JOURNAL OF MARITIME RESEARCH

Vol XXII. No. II (2025) pp 421–431

ISSN: 1697-4840, www.jmr.unican.es

# Analysis of technical efficiency with frontier techniques: The case of Tunisian ports

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*ARTICLE INFO*

***Article history:***
Received 16 Nov 2024;
in revised from 20 Nov 2024;
accepted 15 Mar 2025.

***Keywords:***
Technical efficiency, Data Envelopment Analysis (DEA), Stochastic Frontier Analysis (SFA), Tunisian ports.

***JEL Classification:***
L51, L91, L92, O18.



*ABSTRACT*

This paper evaluates and examines the technical efficiency of Tunisian ports by utilizing Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) models, while also investigating the influence of infrastructure features on port efficiency. The analysis draws on panel data from six major ports—Bizerte, Goulette, Rades, Sousse, Sfax, Gabes, and Zarzis—spanning the years 2007 to 2019. Variables linked to infrastructure, such as the number of berths, land area, gears, and workforce numbers, were used as inputs. The outcome represents the average difference in efficiency between the DEA and SFA models. The Battese and Coelli (1995) model, applied through SFA, highlights the significant contribution of berth availability to Tunisian ports' output. Additionally, private sector involvement in handling operations is shown to have a notable negative impact on technical efficiency. According to DEA results, total technical efficiency is calculated at 68.8%, pure technical efficiency at 81.4%, and scale efficiency averages around 83.8%.

## 1. Introduction.

The maritime transport industry plays a pivotal role in globalization and international trade, with 80% of global merchandise being delivered by sea. Shipping provides a cost-effective and efficient method for transporting goods, promoting economic growth and fostering trade between countries and populations. One of the main benefits of sea transport is its reliability, speed, and capacity to move large quantities of cargo and passengers at relatively low costs.

In a volatile and indecisive economic climate, seaport customers have a strong need for a port service that can meet their demanding requirements. The port community is in a delicate position, since it should always offer high-quality service.

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As a result, seaports have found themselves obliged to improve port practices by adopting development strategies based essentially on optimizing the port's cost-quality-delay triptych, integrating ports into global value chains and improving the commercial attractiveness of seaports, in order to steer seaports towards a high level of efficiency. In this respect, the study of port efficiency has set many pens in motion. Mandl, Dierx and Ilzkovitz (2008), Wan, yuen and zhang (2013), George kobina van dyck (2015) and Renata M.A et al (2019). Researchers have focused more on measuring port efficiency, using two main methods, the DEA method and the SFA method.

In this vein, we can point out that studies examining port efficiency in the case of Asian, European and American countries are abundant, but few in the case of the African continent. The present research is largely aimed at filling this gap, focusing on African ports, and Tunisian ports in particular, since they have undergone a profound transformation over the last decade, with the help of a series of continuous efforts based essentially on huge investments in physical capital, with a view to taking advantage of the external demand addressed to the African continent, and not escaping the various new global trends in maritime trade.

How effectively a group or DMU uses its resources to produce outputs is what we mean when we talk about efficiency. The link between inputs and outputs is a simple definition of efficiency. Both technical efficiency—which shows how well a company can maximize output from a specific set of inputs—and allocative efficiency—which shows how well a company uses inputs in the best possible combination given input costs—are essential components of efficiency, according to Farell (1957). When technical and allocative efficiency are combined, the outcome is economic efficiency as a whole.

According to a survey of the literature, the vast majority of studies have focused on Asian and European ports. Nevertheless, no one has been to North African ports just yet. Bizerte, Goulette, Radès, Sousse, Sfax, Gabès, Skhira, and Zarzis are the eight commercial ports of Tunisia. Their strategic position and complementary functions allow them to accommodate a variety of vessels and cargo. It is critical to analyze the effectiveness of Tunisian ports because the country is now reforming its port regulations and investing heavily in infrastructure, such the Enfidha port project, which is meant to accept Panamax and post-Panamax ships.

The purpose of this essay is to use two approaches, DEA and SFA, to assess the technological efficiency of six ports in Tunisia. Cobb-Douglas function, DEA-CCR (Charnes, Cooper, Rhodes, 1978), and DEA-BCC (Banker, Charnes, Cooper, 1984) are all part of the technical efficiency study. In order to overcome inefficiencies caused by input overuse, the output-oriented DEA model is also used to optimize port output while keeping inputs constant.

In other words, the aim is to provide some answers to the following question: What assessment can we make of the efficiency of Tunisian commercial ports?

The hypotheses underlying this study are as follows:

H1: the technical efficiency of Tunisian ports is affected by the Tunisian revolution.

H2: when the private sector is involved in handling operations, the technological efficiency of Tunisian ports improves.

H3: Tunisia's main ports record average technical inefficiencies.

To achieve this, we first explore the theoretical and empirical underpinnings of DEA and SFA. Secondly, we examine the main seaports in our study, and provide an overview of the literature on port efficiency measurement. Thirdly, we present a survey of the information and share the findings of the empirical research, together with empirical validation using the DEA and SFA approaches. Finally, we address the policy implications and conclude this article.findings, engages in a discussion of these findings, and concludes with a summary of the study's outcomes.

## 2. Literature Review.

In the literature, it appears that the main methods used to date for estimating port technical efficiency are the stochastic frontier method (SFA) and the data envelopment analysis (DEA) method.

### *2.1. Empirical port efficiency by using DEA.*

The initial attempts for DEA use in the analysis of the seaport's efficiency were made by (Roll and Hayuth, 1993). The researchers employed cross-sectional data to assess the efficiency of 20 seaports, focusing exclusively on the implementation of DEA-CCR., which is a standard DEA model.

Martinez et al. (1999) categorized 26 ports in Spain as either very complex, moderately complex, or very simple. In order to determine how technically efficient these ports were, they used the DEA-CCR and DEA-BCC models. Seaports with a lot of moving parts tend to be more efficient, according to the authors.

Tongzon (2001) analyzed the technical efficiency of four Australian ports and twelve international ports using the DEA-CCR and DEA-additive models. The least efficient ports in the sample were found to be Osaka, Rotterdam, Yokohama, and Melbourne.

Valentine and Gray (2001) analyzed data from 1998 using the DEA-CCR model to explore the link between port efficiency and specific ownership or organizational structures in 31 of the top 100 container seaports worldwide. In a separate study, Barros and Athanassiou (2004) applied both DEA-CCR and DEA-BCC models to assess the efficiency of 6 seaports, 4 in Portugal and 2 in Greece, concluding that all ports were efficient except for Thessaloniki.

Park (2005) employed DEA window analysis to evaluate the performance of 11 Korean container terminals between 1999 and 2002. The inputs for this study included variables like quay length, the number of cranes, manpower, storage size, and productivity metrics, with throughput and capacity as the outputs.

Cullinane and Wang (2006) focused on 69 container terminals in Europe that processed over 10,000 TEU annually, using cross-sectional data from 2002. They employed DEA-CCR and DEA-BCC models, determining that many of these terminals were operating inefficiently.

Using data from 2000 to 2005, Al-Eraqi et al. (2008) evaluated the technological efficiency of 22 seaports in the Middle East and Africa using both normal DEA and DEA window analysis. Their findings demonstrated that DEA-BCC outperformed DEA-CCR in terms of efficiency, with Djibouti and Khor Fakkan being named the top two ports in terms of performance.

Furthermore, Munisamy and Singh (2011) evaluated the technological efficacy of 69 Asian container ports using the DEA-CCR and DEA-CCR models. Based on their research, they determined that the Philippines, Bangladesh, China, Cambodia, India, and Singapore had the best Asian ports.

Rajasekar and Deo (2013) examined the technical efficiency of several key Indian ports between 1993 and 2011 using both standard DEA and DEA-additive models. Their analysis revealed that port size was not a decisive factor in determining efficiency, as both large ports like JNPT and Mormugao and smaller ones like Tuticorin and Ennore were consistently efficient in their operations.

Zheng and Park (2016) conducted their own analysis of 30 seaports' 2014 efficiency using the DEA-CCR and DEA-BCC models. The results demonstrated that the primary terminals in Korea and China were almost identical in terms of efficiency (DEA-CCR: 0.815, DEA-BCC: 0.886).

Additionally, Hanaa Abdelaty (2016) used standard DEA to assess the performance of 9 Saudi Arabian ports in 2014, employing two outputs and three inputs to measure their efficiency. The results indicated that the port of Jazan was inefficient, and most of the other ports were also operating below their potential.

Using the DEA approach, Schøyen et al. (2018) examined the effectiveness of container ports situated in six nations in Northern Europe. Some ports are quite sensitive to the inclusion or exclusion of logistics service providing outcomes, according to the research.

Shaheen and Elkalla (2019) used the DEA-CCR and DEA-BCC models to examine the effectiveness of Middle Eastern container ports. Increasing returns to scale were observed in 80% of the ports, according to their research.

After looking at the technological efficiency of Indian container ports, Iyer and Nanyam (2021) came to the conclusion that expanding operations to a larger scale would be more effective than building new terminals to improve terminal efficiencies.

More recently, Ben Mabrouk et al. (2022) evaluated changes in efficiency and productivity in Tunisian seaports from 2005 to 2016 using the DEA approach and the Malmquist index. The findings demonstrated that Tunisian ports are inefficient, with a decrease in technical innovation being the primary cause of the total factor productivity reduction.

### 2.2. *Empirical port efficiency by using SFA.*

To test the notion that public sector ports are not as efficient as private ports, Liu (1995) utilized technological efficiency in conjunction with a translog production feature, one of the SFA applications to the port business. For this study, we consulted a set of panel data that included the intakes and outputs of 28 different British ports from 1983 to 1990.

Coto-Millan et al. (2000) assessed the fiscal efficacy of twenty-seven ports in Spain from 1985 to 1989 using the translog cost function. They discovered that smaller ports worked better. They contended that the level of autonomy, rather than size, was the determining factor, as less autonomous ports are considered to be very efficient.

In order to obtain access to the privatization of five container terminals in Korea and Britain, Cullinane and Song (2003) used SFA with the Cobb-Douglas cost function. Their implementation was based on cross-sectional and panel data versions. They included in management fees, staff wages, the net book value of mobile, freight, and handling equipment, and the capital cost of terminal operations as inputs. We included container terminal service income on the output side, but we didn't include real estate sales.

Tongzon and Heng (2005) examined the relationship between port efficiency and particular port features by measuring the efficiency levels of 25 ports/container terminals using the SFA approach. They discovered that private sector engagement in the port industry can improve operational efficiency, leading to a boost in the port's competitiveness.

Barros (2005) used the translog cost function to look at the Portuguese port's technological efficiency and the extent to which it changed from 1999 to 2000. There was a lot of inefficiency in ports administration, according to his results (average inefficiency score: 39.6%). The cost of capital and labor are examples of inputs. Ship count and total cargo were the outputs.

The production efficiency was estimated by Sun et al. (2006) using the Cobb-Douglas production function. Annual panel data from 1997 to 2005 was gathered for each of the 83 container terminal operators. Their input was ship-to-quay handling capacity, quay-to-yard handling capacity, number of berths, quay line length, terminal area, port storage capacity and benchmarks, while freight throughput was the output.

In their evaluation of 22 European ports' technological efficiency and law, Trujillo and Tovar (2007) used cross-sectional data from 2002 and the Cobb-Douglas production function. Their research failed to capture the elements that dictated a port's efficiency.

To assess the effects of port reforms in the 1990s and improvements in the technical efficiency of transportation infrastructures, a translog output function was used with panel data for nine ports in Spain from 1990 to 2002, following González and Trujillo (2008). The results demonstrate that the reforms caused a shift in the mean technical performance.

Barros et al. (2016) used a stochastic frontier model to examine the effects of cost and operating variables on the main Chinese ports with panel data spanning from 2002 to 2012. The inputs included the prices of labor, capital, and intermediate consumption. One example of an output variable is the quantity of passengers and containers handled. Based on their findings, profitability estimations for Chinese seaports are affected by the high degree of variability in the industry.

Furthermore, utilizing the SFA approach and operational performance indicators, Lopez-Bermúdez et al. (2019) examined the productivity and efficiency of twenty container terminals in Brazilian ports from 2008 to 2017. According to their research, private terminals are actually rather efficient.

Finally, Pérez et al. (2020) used the SFA methodology to examine the efficiency of 27 ports in Spain. Bigger, more specialized ports were more efficient, according to these writers. Despite the wealth of research conducted on port efficiency, most studies have used one of the DEA or SFA methods to measure efficiency. However, to our knowledge, there are few studies that have used both methods on the same dataset and compared the results obtained (Cullinane et al., 2006; Nguyen et al., 2011; Bergantino et al., 2013; Kammoun, 2018; Hlali, 2018).

## 3. Methodology.

### 3.1. *Stochastic frontier analysis (SFA).*

The stochastic frontier is based on the combination of two types of error. One symmetrical, the other asymmetrical. The former is nothing other than the classic symmetrical error variable, ($v$). On the other hand, the second is the variable, ($u$), representing inefficiency ($u > 0$). Pioneers of the stochastic frontier formulation are Aigner, Lovell and Schmidt (1977), and Meeusen and van den Broeck (1977), who were the first to propose a compound error model. Empirical studies that have used this type of support have relied on statistical information involving cross-sectional data have limitations. Firstly, a particular assumption must be made concerning the distribution of the asymmetric variable $u$. Secondly, neither heterogeneity nor time variation in technical efficiency can be studied. We can overcome these difficulties if we use panel data. The primary reason for using panel data is to control for unobservable heterogeneity. Furthermore, if we estimate the model on Panel data, we can avoid assuming the distributions of the error terms ($v$ and $u$). Furthermore, with panel data it is possible to study how the productive efficiency of companies varies over time.

The parametric stochastic production frontier model we'll be estimating is that of Battese and Coelli (1995) for panel data. It comprises two equations: the first defines the stochastic production frontier and the second the technical inefficiency model:

$$Y_{it} = X_{it}\,\beta + (v_{it} - u_{it})$$

$$u_{it} = Z_{it}\delta + W_{it}$$

Where $Y_{it}$ denotes the total cargo volume of port "i" in year "t", $X_{it}$ is a vector (1*k) of inputs used by port "i" in year "t", $\beta$ is a vector (k*1) of unknown parameters to be estimated, $v_{it}$is the symmetrical random error term, assumed to be i.i.d. according to N$(0,\ \sigma^2{}_v)$, $u_{it}$ is the error term reflecting the technical inefficiency of port "i" in year "t".

$Z_{it}$ is a vector (1*m) of variables that can influence the efficiency of a port, $\delta$ is a vector (m*1) of unknown parameters to be estimated, $W_{it}$is an unobservable random variable defined by the truncation of a normal distribution with mean zero and variance $\sigma^2$.

The parameters of the stochastic frontier model and those of the inefficiency effects model can be estimated simultaneously by the maximum likelihood method. The variance parameters of the maximum likelihood function are $\sigma^2 = \sigma^2{}_v + \sigma^2{}_u$ and $\gamma = \sigma^2{}_u/(\sigma^2{}_v + \sigma^2{}_u)$. The parameter $\gamma$ is defined as being between 0 and 1 by definition. A value of $\gamma = 1$ implies that technological inefficiency is the sole cause of the deviation from the frontier, whereas a value of $\gamma = 0$ shows that random shocks are the sole cause of the deviation from the frontier. Technical inefficiency and random shocks describe production variation when $0< \gamma < 1$ (Battese and Coelli, 1995).

The level of technical efficiency ($ET_{it}$) is defined by the equation below:

$$ET_{it} = exp(-Z_{it}\delta - -W_{it}) = exp(-u_{it})$$

In the literature, the two functional forms most commonly used in efficiency studies are the translog form and the Cobb-Douglas form. The translog form is more flexible and allows substitution elasticities to be calculated, whereas these are unitary in a Cobb-Douglas function (Christensen et al., 1971). In this work, the functional form that best meets our objectives is the Cobb-Douglas production function. A simple functional form was chosen to study the technical efficiency of Tunisian ports due to data limitations, i.e. the sample size of the study did not allow us to estimate and test the translog functional form due to the degrees-of-freedom problem.

The literature recommends two methods for estimating the frontier and the determinants of inefficiency: the two - stage method and simultaneous estimation. The two-step method consists of first determining efficiency indices from the frontier estimate, and then regressing them against the various factors suspected as determinants of efficiency. This method has been widely criticized by Kumbhakar et al. (1991) and Battese and Coelli (1995) for violating one of the basic assumptions that inefficiency effects are independently distributed in the stochastic production frontier. The second method is the simultaneous estimation method proposed by Battese and Coelli (1995), which consists of simultaneously estimating two equations, one representing the frontier and the other the relationship between inefficiency and explanatory factors. In the present study, we use the simultaneous estimation method. Parameters will be estimated by the maximum likelihood method using STATA software.

### *3.2. Data envelopment analysis (DEA).*

Charnes et al. (1978) created the DEA method, which is essentially a linear programming method that takes in a lot of data and provides a metric for efficiency. In order to accomplish this transformation, all of the decision-making units (DMUs) have their inputs and outputs compared to one another. Finding the most efficient units in a population and quantifying their inefficiency are two main contributions of DEA. It should be mentioned that DEA measures relative or comparative efficiency rather than absolute efficiency.

A mathematical programming foundation supports this method. Since it does not examine the input-output-efficiency relationship using a predefined production function that is the same for all businesses, it is categorized as non-parametric.

Two basic models are used in DEA, each leading to the identification of a different efficiency frontier. The first model, CCR, originally presented by Charnes et al. (1978), assumes that DMUs evolve in a situation of constant returns to scale. The second BCC model, proposed by Banker et al. (1984), assumes that DMUs evolve in a situation of variable returns to scale. Both models can be input-oriented (minimizing inputs for a given level of outputs) or output-oriented (maximizing outputs for a given level of inputs).

Borenstein et al (2004) point out that the aim of the DEA technique is to identify those DMUs that are operating efficiently and therefore belong to the production frontier, as well as those DMUs that are not operating efficiently, so that appropriate adjustments can be made to their inputs and outputs to achieve efficiency. In addition, the authors point out that with this technique, it is possible to: (i) quantitatively calculate the relative efficiency of DMUs; and (ii) identify the sources and quantities of relative inefficiency in each DMU.

The two output-oriented models used in this article are presented in the table 1 below:

Table 1: Output-oriented DEA-CCR and DEA-BCC models.

| Output-oriented dual CCR model : | Output-oriented BCC dual model |
|---|---|
| Max $Z_0 = \Phi + \varepsilon(s1'OS + m1'IS)$<br>Under constraints :<br>$\Phi\, y_{r0} - \sum_{j=1}^{n} \lambda_j\, y_{rj} + OS_r = 0$<br>$-x_{i0} + \sum_{j=1}^{n} \lambda_j\, x_{ij} + IS_i = 0$<br>$\Phi, \lambda, OS, IS \geq 0$ | Max $Z_0 = \Phi + \varepsilon(s1'OS + m1'IS)$<br>Under constraints :<br>$\Phi\, y_{r0} - \sum_{j=1}^{n} \lambda_j\, y_{rj} + OS_r = 0$<br>$-x_{i0} + \sum_{j=1}^{n} \lambda_j\, x_{ij} + IS_i = 0$<br>$N1'\lambda = 1$<br>$\Phi, \lambda, OS, IS \geq 0$ |

Source: Authors.

Where Φ is efficiency score, $y_{r0}$ observed quantities of output "r" from the port whose efficiency is being measured, with r =1, $x_{i0}$ observed quantities of input "i" from the port whose efficiency is being measured, where i =1, 2, 3, 4, $y_{rj}$ observed quantities of output r from port "j", where j =1,2,...n, $x_{ij}$ observed quantities of input "i" from port "j", $_j$ weighting coefficients, $OS_r$ output variance variables "r " and $IS_i$: input deviation variables "i".

*3.3. Data.*

This study uses cylindrical panel data from six Tunisian ports from 2007 to 2019, a total of 78 observations, to estimate technical efficiency. Just six ports in various regions of Tunisia are part of this project. Here are the grounds behind this decision: (i) TRAPSA exclusively handles liquid bulk, or crude oil, at the port of Skhira; (ii) La Goulette handles passenger and cruise traffic; and (iii) OMMP oversees a group of ports that are almost identical in their operations (Ben Mabrouk et al., 2022).

We have compiled physical data for each of the six ports, including the amount of import and export goods handled, the number of berths, the number of gears, the land area, and the number of personnel. This data is used as outputs. Furthermore, the port's external technical inefficiency is explained by two control factors. Our data came from OMMP's official websites and annual reports as well as secret documents from port operators like STAM, STUMAR, GMC, GMS, GMGA, and GMZ.

In the DEA and SFA application to the evaluation of port operations, numerous outputs could be taken into account, such as: total cargo volume (general, container, dry bulk, liquid bulk, RO-RO), number of ships calling, ship turnaround time and total number of passengers. From the summary of DEA and SFA applications in ports, it is clear that the total volume of cargo handled is undoubtedly the most significant output measure. Seaports aim to do this. Because of its strong correlation with the demand for cargo handling facilities and other services, total cargo volume has long been used as an indicator of port output, which is why it has been chosen as an output variable.

Land, labor, and capital are all examples of input factors that are utilized to create an output. Dowd and Leschine (1990) state that according to economic theory, the most important factor in effectively managing cargo quantities is the port's ability to utilize land, labor, and capital efficiently. Potential input variables in port operations include the following: the total number of terminals; the length of the quays; the area of the medians; the total number of warehouses; and the towing and handling equipment, including tugboats, gantry cranes, quay cranes, stacker straddles, forklifts, and loading arms. Thus, because data for all variables was unavailable, we have kept only four inputs: for the land factor, we have chosen the total number of berths and open land surface area; for the capital factor, we have chosen the total number of machines; and for the labor factor, we have chosen the total number of workers (exclusively related to stevedoring activity) employed by each port.

As Kumbhakar and Lovell (2000) point out, the aim of studying efficiency is not to calculate the level of efficiency as such, but rather to identify the factors that influence it. In this paper, two binary variables have been selected as factors likely to influence the technical efficiency of Tunisian ports. The 2011 value of 1 for the first variable represents the impact of the "Jasmine" revolution on the technological efficiency of Tunisian ports. If a private stevedore is engaged in handling operations within the port, the second variable, which is defined as the presence of private sector engagement in handling operations, takes the value of 1, and otherwise, it takes the value of 0. Private companies now own and operate a portion of Tunisia's port infrastructure, thanks to the country's concessions law (2008-23). In our sample, the Tunisian Stevedoring and Handling Company (STAM)[3] is responsible for all stevedoring activities in the port of Rades. In the other ports, however, five private stevedores (STUMAR[4], GMC[5], GMS[6], GMGA[7], and GMZ[8]) operate alongside STAM.

## 4. Empirical Results.

We have two types of results relating to our two methods in this paper. The parametric method (SFA) and the non-parametric method (DEA).

Descriptive statistics for these different variables are summarized in table 2.

Table 2: Descriptive analysis of model variables.

| Variables | Mean | SD | Min | Max |
|---|---|---|---|---|
| Cargo throughput Y | 3707.526 | 1851.589 | 678 | 6932 |
| Number of berths $X_1$ | 10.5 | 3.222284 | 6 | 15 |
| Number of gears $X_2$ | 43.61538 | 49.89163 | 5 | 184 |
| Number of workers $X_3$ | 188.3462 | 235.151 | 12 | 813 |
| Land area $X_4$ | 23.28333 | 7.446178 | 14.7 | 36 |
| Revolution | 0.0769231 | 0. 2681941 | 0 | 1 |
| Private sector participation | 0. 8333333 | 0. 3750902 | 0 | 1 |

Source: Authors.

Over the entire study period, average production in Tunisian ports was 3707.52 tonnes. The relatively high standard deviation (1851.58) can be explained by variability in the use of

[3] STAM: public entity.
[4] STUMAR: private stevedore in the port of Bizerte.
[5] GMC: private stevedore in the port of Sousse.
[6] GMS: private stevedore in the port of Sfax.
[7] GMGA: private stevedore in the port of Gabès.
[8] GMZ: private stevedore in the port of Zarzis.

inputs between ports. This leads to great variability in production. The average number of berths, surface areas and equipment used in handling operations is 10.5, 23.28 and 43.61 respectively. The average size of workers in the study sample is estimated at 163.

### *4.1. The stochastic frontier analysis .*

Table 3 shows the values estimated by the maximum likelihood method for the stochastic production frontier model and the technical inefficiency effects model for Tunisian ports.

Before estimating, it is essential to test the hypothesis of the presence or absence of the technical inefficiency effect in the model: $H_0$: $\gamma = \delta_0 = \delta_1 = \delta_2 = 0$ and $H_1$: $\gamma \neq 0$.

This hypothesis is tested using the general likelihood ratio statistic:

$$LR = -2\,[\ln(L(H_0))\,/\,\ln(L(H_1))] = -2\,[\ln(L(H_0)) - \ln(L(H_1))]$$

Where (H_0) and (H_1) are the values of the likelihood function under the null hypothesis $H_0$ : $\gamma = \sigma^2{}_u\,/\,(\sigma^2{}_v + \sigma^2{}_u)$= 0 and the alternative hypothesis $H_1$: $\gamma > 0$, respectively. The crucial value of the Chi-square distribution ($\chi^2$) suggested by Kodde and Palm (1986) with a 1% tolerance level should be compared with the computed test statistic. With 5 degrees of freedom, the computed LR test statistic is 36.98, surpassing the critical Chi-square value of 14.325 at a 1% significance level (see to Table 3 for details). Therefore, at the 1% level of significance, the null hypothesis that technical inefficiency effects are not present in the data is rejected. Therefore, this study's examination of Tunisian ports does not make use of the average traditional production function (OMP).

The results from Table 3 show a value for the lambda estimator λ equal to 167.6398 and being significant at the 1% threshold. This value gives an indication of the relative variance of the two composite errors that make up the total variation. The two variances of the two error components indicate that the technical inefficiency component $u$ varies more widely than the uncontrollable random exogenous component $v$. This means that technical inefficiency contributes more significantly to the variability of the total error in our model.

It is important to note that the results presented in Table 3 indicate that all the coefficients of the stochastic frontier model are significantly different from zero.

The coefficients ( $\beta_1$ , $\beta_2$ and $\beta_3$) respectively of the production factors (number of berths, number of gears and number of workers) are significant and show the expected positive signs, the exception being the land area factor (significant but with a negative sign). This means that if we increase the quantities of the factors berth, number of machines and number of workers by 10%, port production will increase by 15.637%, 0.322% and 1.417% respectively. As for the land area factor, a 10% increase in this factor reduces cargo volume by 4.847%. This means that the marginal productivity of the land area was negative. In sum, we find that the berth variable has a higher contribution to port production growth, with a coefficient of 1.5637.

Table 3: Estimation using the maximum likelihood method.

| Dependent variable lny | | |
|---|---|---|
| Independent Variables | Coefficient | P-value |
| Constant | 5.5824*** | 0.000 |
| $\ln\mathbf{x_1}$ | 1.5637*** | 0.000 |
| $\ln\mathbf{x_2}$ | 0.0322* | 0.102 |
| $\ln\mathbf{x_3}$ | 0.1417** | 0.002 |
| $\mathbf{\ln x_4}$ | -0.4847*** | 0.000 |
| *Inefficiency model* | | |
| Constant | -1.3914 | 0.165 |
| RC ($\boldsymbol{\delta_1}$) | 0.0689 | 0.729 |
| PSP ($\boldsymbol{\delta_2}$) | 1.7564* | 0.052 |
| *Variance parameters* | | |
| $\boldsymbol{\sigma_u}$ | 0.3520*** | 0.000 |
| $\boldsymbol{\sigma_v}$ | 0.0020 | 0.581 |
| $\boldsymbol{\sigma^2}$ | 0.131643 | |
| λ (lambda) | 167.6398*** | 0.000 |
| **γ** (gamma) | 0.99 | |
| Log-likelihood function | 2048.40 | |
| LR test | 36.98 | |
| $\boldsymbol{\chi}^2$ (1%) | 14.325 | |
| Observations | 78 | |

*Note:* *(10%) ; **(5%) ; ***(1%).

Source: Authors.

The results of the technical inefficiency function reveal that the variable "presence of private sector participation" is significant and positive (1.7564), implying that this parameter contributes to increasing the technical inefficiency of Tunisian ports. This result is contrary to that found by Tongzon and Heng (2005), Coto-Milan et al. (2016) and López-Bermúdez et al. (2019), who concluded that private sector participation in the port industry has a positive effect on technical efficiency. This can be explained by STAM's superiority over private stevedores under competitive conditions since the concession. In addition, the latter's share of loading and unloading activities is low (almost every stevedore handles no more than 30% of the total cargo volume). The "Tunisian revolution" variable has a positive sign, but is not statistically significant.

Following the estimation of the production frontier, we were able to derive a technical efficiency index that varies between 0 and 1. Table 4 shows the technical efficiency indices for each port included in our estimation.

We can draw the following key conclusions from the data we have. From 2007 to 2019, the Tunisian ports that were taken into consideration had a technical efficiency of 69%. This means that they could have achieved a 31% increase in production using the same amount of inputs.

The port of Rades was judged the most efficient (92.2%), followed by those of Bizerte (74.7%) and Sousse (68.3%); and the least efficient were: the port of Sfax (51.1%), the port of Gabès (64.6%) and the port of Zarzis (63%).

While STAM (a public institution) handles all handling ac-

Table 4: Estimation of the production frontier for the technical efficiency index.

| Scores Ports | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | Mean |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Bizerte** | 0.847 | 0.902 | 0.729 | 0.614 | 0.706 | 0.853 | 0.740 | 0.777 | 0.768 | 0.730 | 0.668 | 0.711 | 0.668 | **0.747** |
| **Rades** | 0.996 | 0.966 | 0.868 | 0.987 | 0.853 | 0.752 | 0.907 | 0.903 | 0.959 | 0.997 | 0.983 | 0.902 | 0.918 | **0.922** |
| **Sousse** | 0.733 | 0.816 | 0.576 | 0.727 | 0.649 | 0.556 | 0.598 | 0.616 | 0.721 | 0.682 | 0.690 | 0.802 | 0.722 | **0.683** |
| **Sfax** | 0.644 | 0.652 | 0.533 | 0.594 | 0.474 | 0.436 | 0.450 | 0.505 | 0.464 | 0.474 | 0.476 | 0.490 | 0.452 | **0.511** |
| **Gabes** | 0.927 | 0.920 | 0.851 | 0.995 | 0.491 | 0.564 | 0.601 | 0.502 | 0.403 | 0.504 | 0.559 | 0.581 | 0.510 | **0.646** |
| **Zarzis** | 0.533 | 0.603 | 0.742 | 0.988 | 0.806 | 0.537 | 0.491 | 0.448 | 0.489 | 0.510 | 0.556 | 0.781 | 0.712 | **0.630** |
| **Mean** | | | | | | | **0.690** | | | | | | | |

Source: Authors.

tivities at the port of Rades, private stevedores operate at the ports of Bizerte, Sousse, Sfax, Gabès, and Zarzis, making them less efficient.

### *4.2. The data envelopment analysis.*

While the average score for technical efficiency under the premise of continuous returns to scale is 68.8%, the data show that pure technical efficiency and scale efficiency have considerably higher average scores (81.4% and 83.8%, respectively). Most Tunisian ports are inefficient due to factors such as diseconomies of scale (scale inefficiency), a lack of competent management, and external factors (the financial and economic crisis, the Tunisian revolution, etc.) (see Table (5) and Appendix A1).

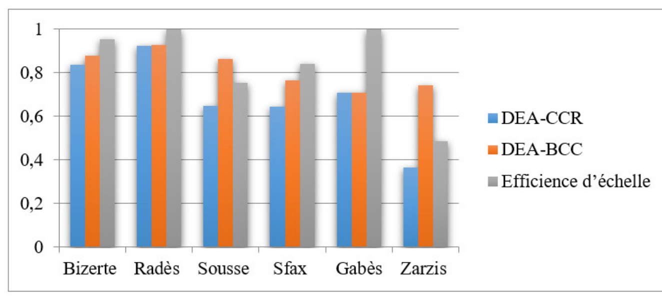
Table 5: Average efficiency scores for Tunisian ports.

| Ports | DEA-CCR | DEA-BCC | Scale efficiency |
|---|---|---|---|
| **Bizerte** | 0.838 | 0.877 | 0.953 |
| **Radès** | 0.926 | 0.928 | 0.998 |
| **Sousse** | 0.650 | 0.864 | 0.753 |
| **Sfax** | 0.644 | 0.766 | 0.841 |
| **Gabès** | 0.709 | 0.709 | 1.000 |
| **Zarzis** | 0.365 | 0.744 | 0.487 |
| **Mean** | **0.688** | **0.814** | **0.838** |

Source: Authors.

The average overall technical efficiency score for the entire sample was 68.8% over the study period (table (5) and figure 1. This result indicates that Tunisian ports waste 31.2% of their resources in the production process.

Figure 1: Average efficiency score by port.




Source: Authors.

However, there is a wide divergence between the average scores achieved by Tunisian ports. The port of Rades consistently ranks first in Tunisia for technological efficiency, with an average of 92.71%. It serves as an example for other ports to follow. The improved efficiency at this port is directly attributable to the way cargoes are handled. Conversely, a shockingly low efficiency rate of 36.5% is observed at the port of Zarzis. To sum up, the port's logistical capabilities is severely limited due to its size. Large vessels or those transporting containerized products cannot dock at this port because of this. This data is consistent with what Ben Mabrouk et al. (2022) found for ports in Tunisia.

To better understand the source of technical inefficiency in Tunisian ports over the period 2007-2019, we decompose technical efficiency into pure technical efficiency and scale efficiency.

From table 5, we also see that Tunisian ports recorded an average pure technical efficiency of 81.4% over the period examined. This means that optimal exploitation of the inputs used could improve port production by 18.6%. This inefficiency is the result of conventional management, which does not develop new strategies until major problems are identified. In addition to the absence of modern equipment that facilitates the loading and unloading of ships. However, pure technical efficiency scores are better than technical efficiency scores, but remain volatile. Moreover, the results show that each port was efficient at least once during the study period (see Appendix A1).

Ports are able to function at their most efficient while operating at a large scale. To rephrase, the optimal size for a port to maximize output while minimizing costs can be defined globally thanks to efficiency of scale.

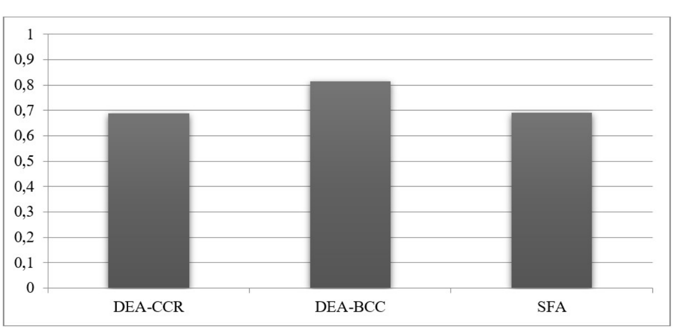
Interpretation of these results shows that Tunisian ports are more efficient in terms of scale efficiency than in terms of pure technical efficiency. As a result, the average pure technical efficiency score is 81.4% (compared with an average scale efficiency of 83.8%). This difference in average is due to the very limited performance of the smaller ports, in this case the port of Zarzis (with an average of 48.7%). This port needs to increase its volume and logistics capacity if it is to achieve higher levels of scale efficiency. On the other hand, the ports of Rades and Gabes managed to achieve scale efficiency scores close to 100% during the period under review. We believe that the pressure exerted by global flows on these two ports has resulted in a certain degree of scale efficiency.

### *4.3. Comparison between SFA and DEA.*

To further explore the relationship between the two boundary techniques DEA and SFA, we compare the average technical efficiency scores generated by the different models retained in this study and the correlations between them.

Figure 2 shows the average technical efficiency scores obtained by the various models used in this research. It is clear that the DEA-BCC model gives a much higher average measure of technical efficiency, while the other estimation models give reasonably lower but above-average average technical efficiency scores (BC95= 0.69; DEA-CCR= 0.688).

Figure 2: Comparison of technical efficiency obtained from different models.




Source: Authors.

Table 6 shows the Spearman rank correlation coefficient between the different levels of technical efficiency estimated by the different forms of model. The generally high coefficient values indicate that these alternative models give fairly similar estimates of technical efficiency. This reinforces the robustness of the analysis, at least as far as the rankings of the ports studied are concerned.

Table 6: Spearman's rank correlation coefficient between the selected models.

| | DEA-CCR | DEA-BCC | SFA |
|---|---|---|---|
| **DEA-CCR** | 1 | | |
| **DEA-BCC** | 0.7199 | 1 | |
| **SFA** | 0.7808 | 0.8147 | 1 |

Source: Authors.

A number of studies have compared efficiency estimates obtained from DEA and SFA models. Our results show that the average technical efficiency scores from the DEA and SFA models are: DEA-BCC (81.4%) > SFA (69%) > DEA-CCR (68.8%). This result is similar to that obtained by Kammoun (2018) in the Tunisian context

## Conclusions.

In this research, we applied two popular methods—output-oriented data envelopment analysis (DEA) and stochastic frontier analysis (SFA)—to assess the technological efficiency of six Tunisian ports (Bizerte, Radès, Sousse, Sfax, Gabès, and Zarzis)from 2007 to 2019. It is believed that the technical efficiency of Tunisian ports was influenced by two environmental variables, and that four inputs—the number of berths, gears, workers, and land area—were combined to produce a single output—total cargo volume. Both the Tunisian revolution and the rise of private companies as agents of change fall within this category.

Following this analysis, the main research findings of this study can be summarized as follows: (i) the existence of technical and scale inefficiency in the Tunisian port sector (DEA-CCR: 68.8%, DEA-BCC: 81.4%, scale efficiency: 83.8% and SFA: 69%). This relatively limited efficiency of Tunisian ports indicates the need for improved use of existing resources or appropriate investments in port infrastructure/superstructure; (ii) throughout the study period, the port of Rades is considered the most efficient port, as it achieved overall technical efficiency scores close to one; (iii) the berths variable has the strongest influence on port cargo volume, as it displays the highest positive coefficients; (iv) the "Tunisian revolution" variable has a positive sign but is not statistically significant; (v) the presence of private sector participation in handling activities has a negative effect on technical efficiency.

Based on these findings, we can test the hypotheses stated in the introduction. We find that the Tunisian revolution has no effect on the technical efficiency of Tunisian ports, contrary to the first hypothesis. We also confirm the third hypothesis, which states that the main ports of Tunisia generally record technical inefficiencies, and we reject the second and third hypotheses, respectively, that state that the private sector's involvement in handling activities has a positive effect on the technical efficiency of Tunisian ports.

A number of limitations exist in this study, as do any research studies. These limitations are most apparent in the data used and in the factors that were not considered relevant based on the literature. Furthermore, it is hard to quantify economic and allocative efficiency due to the absence of data on input and output prices.

Future research might expand our current knowledge of these Tunisian ports by examining their outputs (the number of ships) and inputs (tugs, stores, etc.). To add to that, one promising avenue for future research could be to monetize the inputs and outputs in order to gauge economic and allocative efficiency.

**Declaration of Competing Interest.**

The authors 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.

**Table A1.**

| Years | 2007 | | | | 2008 | | | | 2009 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Ports | CCR | BCC | SE | SR | CCR | BCC | SE | SR | CCR | BCC | SE | SR |
| Bizerte | 0.949 | 0.949 | 1.000 | - | 1.000 | 1.000 | 1.000 | - | 0.757 | 0.854 | 0.887 | drs |
| Rades | 1.000 | 1.000 | 1.000 | - | 0.968 | 0.970 | 0.998 | drs | 0.875 | 0.878 | 0.997 | drs |
| Sousse | 0.685 | 1.000 | 0.685 | irs | 0.781 | 1.000 | 0.781 | irs | 0.528 | 0.734 | 0.720 | irs |
| Sfax | 0.764 | 0.903 | 0.847 | drs | 0.814 | 1.000 | 0.814 | drs | 0.631 | 0.759 | 0.831 | drs |
| Gabes | 1.000 | 1.000 | 1.000 | - | 1.000 | 1.000 | 1.000 | - | 0.862 | 0.862 | 1.000 | - |
| Zarzis | 0.353 | 1.000 | 0.353 | irs | 0.425 | 1.000 | 0.425 | irs | 0.439 | 0.759 | 0.579 | irs |

| Years | 2010 | | | | 2011 | | | | 2012 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Ports | CCR | BCC | SE | SR | CCR | BCC | SE | SR | CCR | BCC | SE | SR |
| Bizerte | 0.641 | 0.721 | 0.889 | drs | 0.735 | 0.826 | 0.890 | drs | 0.977 | 1.000 | 0.977 | drs |
| Rades | 0.984 | 0.991 | 0.993 | drs | 0.852 | 0.861 | 0.990 | drs | 0.757 | 0.757 | 1.000 | - |
| Sousse | 0.657 | 0.928 | 0.708 | irs | 0.586 | 0.829 | 0.707 | irs | 0.539 | 0.695 | 0.775 | irs |
| Sfax | 0.696 | 0.847 | 0.821 | drs | 0.556 | 0.675 | 0.824 | drs | 0.571 | 0.672 | 0.850 | drs |
| Gabes | 1.000 | 1.000 | 1.000 | - | 0.493 | 0.493 | 1.000 | - | 0.636 | 0.636 | 1.000 | - |
| Zarzis | 0.620 | 1.000 | 0.620 | irs | 0.506 | 0.815 | 0.620 | irs | 0.284 | 0.600 | 0.473 | irs |

| Years | 2013 | | | | 2014 | | | | 2015 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Ports | CCR | BCC | SE | SR | CCR | BCC | SE | SR | CCR | BCC | SE | SR |
| Bizerte | 0.856 | 0.876 | 0.977 | drs | 0.900 | 0.931 | 0.966 | drs | 0.886 | 0.921 | 0.962 | drs |
| Rades | 0.918 | 0.918 | 1.000 | - | 0.914 | 0.914 | 1.000 | - | 0.965 | 0.965 | 1.000 | - |
| Sousse | 0.582 | 0.752 | 0.775 | irs | 0.600 | 0.777 | 0.772 | irs | 0.699 | 0.905 | 0.772 | irs |
| Sfax | 0.587 | 0.691 | 0.850 | drs | 0.657 | 0.774 | 0.850 | drs | 0.605 | 0.712 | 0.850 | drs |
| Gabes | 0.691 | 0.691 | 1.000 | - | 0.578 | 0.578 | 1.000 | - | 0.461 | 0.461 | 1.000 | - |
| Zarzis | 0.258 | 0.545 | 0.473 | irs | 0.237 | 0.500 | 0.437 | irs | 0.257 | 0.544 | 0.473 | irs |

| Years | 2016 | | | | 2017 | | | | 2018 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Ports | CCR | BCC | SE | SR | CCR | BCC | SE | SR | CCR | BCC | SE | SR |
| Bizerte | 0.838 | 0.870 | 0.963 | drs | 0.770 | 0.800 | 0.962 | drs | 0.823 | 0.856 | 0.961 | drs |
| Rades | 1.000 | 1.000 | 1.000 | - | 0.987 | 0.987 | 1.000 | - | 0.906 | 0.906 | 1.000 | - |
| Sousse | 0.659 | 0.853 | 0.772 | irs | 0.667 | 0.863 | 0.773 | irs | 0.776 | 1.000 | 0.776 | irs |
| Sfax | 0.624 | 0.735 | 0.850 | drs | 0.627 | 0.738 | 0.850 | drs | 0.646 | 0.760 | 0.850 | drs |
| Gabes | 0.581 | 0.581 | 1.000 | - | 0.647 | 0.647 | 1.000 | - | 0.672 | 0.672 | 1.000 | - |
| Zarzis | 0.270 | 0.573 | 0.472 | irs | 0.297 | 0.631 | 0.471 | irs | 0.419 | 0.889 | 0.471 | irs |

| Years | 2019 | | | |
|---|---|---|---|---|
| Ports | CCR | BCC | SE | SR |
| Bizerte | 0.774 | 0.805 | 0.961 | drs |
| Rades | 0.923 | 0.923 | 1.000 | - |
| Sousse | 0.699 | 0.903 | 0.774 | irs |
| Sfax | 0.597 | 0.703 | 0.850 | drs |
| Gabes | 0.596 | 0.596 | 1.000 | - |
| Zarzis | 0.387 | 0.823 | 0.470 | irs |