative advantages of European ports in Africa, as they must comply with restrictions that their direct competitors are not required to follow, leading to a potential decline in port activity. This impact is particularly significant for European ports located in island regions, where port activity is a crucial industry and almost every of goods arrive by sea (Trujillo et al., 2025). This reality poses a threat not only to the industry but also to the specific social and economic fabric of the Canary Islands.

In this context, if future environmental or bureaucratic requirements were to compromise the current levels of legal stability or increase administrative complexity, European ports located in Africa could lose their *institutional edge*. This would potentially lead to a diversion of maritime traffic toward more agile and less regulated West African ports, thereby reshaping regional competitive dynamics. While African ports are not currently subject to the same regulatory pressures—particularly regarding carbon emissions—any tightening of the regulatory landscape for European-administered ports could reduce their operational efficiency and strategic attractiveness.

This raises a broader policy dilemma: while the EU advocates for free competition and environmental ambition, it must also ensure that this does not come at the expense of regions that, due to their insularity and economic dependence on maritime trade, require a differentiated approach. The Canary Islands could serve as a paradigmatic case for future discussions about regulatory adaptation and territorial equity.

6. Conclusion and discussion

This study presents an updated efficiency analysis of West African ports using the Bootstrap DEA approach, recognized as the most robust methodology for addressing overestimation issues in standard DEA models. The research contributes to the literature by updating the efficiency calculations for African ports, a topic that remains underexplored, and establishes a comparative framework with European ports on the African West coast. This framework provides valuable insights into the competitive dynamics between African and European ports, especially given their geographical proximity and overlapping hinterlands.

The findings reveal that, when using the Bootstrap approach to obtain a more realistic and robust estimation, none of the ports reach the efficiency frontier, suggesting that there is no immediate need for further investments to expand port infrastructure unless container traffic demand significantly increases. This result challenges the conventional notion that African ports require continuous capacity expansion and instead suggests a more strategic approach to resource allocation.

The comparison between the ports in the sample (including those from Africa and the EU) reveals a critical insight: there are no significant differences in terms of infrastructure and TEU movements between the two groups. This finding suggests that operational efficiency in African ports is not primarily constrained by infrastructure limitations but rather by non-operational factors. Notably, when the Base and Adjunct models were considered (both with and without the inclusion of the CPI), the regulatory and institutional environment emerged as a decisive factor influencing efficiency levels. The results demonstrate that the competitive advantage of European ports is significantly strengthened by their robust regulatory frameworks, which enhance security, transparency, and operational consistency. This observation is consistent with previous studies that emphasize regulatory stability as a key competitive advantage for European ports.

However, the study also reveals that African ports have the potential to achieve better efficiency levels, comparable to their European counterparts, if non-operational barriers such as policy and bureaucracy-related constraints are addressed. This underscores the importance of institutional reforms to enhance competitiveness, particularly as African ports face increasing competition from European ports geographically located in Africa.

The regulatory landscape plays a crucial role in shaping competitive dynamics. As emerging environmental policies, like the Emissions Trading System (ETS) and the *Fit for 55-FuelEU* Maritime initiative are implemented exclusively in the EU, ports in Africa will not face the same compliance costs or operational restrictions. This regulatory asymmetry could shift the competitive balance, providing Africa ports with a cost advantage. Conversely, European ports competing directly with African counterparts could face significant competitive pressures, particularly in regions where they share overlapping trade routes and hinterlands.

This study offers valuable information for policymakers. As European ports are increasingly subject to stringent environmental regulations, it is essential to consider the competitive impact on EU ports geographically located in Africa (also because the Canary Islands are considered outermost regions of the EU). Policymakers should weigh the long-term consequences of regulatory asymmetries on trade flows, competitiveness, and the strategic positioning of European ports. In this regard, the study highlights the need for a coordinated regulatory strategy that considers the unique competitive dynamics faced by European ports operating in African contexts.

7. Future research

A key constraint we encountered—common to many empirical studies on African ports—is the difficulty of accessing reliable and comprehensive data across countries in the region. In particular, first-hand feedback from stakeholders in the African port sector has confirmed that some of the official sources used for data collection may be affected by manipulation or misreporting, raising concerns about the accuracy of the available information.

This constraint restricts the number of ports and variables that can be included in cross-country comparative studies. Nevertheless, we remain optimistic that continued efforts devoted to the African maritime-port sector, combined with improved collaboration with regional authorities, will lead to future datasets with greater coverage and quality, thereby enabling more robust and detailed evaluations.

In addition, we identify a natural continuation of this research in the form of a longitudinal reassessment once the environmental regulations discussed—particularly the *FuelEU* Maritime Regulation—have been fully implemented and enforced. While this study offers a forward-looking perspective based on projected regulatory impacts, it would be especially valuable to replicate this analysis in the coming years, drawing on data from periods in which the new framework is already in effect.

Such a follow-up study would allow for the empirical identification of the actual impact of environmental regulation on port efficiency, particularly in the case of ports located in unique institutional and geographic contexts, such as those in the Canary Islands. This would further enrich the understanding of how sustainability goals interact with port competitiveness in an increasingly regulated global maritime environment.

Furthermore, future work will explore the role of broader institutional and governance indicators—such as the World Bank's Logistics Performance Index—in shaping port performance and integration across regions with high regulatory asymmetries. In line with recent qualitative findings (Rodríguez et al., 2025), we also intend to develop complementary empirical models that assess the relationship between institutional quality and port choice behaviour or throughput growth. This would allow us to rigorously test the contextual interpretations discussed in this study and to further align our methodological approach with policy-relevant questions regarding regional competitiveness.

CRediT authorship contribution statement

Andrea Rodríguez: Writing – original draft, Visualization, Formal analysis, Data curation. **Antonio Gil Ropero:** Software, Methodology, Formal analysis. **M. Mar Cerban:** Writing – review & editing, Supervision, Conceptualization. **Lourdes Trujillo:** Validation, Supervision, Resources, Investigation.

Submission declaration and verification

The work described has not been published previously.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this paper, the author(s) used Quillbot to search for synonyms, find proposed alternative wording for some sentences and identify possible errors caused by dyslexia disorders in one of the authors. After using this tool/service, the author(s) reviewed and edited the content as necessary and take full responsibility for any errors.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Lourdes Trujillo reports financial support was provided by University of Las Palmas de Gran Canaria. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

In DEA, Bootstrap techniques are frequently employed to improve the reliability of efficiency scores by addressing DEA's deterministic assumptions by Gil-Ropero et al. (2019). Standard DEA models, which create an efficiency frontier based on observed data, assume that any deviation from this frontier is due solely to inefficiency. However, this approach can be sensitive to sample variations and often fails to consider random noise within the data. Bootstrap methods offer a statistical approach to evaluate these efficiency scores, helping to differentiate genuine inefficiency from random variation.

Resampling to Adjust for Bias: Bootstrapping in DEA involves creating numerous resamples of the initial dataset, generating a distribution of efficiency scores that allows researchers to identify and correct any bias in the original scores, resulting in more accurate estimates. Through resampling, Bootstrapped DEA can also produce confidence intervals, providing a range within which the actual efficiency score is likely to be found. This statistical adjustment enhances the robustness of DEA results, yielding insights that are less susceptible to sampling error.

Types of Bootstrap DEA Models:

- Bias-Corrected Efficiency Scores Using Bootstrap: This method involves recalculating efficiency scores through multiple resampling iterations, providing a bias-adjusted score for each DMU.
- Hypothesis Testing with Bootstrap: Researchers apply Bootstrap techniques to test hypotheses concerning returns to scale, productivity variations, and performance differences among DMUs. This added statistical rigor enhances the reliability of efficiency comparisons across different groups and supports analyses of efficiency trends over time.

In Figure A.1 notation DEA* represents the Bootstrap-adjusted efficiency frontier. Bias is defined as the difference between the original DEA frontier and the bias-corrected frontier at the same output level.

$$\textit{Bootstrap}\ \text{Output} - \text{oriented (BCC)} : \frac{AD - AC}{AY_O} = \frac{AC - AB}{AY_O}$$

The idea explained above, illustrated in Figure A.1, where shows a problem of variable scale returns with Production Possibility, Standard DEA and Bootstrap DEA frontiers. The hope is that when assuming that the smoothed Bootstrap it holds that:

$$\left[\widehat{\theta}^{*}(x_0, y_0) - \widehat{\theta}(x_0, y_0)\right] \sim \left[\widehat{\theta}(x_0, y_0) - \theta(x_0, y_0)\right] \tag{A.1}$$

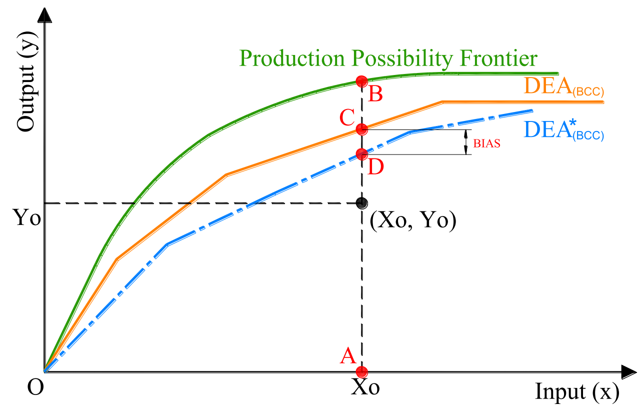

Fig. A.1. Graphic representation of Bootstrap Output-Oriented.

Source: Gil Ropero et al. (2019).

Bootstrap methods offer distinct advantages for efficiency assessments of container terminals in LAC, where datasets are often small and where inputs and outputs are highly variable due to external market shifts and regional trade patterns. In these environments, bootstrapping refines the accuracy of DEA results by compensating for statistical noise, which is especially prevalent in settings marked by inconsistent data. By providing bias-corrected efficiency scores, bootstrapping allows a more precise view of each terminal's relative efficiency, even when faced with irregularities. This approach is particularly relevant for LAC container terminals, where fluctuating container volumes, seasonal demand, and varied terminal capacities often impact operational stability.

The application of Bootstrap techniques in DEA also enhances the robustness of efficiency evaluations by generating confidence intervals, allowing researchers and port authorities to analyze terminal performance with increased statistical rigor. These intervals facilitate more dependable comparisons across terminals and clarify whether observed efficiency levels are statistically significant or may be attributed to random variations. Additionally, Bootstrap methods enable hypothesis testing, which allows for in-depth examination of scale efficiencies and productivity trends over time. This comprehensive framework is critical for LAC ports striving to fine-tune operational strategies, attract investment, and bolster their competitiveness in an increasingly dynamic global trade landscape.

A.1. Bootstrap in DEA/FDH Models

The Bootstrap (Efron, 1979, 1992) provides an alternative approach for inference and hypothesis testing in DEA/FDH models. In fact, for DEA models with multiple inputs and outputs, the Bootstrap is the only existing approximation.

The Bootstrap is based on the analogy principle (Manski, 1988). In the real world, observed data Sn are generated by:

$$\mathrm{F} = \mathrm{F}\ (\mathrm{T}, f(\mathrm{x}, \mathrm{y})) \tag{A.2}$$

However, in the real world, F, T, and θ(x,y) are unobservable and must be estimated from the sample data S_n.

Let $F(S_n)$ be a consistent estimator of F:

$$\widehat{\mathrm{F}}(S_n) = \mathrm{F}\ (\widehat{\mathrm{T}}, \widehat{f}(\mathrm{x}, \mathrm{y})) \tag{A.3}$$

It is straightforward to simulate real-world occurrences by drawing a new sample S_n^* from $\widehat{\mathrm{F}}\ (S_n)$ and applying the original estimator to these new data. If the original estimator for a point (x_0,y_0) (not necessarily contained in S_n) is, for instance, $\widehat{\theta}_{BCC}(x_0, y_0)$ can be obtained $\widehat{\theta}^*_{BCC}(x_0, y_0)$ by solving:

$$\left[\widehat{\theta}^*_{BCC}(x_0, y_0)\right]^{-1} = max\{\theta | \theta y_0 < Y^*\lambda, x_0 > X^*\lambda, 1\lambda = 1, \lambda \in \mathbb{R}^n_+\} \tag{A.4}$$

Where $Y^* = [y_1^*,...,y_n^*], X^* = [x_1^*, ..., x_n^*]$ y $(x_1^*, y_1^*), i = 1, ..., n$, represent the pseuds-sample observations. By repeating this process B times (with B being a conveniently large number, around 2000), a set of $\{\widehat{\theta}^*_{BCC,b}(x_0, y_0)\}_{b=1}^B$ values is obtained. When the Bootstrap is consistent, it holds that:

$$\left[\widehat{\theta}^*(x_0, y_0) - \widehat{\theta}(x_0, y_0)\right] \sim \left[\widehat{\theta}(x_0, y_0) - \theta(x_0, y_0)\right] \tag{A.5}$$

Given the original estimate $\widehat{\theta}_{BCC}(x_0, y_0)$ and the set of Bootstrap values $\{\widehat{\theta}^*_{BCC,b}(x_0, y_0)\}_{b=1}^B$, the left side of expression (*A.5*) is known with arbitrary precision (determined by the choice of B). The approximation improves as the sample size n increases.

Equation (*A.1*) encapsulates the essence of the Bootstrap. In principle, since F $(\widehat{\mathrm{T}}, \widehat{f}$ (x, y)) is known, the distribution of the left side of the equation could be determined analytically. However, in most problems, such a derivation proves intractable. Consequently, Monte Carlo simulations are opted for to approximate the distribution. The B Bootstrap values generated, $\{\widehat{\theta}^*_{BCC,b}(x_0, y_0)\}_{b=1}^B$, provide this empirical approximation of the distribution. Once these values are calculated, the derivation of confidence intervals for $\theta(x_0, y_0)$ is immediate. It should be noted that if the true distribution of $[\widehat{\theta}(x_0, y_0) - \theta(x_0, y_0)]$ were known, it would be trivial to find values a_α and b_α such that:

$$Pr\left[-b_\alpha < \widehat{\theta}(x_0, y_0) - \theta(x_0, y_0) < a_\alpha\right] = 1 - \alpha \tag{A.6}$$

Of course, a_α and b_α are unknown. Nevertheless, from the Bootstrap distribution of the pseudo-estimates $\widehat{\theta}_b^*(x_0, y_0)$, for b = 1 …,B, values $\widehat{a}_\alpha$ and $\widehat{b}_\alpha$ can be found such that:

$$Pr\left[-b_\alpha < \widehat{\theta}^*(x_0, y_0) - \widehat{\theta}(x_0, y_0) < -a_\alpha | \widehat{F}(S_n)\right] = 1 - \alpha \tag{A.7}$$

The calculation of $\widehat{a}_\alpha$ and $\widehat{b}_\alpha$ requires ordering the values of $[\widehat{\theta}_b^*(x_0, y_0) - \widehat{\theta}(x_0, y_0)]$, for b = 1, …,B, in ascending order and removing the (α/2) × 100 percent of elements from both ends of the list, taking $-\widehat{a}_\alpha$ and $-\widehat{b}_\alpha$ as the values at both ends of the truncated list, such that $\widehat{a}_\alpha < \widehat{b}_\alpha$.

Thus, the Bootstrap approximation of (*A.6*) is:

$$Pr\left[-\widehat{b}_\alpha < \widehat{\theta}(x_0, y_0) - \theta(x_0, y_0) < -\widehat{a}_\alpha\right] \approx 1 - \alpha \tag{A.8}$$

And the estimated confidence interval is:

$$\widehat{\theta}(x_0, y_0) + \widehat{a}_\alpha \leq \theta(x_0, y_0) \leq \widehat{\theta}(x_0, y_0) + \widehat{b}_\alpha \tag{A.9}$$

This procedure can be normalized for any $(x_0, y_0) \in \mathbb{R}_+^{p+q}$ for which a value $\widehat{\theta}(x_0, y_0)$ exists. Since researchers are typically interested in indices for all observed units, the suggested procedure can be repeated *n* times, for $(x_0, y_0) = (x_i, y_i)$, i = 1, …, n, yielding a set of *n* confidence intervals of the type (*A.10*).

This method differs slightly from that proposed by Simar and Wilson (1998). Here, the explicit use of a bias estimator is avoided, as it unnecessarily adds statistical noise to the estimated confidence intervals. However, bias estimation itself is of interest. By definition:

$$BIAS\left[\widehat{\theta}(x_0, y_0)\right] = E\left[\widehat{\theta}(x_0, y_0)\right] - \theta(x_0, y_0) \tag{A.10}$$

The Bootstrap estimate of the bias of the original estimator $\widehat{\theta}(x_0, y_0)$ is the empirical version of (*A.6*):

$$\widehat{BIAS}_B\left[\widehat{\theta}(x_0, y_0)\right] = B^{-1}\sum_{b=1}^{B}\left[\widehat{\theta}_b^*(x_0, y_0)\right] - \widehat{\theta}(x_0, y_0) \tag{A.11}$$

Similarly, it seems reasonable to construct a bias-corrected estimator of $\theta(x_0, y_0)$, calculated as:

$$\widehat{\theta}(x_0, y_0) = \widehat{\theta}(x_0, y_0) - \widehat{BIAS}_B\left[\widehat{\theta}(x_0, y_0)\right] = 2\widehat{\theta}(x_0, y_0) - B^{-1}\sum_{b=1}^{B}\left[\widehat{\theta}_b^*(x_0, y_0)\right] \tag{A.12}$$

However, it is known that this correction introduces additional noise (see, for example, Efron and Tibshirani, 1993). The mean squared error of $\widehat{\theta}(x_0, y_0)$ can be greater than that of $\widehat{\theta}(x_0, y_0)$. The variance of the sum in (*A.11)* can be arbitrarily reduced by increasing B. But even when B→∞, the corrected estimator $\widehat{\theta}(x_0, y_0)$ will have a variance four times greater than that of the original estimator $\widehat{\theta}(x_0, y_0)$ (again illustrating the fact that the Bootstrap estimator is based on an asymptotic procedure). The sample variance of the Bootstrap values $\widehat{\theta}_b^*(x_0, y_0)$ provides an estimate $\widehat{\sigma}^2$ of the variance of $\widehat{\theta}(x_0, y_0)$:

$$\widehat{\sigma}^2 = B^{-1}\sum_{b=1}^{B}\left[\widehat{\theta}_b^*(x_0, y_0) - B^{-1}\sum_{b=1}^{B}\widehat{\theta}_b^*(x_0, y_0)\right]^2 \tag{A.13}$$

Therefore, bias correction should not be used unless:

$$\widehat{\sigma}^2 < \frac{1}{3}\left[\widehat{BIAS}_B\left[\widehat{\theta}(x_0, y_0)\right]\right]^2 \tag{A.14}$$

A.2. Applying the Bootstrap Methodology

Throughout numerous studies, it has been observed that the generation of the pseudo-sample S_n^* is of crucial importance in determining whether the Bootstrap provides consistent estimates of confidence intervals, bias, etc. (Simar and Wilson, 1998, 1999a, 1999b, 2000a, 2000b). In the classical linear regression model, samples can be drawn from the estimated residuals or from the original sample to construct the pseudo-sample S_n^*. In both cases, the Bootstrap produces consistent estimators. Both approaches are variants of what has been termed the naive Bootstrap.

However, in our context, there is a fundamental difference from the classical linear regression model: the data generating process (DGP) F is bounded by T, whereas in the classical linear regression model, the DGP is unbounded. A related problem is that, under our assumptions, the conditional density f (θ (x, y) |x, η) is bounded by the interval (0,1] and is discontinuous from the right at 1. These types of problems can cause the naive Bootstrap to produce inconsistent estimators. This problem also arises in our context, as demonstrated in Simar and Wilson (1999a, 1999b, 2000a).

To address the bounding issues that invalidate the naive Bootstrap in our context, pseudo-samples can be drawn from a uniform, consistent, and non-parametric estimate of the DGP $\underline{F}$, represented by f (x, ω, η) with the following expression:

$$f\ (\mathrm{x},\omega,\eta) = f\ (\omega|\mathrm{x},\eta) f(\eta|\mathrm{x})\ f(\mathrm{x}) \tag{A.15}$$

Where all conditional densities exist. Specifically, $f(\mathrm{x})$ is defined on $\mathbb{R}^p_+$, $f(\eta|\mathrm{x})$, is defined on $[0, \pi/2]^{\ q-1}$ and $f\ (\omega|\mathrm{x}, \eta)$ is defined on $\mathbb{R}^1_+$.

In Simar and Wilson (1998), values θ^* are drawn from a kernel estimate $\widehat{f}\ (\theta)$ of the marginal density of the original estimates $\widehat{\theta}(x_i, y_i)$ for i = 1 …, n. Given that efficiency values are between 0 and 1, the above is equivalent to assuming that $f\ (\omega|\mathrm{x}, \eta) = f\ (\omega)$ in expression (*A.15*), meaning that the distribution of inefficiencies is homogeneous and does not depend on the position within the production possibility set *T*. This assumption can be relaxed, at the cost of increased complexity (Simar and Wilson, 2000b). The focus here is on the case of homogeneity (Smoothed Bootstrap).

Kernel density estimation has been extensively studied and is easily performed. Given real values z_i, for i = 1 …,n, the kernel estimate of the density g(z) is given by:

$$\widehat{F}_{G,h}(t) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{t-\widehat{\theta}_i}{h}\right) \tag{A.16}$$

where *K* is a kernel function and *h* is a bandwidth parameter. Well-established guidelines exist to aid in choosing *K* and *h*. Specifically, the kernel function *K* must be continuous and satisfy the following conditions:

$$\int_{-\infty}^{\infty} K(u)du = 1 \tag{A.17}$$

$$\int_{-\infty}^{\infty} uK(u)du = 0 \tag{A.18}$$

Therefore, any symmetric density function with zero mean is a valid kernel function. Any even-order polynomial bounded on some interval, whose coefficients are chosen such that its integral over that interval equals unity, would also be valid. However, Silverman (1986) demonstrates that, to obtain a good estimate of $f(z)$ (one with low mean squared error), the choice of the kernel function is much less important than the choice of the parameter $\underline{\boldsymbol{h}}$.

For the kernel density estimator to be consistent, the bandwidth must be chosen such that $h = O(n^{-1/5})$ in the univariate case. If the data are approximately normally distributed, the normal reference rule can be used, setting $h = 1{,}06\widehat{\sigma}\, n^{-1/5}$, where $\widehat{\sigma}$ is the sample standard deviation of the data whose density is being estimated (Silverman, 1986). In cases where the data clearly do not follow a normal distribution, as happens when estimating the density $f(\theta)$, density estimates can be plotted for various values of $\underline{\boldsymbol{h}}$, choosing the value that provides a reasonable estimate (Silverman, 1986; Simar and Wilson, 1998). However, this approach introduces an element of subjectivity. A preferable approach involves using least-squares cross-validation, which implies choosing the value of h that minimizes an approximation of the mean squared error (Silverman, 1986). In high-dimensional cases ($p + q$), many of the estimated distance functions will take the value 1, generating a discrete distribution problem in the cross-validation procedure, which is especially true when using BCC and FDH estimators.

Wilson & Simar (1995) state that small values of $\underline{\boldsymbol{h}}$ yield smooth density estimates that follow the empirical distribution function too closely to the upper confidence interval. Larger values of $\underline{\boldsymbol{h}}$ provide excessively smooth density estimates with long tails to the left (below the smallest observed value of $\widehat{\theta}$). In practice, h takes values between 0.01 and 0.02. In our models, $\underline{\boldsymbol{h = 0.014}}$ was chosen, which provides a reasonably smooth estimate of *F*.

Regardless of how the parameter $\underline{\boldsymbol{h}}$ is selected, it is important to realize that current kernel estimators, such as that in (*A.16*), of densities over a bounded interval are biased at the ends of that interval. For (x,y) ∈ *T*, necessarily $0 \le \theta(x,y) \le \widehat{\theta}(x,y) \le 1$, causing a problem when estimating $f(\theta)$.

It is easy to see where this problem arises: in (*A.17*), when *K* is symmetric with zero mean, the density estimate for a point on the real number line is determined by summing the values of *K* functions centered on the observed data along the real number line, on both sides of the point for which the density estimate is being evaluated. If, for example, the standard normal density function is chosen as *K*, the relative contribution of observations close to the density estimate at that point is greater than that of observations further away on the real number line. When (*A.16*) is used in our application to evaluate the density estimate at 1, if *K* is symmetric, there will be no data to the right of the boundary contributing to the uniformity of the function, causing the bias problem. An obvious solution would be to allow the kernel function to become increasingly asymmetric as it approaches the boundary, although this solution is not without several problems, as shown by Scott (1992).

A much simpler solution is to use the reflection method (Simar and Wilson, 1998). This method involves reflecting each of the *n* original estimates $\widehat{\theta}(x_i, y_i)$ across the boundary (at the value 1), calculating $1 - \widehat{\theta}(x_i, y_i)$ for each $\widehat{\theta}(x_i, y_i)$, for i = 1, …,n, to obtain $\underline{\boldsymbol{2n}}$ points on the real number line. Distance function estimates are equally bounded to the left of 0, but generally there will be no values near zero, suggesting that the density is close to zero at this end of the interval. Therefore, the effect of the left boundary is ignored, and the focus is placed on the boundary at the value 1. Considering the reflected data as unbounded, with $\underline{\boldsymbol{2n}}$ observations, the density of these data can be estimated using estimator (*A.16*) without particular problems. Subsequently, this unbounded density estimate can be truncated to the right at unity, obtaining an estimate of the density of $\widehat{\theta}$ over the interval (0,1].

Once the kernel function K and the parameter $\underline{\boldsymbol{h}}$ have been selected, it is not necessary to evaluate the kernel estimate of the density in ($A.16$) to draw random values. Instead, the computational shortcut proposed by Silverman (1986) can be used for cases where the kernel function K is a common density function. It is necessary to draw n values θ^* from the estimated density of the original estimates of the distance function. Let $\{\varepsilon_i\}_{i=1}^n$ a set of n i.i.d. draws from the density function used to define the kernel function; let Zi be a set of values drawn independently, uniformly, and with replacement from the set of reflections of the distance function estimates $\mathbb{R} = \{\widehat{\theta}(x_i, y_i), 2 - \widehat{\theta}(x_i, y_i)\}$; and let $\overline{d} = n^{-1}\sum_{i=1}^n d_i$.

Calculate:

$$d_i^* = \overline{d} + \left(1 + h^2/s^2\right)^{1/2}\left(d_i + h\varepsilon_i - \overline{d}\right) \tag{A.19}$$

Where s^2 is the sample variance of the values $v_i = d_i + h\varepsilon_i$. By making use of the convolution theorem, it can be demonstrated that $v_i \sim \widehat{g}$, where $\widehat{g}$ is the kernel estimate of the density of the original distance function estimates and their reflections in $\mathbb{R}$. As is usual with kernel density estimates, the variance of v_i must be rescaled upwards as in (A.16).

Immediate manipulations reveal that:

$$E\left(d_i^*|\mathbb{R}\right) = 1 \tag{A.20}$$

$$VAR\left(d_i^*|\mathbb{R}\right) = s^2\left(1 + \frac{h^2}{n(s^2 + h^2)}\right) \tag{A.21}$$

So that the variance of d_i^* is asymptotically correct. All that remains is to reflect d_i^* across unity by calculating, for each i = 1, …,n, the following values:

Values of θ_i^* INPUT ORIENTATION OUTPUT ORIENTATION – CCR	Values OF θ_i^* OUTPUT ORIENTATION – BCC
$d_i^* si d_i^* \leq 1$	$d_i^* si d_i^* \geq 1$
$2 - d_i^* si d_i^* > 1$	$2 - d_i^* si d_i^* < 1$

The final step involves “folding” the right side of the estimate $\widehat{g}$, symmetric around the value 1, to the left of 1, ensuring that $d_i^* \leq 1$ ($d_i^* \geq 1$, in output orientation, BCC model) for all i.

By combining all this, estimates of confidence intervals, bias, etc., for the output distance function $\theta(x_0, y_0)$ evaluated at a specific point $(x_0, y_0) \in \mathbb{R}_+^{p+q}$, such that the corresponding estimate $\theta(x_0, y_0)$ exists, can be obtained using the following algorithm:

a) For each observation $(x_i, y_i) \in S_n$, one of the distance functions defined in section 3.1 is applied to obtain the estimates $\widehat{\theta}(x_i, y_i)$, for i = 1 …,n.
b) If $(x_0, y_0) \notin S_n$, step (1) is repeated for x_0, y_0 and $\widehat{\theta}(x_i, y_i)$ is obtained.
c) The n estimates $\widehat{\theta}(x_i, y_i)$ are reflected across unity, and the bandwidth parameter $\underline{\boldsymbol{h}}$ is determined by least-squares cross-validation. For our case, $\underline{\boldsymbol{h} = \boldsymbol{0.014}}$ has been fixed.
d) The computational shortcut in ($A.19$) is used to draw $\underline{\boldsymbol{n}}$ Bootstrap values $\theta_i^*(x_i, y_i)$, for i = 1, …,n, from the kernel estimate of the density $f\,(\widehat{\theta})$.
e) A pseudo-sample S_n^* is constructed whose elements (x_i^*, y_i^*) are given by:

Values of (x_i^*, y_i^*)- INPUT ORIENTATION	Values of (x_i^*, y_i^*)- OUTPUT ORIENTATION
$x_i^* = \widehat{\theta} x_i/\theta_i^*$	$x_i^* = x_i$
$y_i^* = y_i$	$y_i^* = \theta_i^* y_i/\widehat{\theta}(x_i, y_i)$

f) Expression ($A.8$), or an analogous one if CCR estimators are being used, is utilized to calculate the Bootstrap estimate $\widehat{\theta}^*(x_0, y_0)$.
g) Steps (d)-(f) are repeated $\underline{B}$ times to obtain a set of $\underline{B}$ Bootstrap estimates $\{\widehat{\theta}_b^*(x_0, y_0)\}_{b=1}^B$.
h) Expression ($A.7$) is used to determine $\widehat{a}_\alpha$ and $\widehat{b}_\alpha$ and, subsequently, expression (9) along with the original estimate $\widehat{\theta}(x_0, y_0)$ is used to construct the estimated confidence interval of θ. Additionally, the Bootstrap estimates can be used in expression ($A.11$) to obtain an estimate of the bias of $\widehat{\theta}(x_0, y_0)$ and in expression ($A.12$) to obtain a bias-corrected estimator if condition ($A.14$) is satisfied.

Appendix B

Table B.1
Efficiency results by years (2011–2015)

Port Name	2011				2012				2013				2014				2015			
	DEA		BOOTSTRAP		DEA		BOOTSTRAP		DEA		BOOTSTRAP		DEA		BOOTSTRAP		DEA		BOOTSTRAP	
	BM	*AM*	*BM*	*AM*	*BM*	*AM*	*BM*	*AM*	*BM*	*AM*	*BM*	*AM*	*BM*	*AM*	*BM*	*AM*	*BM*	*AM*	*BM*	*AM*
Cape Town	0,57111	0,84073	0,50382	0,78664	0,61832	0,80611	0,54472	0,75827	0,57417	0,65842	0,50250	0,62779	0,55904	0,63658	0,49494	0,59827	0,56232	0,67574	0,49404	0,63864
Casablanca	1,00000	1,00000	0,75320	0,83771	1,00000	1,00000	0,75850	0,84712	1,00000	1,00000	0,75995	0,86478	1,00000	1,00000	0,73783	0,84842	1,00000	1,00000	0,75040	0,85326
d’Abidjan	0,46253	0,46253	0,42622	0,43986	0,54531	0,54531	0,50047	0,51642	0,52218	0,57230	0,49343	0,55805	0,46887	0,50134	0,44165	0,48174	0,49420	0,56207	0,46280	0,54304
Dakar	0,45786	0,45786	0,42806	0,44502	0,38989	0,38989	0,37064	0,37849	0,50450	0,50450	0,47998	0,48844	0,42811	0,42811	0,40909	0,41198	0,43282	0,43282	0,40242	0,41206
Douala	0,38322	0,38322	0,33363	0,36486	0,32141	0,32141	0,27275	0,30286	0,39534	0,39534	0,34178	0,37864	0,34798	0,34798	0,29361	0,32800	0,68546	0,68546	0,58539	0,65056
Durban	1,00000	1,00000	0,75517	0,84982	1,00000	1,00000	0,76054	0,84695	1,00000	1,00000	0,76281	0,86364	1,00000	1,00000	0,75018	0,84389	1,00000	1,00000	0,74656	0,85892
East London	1,00000	1,00000	0,75426	0,83886	1,00000	1,00000	0,75952	0,85350	1,00000	1,00000	0,76183	0,86444	1,00000	1,00000	0,74383	0,84569	1,00000	1,00000	0,74960	0,85242
Port Elizabeth	0,36763	1,00000	0,30715	0,84634	0,31659	1,00000	0,26665	0,85116	0,32388	1,00000	0,27264	0,86076	0,28392	1,00000	0,23470	0,84512	0,23934	1,00000	0,19982	0,86090
Tanger Med	1,00000	1,00000	0,78379	0,85455	1,00000	1,00000	0,80247	0,86612	1,00000	1,00000	0,77805	0,87355	1,00000	1,00000	0,75552	0,84685	1,00000	1,00000	0,75919	0,86665
Tema	0,57525	0,57525	0,51096	0,54365	0,66807	0,71532	0,60525	0,66946	0,64353	1,00000	0,59071	0,87405	0,58401	0,85090	0,53305	0,79005	0,54040	0,83712	0,46730	0,78495
Walvis Bay	0,34350	1,00000	0,31242	0,84197	0,50457	1,00000	0,46656	0,85270	0,43879	1,00000	0,40681	0,86725	0,32212	1,00000	0,29311	0,84147	0,35514	1,00000	0,32469	0,85874
Cotonou	0,62176	0,62176	0,57461	0,59490	0,62583	0,62583	0,58672	0,60457	0,58690	0,58690	0,55178	0,57187	0,51120	0,51120	0,46909	0,48953	0,42712	0,42712	0,39292	0,40905
Luanda	0,81155	0,81155	0,69592	0,76100	0,86691	0,86691	0,75886	0,81678	0,91418	0,91418	0,78995	0,87523	0,88000	0,88000	0,75237	0,82538	0,86610	0,86610	0,74445	0,81429
Onne	1,00000	1,00000	0,74673	0,84265	1,00000	1,00000	0,75789	0,85165	1,00000	1,00000	0,76447	0,86460	1,00000	1,00000	0,74174	0,84236	1,00000	1,00000	0,74901	0,85327
Las Palmas	0,65709	1,00000	0,57798	0,84482	0,59284	1,00000	0,51790	0,84602	0,49926	1,00000	0,45138	0,86793	0,50270	1,00000	0,45826	0,83926	0,41115	1,00000	0,36925	0,85971
St C. Tenerife	0,58000	1,00000	0,53992	0,84156	0,54787	1,00000	0,51580	0,84567	0,64535	1,00000	0,60672	0,86643	0,66628	1,00000	0,62945	0,83878	0,61269	1,00000	0,56251	0,86012

Source: Own Elaboration.

Table B.2
Efficiency results by years (2016–2020)

Port Name	2016				2017				2018				2019				2020			
	DEA		BOOTSTRAP		DEA		BOOTSTRAP		DEA		BOOTSTRAP		DEA		BOOTSTRAP		DEA		BOOTSTRAP	
	BM	AM	BM	AM	BM	AM	BM	AM	BM	AM	BM	AM	BM	AM	BM	AM	BM	AM	BM	AM
Cape Town	0,50837	0,67464	0,43927	0,62449	0,51545	0,56113	0,45838	0,52519	0,63841	0,63841	0,57573	0,59930	0,40252	0,41105	0,35116	0,38070	0,32284	0,35081	0,28948	0,32718
Casablanca	1,00000	1,00000	0,73934	0,84367	1,00000	1,00000	0,75029	0,84331	1,00000	1,00000	0,74460	0,80928	1,00000	1,00000	0,72435	0,82072	1,00000	1,00000	0,70163	0,81236
d'Abidjan	0,52910	0,62638	0,49561	0,60217	0,61261	0,72609	0,57724	0,70005	0,65237	0,73536	0,61100	0,70412	0,53968	0,56572	0,51375	0,54673	0,04596	0,04971	0,04333	0,04806
Dakar	0,41001	0,41001	0,37669	0,39715	0,43747	0,43747	0,40296	0,42076	0,41419	0,41419	0,38352	0,39074	0,54196	0,54196	0,52791	0,53304	0,45090	0,51310	0,43173	0,50314
Douala	0,52028	0,52028	0,44421	0,49106	0,80982	0,80982	0,70235	0,76228	0,73924	0,73924	0,63580	0,68447	0,64588	0,64588	0,53165	0,59262	1,00000	1,00000	0,70678	0,80605
Durban	1,00000	1,00000	0,73657	0,84706	1,00000	1,00000	0,75300	0,84519	1,00000	1,00000	0,76307	0,82162	1,00000	1,00000	0,74881	0,82467	1,00000	1,00000	0,77652	0,81841
East London	1,00000	1,00000	0,73305	0,84577	1,00000	1,00000	0,74158	0,83758	1,00000	1,00000	0,74899	0,81216	1,00000	1,00000	0,72870	0,81983	1,00000	1,00000	0,69738	0,81115
Port Elizabeth	0,14956	1,00000	0,12318	0,84393	0,15927	1,00000	0,13379	0,83860	0,16301	0,16301	0,13699	0,14869	0,12222	1,00000	0,09977	0,82580	0,09472	1,00000	0,07672	0,80696
Tanger Med	1,00000	1,00000	0,75818	0,84342	1,00000	1,00000	0,76551	0,84514	1,00000	1,00000	0,75987	0,83165	1,00000	1,00000	0,74497	0,82683	1,00000	1,00000	0,75194	0,82823
Tema	0,59624	0,59624	0,50688	0,55595	0,63762	0,63762	0,55414	0,59955	0,74259	0,76970	0,65554	0,71199	0,56499	0,56499	0,51583	0,54092	0,43336	0,48569	0,37777	0,45639
Walvis Bay	0,32973	1,00000	0,30490	0,84220	0,25062	1,00000	0,23414	0,84163	0,25545	1,00000	0,23575	0,81583	0,17663	1,00000	0,15784	0,83098	0,11745	1,00000	0,10584	0,80895
Cotonou	0,45334	0,45334	0,42328	0,43356	0,45156	0,45156	0,41292	0,43119	0,41697	0,41697	0,37292	0,39242	0,52324	0,52324	0,47588	0,50157	0,51958	0,51958	0,48418	0,49951
Luanda	0,81810	0,81810	0,70464	0,76304	0,44840	0,44840	0,38833	0,41809	0,64491	0,64491	0,56610	0,60439	0,39332	0,39332	0,33234	0,36193	0,35546	0,35546	0,30301	0,33093
Onne	1,00000	1,00000	0,73431	0,84250	1,00000	1,00000	0,75093	0,83655	1,00000	1,00000	0,74454	0,81515	1,00000	1,00000	0,72214	0,82834	1,00000	1,00000	0,69776	0,81219
Las Palmas	0,40882	1,00000	0,36464	0,83843	0,53199	1,00000	0,47652	0,83681	0,50629	1,00000	0,44983	0,82328	0,44024	1,00000	0,40762	0,82176	0,40840	1,00000	0,38754	0,81836
St C. Tenerife	0,60251	1,00000	0,54646	0,84161	0,78276	1,00000	0,71296	0,84229	0,56993	1,00000	0,52362	0,82246	0,65782	1,00000	0,63055	0,82295	0,52802	1,00000	0,49853	0,80839

Source: Own Elaboration

Data availability

Data will be made available on request.

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