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The Stochastic Frontier Model for Technical Efficiency Estimation of Interconnected Container Terminals

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Abstract: Nowadays, container terminals are subject to extensive technological changes and specific transformations. Changes applied to terminals tend to increase their ability to offer high- end personalized services to the customers and finally affect the competitiveness. The estimation of efficiency corresponds to terminals' ability to increase the production with a specific level of inputs and has been the topic of many studies, especially those conducted on a wider regional or global level. The main objectives of our research are to evaluate the model, conduct sensitivity analysis, and estimate technical efficiencies on a sample of North Adriatic Ports Association (NAPA) interconnected medium-sized terminals, located in the narrow geographic area, on the same transport corridor thus representing each other's competition. For that purpose, we have implemented a stochastic frontier approach on a balanced panel dataset of first-order and additionally introduced control input variables with Cobb-Douglas and trans-logarithmic functional forms. The stochastic production frontier estimation shows the range of NAPA terminals' technical efficiencies from 65.24% to 93.92%, with a global average of 78.49% and a positive trend of 1.28% over the observed period of time. Our findings also indicate that NAPA terminals with the highest estimated technical efficiencies do not necessarily need to be the most productive ones, and vice versa.

Keywords: interconnected container terminals; transport corridor; stochastic frontier analysis; technical efficiency estimation; direct and indirect effects

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1. Introduction

In recent years, most countries base their growth on export development with an emphasis on effective logistics, the quantity and quality of infrastructure required for goods transportation, as well as the efficient management of such infrastructure and related services [1]. Since around 80% of the international trade volume in goods is carried by sea in containers, ports/container terminals (hereinafter called 'terminals') are playing a crucial role in global logistics trade imposing a constant need for improvement in their overall performance [2–4]. Due to the increasing demand in maritime freight transport, the development of logistics, as well as stronger land transport connections and global competition, have encouraged the modernization of cargo handling technologies [1,5,6]. Accordingly, the increasing demand has imposed the emergence of building modern container ships, resulting in transformations of port infrastructure and superstructure becoming a key factor in achieving efficiency [7,8]. Consequently, berth depth is also becoming an important factor, imposing the need for adapting berth depth to accommodate such vessels [9]. Therefore, to remain competitive, terminals must constantly comply with market requests while aiming to achieve efficient utilization of the available resources and taking into account numerous internal and external impacts [10–12]. Moreover, if terminals are not operating efficiently enough the opportunities in maritime transport will be lost [13,14]. In addition to adapting to market demands, port/terminal operators strive to improve port productivity by minimizing container handling time and vessel turnaround time as these are crucial factors causing excessive costs to carriers and directly affect port competitiveness [9,15]. Following that, the efficiency level will depend on the duration of container handling and vessel turnaround time in a particular port. Ultimately, increasing terminal efficiency level will encourage an increase in transport demand, giving the terminal a higher market share [12].

There is already a significant amount of research dealing with the issue of technical efficiency analysis of terminals, aiming to identify (in)efficiency sources influencing overall and/or individual productivity levels. Such research is ultimately focused on ports/terminals situated in wider geographical regions i.e., North-Europe, Mediterranean, Atlantic, etc. The perceived gap in the existing literature is a lack of significant evidence on conducting such technical efficiency estimations on a set of extremely competitive terminals located in the narrow geographical area i.e., on the same transport corridor.

In this paper, we target a specific testing area of the Northern Adriatic where we investigate technical efficiency levels of five North Adriatic ports/terminals organized into North Adriatic Port Association (NAPA). At the end of the former century investments in the port infrastructure of NAPA terminals were insufficient to compete with other ports in the Mediterranean and North Europe. Hence, they changed development strategies aiming to increase competitiveness with North-European ports and to increase the share of transit cargo-demand from far-east markets. Within those strategies, they boosted investments in port infrastructure and port facilities in the last 10 years.

We developed the base model for estimation of technical efficiency levels considering interdependencies between NAPA interconnected terminals. For that purpose, the stochastic method i.e., Stochastic Frontier Analysis (SFA) based on Battese and Coelli 1992 (BC1992) model specification is used. Through sensitivity analysis, proposed specifications with different functional forms and combinations of input variables are tested to achieve the best representation of the persistent situation in the testing area. Based on the selected model, we provided further analysis of technical efficiency levels.

Briefly, this paper is structured in five mutually dependent sections. Section 2 gives a brief overview of the current state of studies conducted applying technical efficiency levels estimation approaches. Section 3 describes the theoretical and econometrical model specification for the defined sample, as well as the input variables and related output. Section 4 relates to the analysis and discussion of the obtained results. Conclusions on conducted research are drawn in the final, Section 5.

2. Literature Review

When determining port performance, efficiency is often considered as productivity since these two measures are directly related. In other words, a port will improve its performance by increasing productivity and efficiency. Namely, there are three basic concepts associated with efficiency and productivity: input, process, and output. Input data usually refers to resources such as capital, labor, or land, further processed to obtain a certain output—product or service [16]. Hence, port/terminal efficiency will depend on its ability to combine inputs and technology to produce an output. However, efficiency and productivity are not synonymous [13,17]. Efficiency can be described as quality and successful task performance without wasting energy or time, thus showing how well resources are used [18,19]. Furthermore, there are two basic concepts of efficiency analysis: minimization and maximization, where minimization refers to inputs and maximization to outputs [12,20]. This claim was confirmed in [21], finding that firms efficient in minimizing inputs are inefficient in maximizing outputs. Likewise, terminal efficiency can be obtained by comparing the actual, observed performance against its optimal performance where the optimum is determined based on the comparison among the performance of competing terminals [22,23].

In contrast to efficiency, port/terminal productivity is a measure primarily observed with an emphasis on changes over time (for instance, how fast cargo is handled), expressed by the amount of output obtained for input used [24]. Productivity levels differ for each port due to their infrastructure, service quality and the ability to attract demand [25]. Consequently, efficiency indicates the need for technical improvement, while productivity refers to increasing efficiency in the industry. If a port/terminal is unable to produce the maximum possible output, it is considered inefficient. The reasons for inefficiencies may be insufficiently motivated employees, adverse weather conditions, lack of information, etc. [26]. Although a port or terminal may maximize profits, it cannot achieve its optimal performance due to the above-stated reasons. Therefore, a difficult task for port/terminal operators is to build a terminal that will not be inefficient due to overcapacity, i.e., where congestion will not occur due to its under-capacity. In other words, producing the maximum output using the least possible amount of input is the main goal of each terminal operator [18]. The above statement defines the concept of technical efficiency that will be presented in this research. Since the concepts of productivity and efficiency are similar but different, technical efficiency can be defined as the ability to obtain the maximum amount of output/input using specific inputs/outputs, depending on the orientation of the model [27,28]. Based on previous definitions, it can be concluded that technical efficiency is one of the decisive factors of productivity.

Within the framework of technical efficiency estimation, frontier approaches have been established and specially developed. For that purpose, the most commonly used ones are Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA). Both methods allow derivation of relative efficiency ratios within a group of analyzed units. The major difference between those two approaches is in their classification. DEA approach is classified as non-parametric while SFA is classified as a parametric method. A detailed comparison of the fundamental differences between mentioned approaches is given in [29].

There are certain advantages and disadvantages of both approaches. Major conclusions on that topic are drawn out in [30], conducting a performance analysis using the identical datasets for both approaches. Due to high sensitivity to the number of variables, the existence of statistical inconsistency and biased results, as well as a debatable inference procedure, DEA is a less desirable solution. Contrarily, SFA, especially by using a panel data structure, is more reliable for conducting efficiency analysis of terminals i.e., for understanding the dynamics between input/output variables and for port technical efficiency determinants [31]. Another remarkable feature of the SFA approach is the possibility to calculate statistical noise, control exogenous factors, deal with measurement errors and test hypotheses [16,32]. Regardless of all the above-mentioned, opinions are divided, and both of the approaches are very often used in port/terminal technical efficiency estimations.

Once the basic features of estimating frontier and measuring technical efficiency on port/terminal levels have been defined, more recent studies have complemented and expanded the knowledge in that field. Namely, DEA-CCR (Charnes, Cooper and Rhodes) and DEA-BCC (Banker, Charnes and Cooper) input and/or output-oriented models have been widely used to estimate terminals' technical efficiencies, situated in various geographical regions. In order to compare the obtained results and draw out specific conclusions, some authors have applied both approaches (DEA and SFA) in analyzing technical efficiency levels. Table 1 shows the comparison of researches conducted using DEA or DEA and SFA method, specifying the approach/model used, sample/testing area and the objective of each research.

Table 1. Comparison of researches conducted using DEA or DEA and SFA method.

Reference	Approach	Testing Area/Sample	Objective
[33]	DEA-CCR	19 terminals; 12 Middle East Region countries	To measure technical efficiency and to identify potential areas of improvement for inefficient terminals
[34]	DEA-CCR Window Analysis	8 ports; East and West African countries	To measure, analyze and compare the efficiency over time in order to provide port development strategies
[35]	Bi-objective multiple-criteria data envelopment analysis (BiO-MCDEA)	20 ports; Brazil	To examine the correlation between port efficiency and turnaround time, quay length, yard area and cargo throughput

Table 1. *Cont.*

Reference	Approach	Testing Area/Sample	Objective
[11]	DEA and Free Disposal Hull (FDH)	38 terminals; Asian countries	To examine whether investing in infrastructure/equipment influences efficiency and service level
[36]	DEA-Bootstrapping analysis	28 port authorities; Spain	To investigate whether operational and financial efficiency is improved by grouping the ports based on their proximity or seafronts
[37]	DEA-CCR/BCC; SFA-BC1992 model specification, Cobb-Douglas and trans-logarithmic functional form	10 ports; European countries	To determine port activity boundaries and ports' area spatial scope, in order to investigate whether managers' decisions affect ports' performance
[38]	DEA-CCR/ BCC; SFA-BC1992 model specification, Cobb-Douglas functional form	7 ports; Tunisia	To measure the efficiency scores

Contrarily, many authors have assessed port efficiency issues and mainly focused on identifying important factors affecting port efficiency using exclusively SFA with various model specifications and functional forms. Furthermore, most studies typically attempted to compare differences in port productivity in a country or internationally. Moreover, some authors have examined how differences in productivity are related to certain policies or port characteristics such as privatization, port size, the degree of competition, etc. For instance, with a panel dataset of 40 terminals in Latin America and the Caribbean for the 2000–2010 period, a Battese and Coelli 1995 (BC1995) model with trans-logarithmic functional form has been estimated and efficiency analysis has been performed in [14], showing that transshipment ports are less efficient than the others. In [23], a container port performance analysis is carried out on a sample of 203 ports in 70 developing countries with a panel dataset between 2000 and 2010, applying the BC1995 model with both, Cobb-Douglas and trans-logarithmic functional form. The analysis indicates that the level of port efficiency in developing regions is increased by private sector participation, the reduction of corruption in the public sector, as well as by the improvements in liner connectivity and multimodal links. Technical efficiency analysis of container ports in Latin America and the Caribbean has also been conducted in [32] using an input-oriented, BC1995 stochastic frontier model specification with both Cobb-Douglas and trans-logarithmic functional forms, employing a 10-year panel data. The authors have revealed a significant positive correlation between technical efficiency and private port operations. The technical efficiency of 43 Vietnamese ports has been examined in [39] using SFA with Cobb-Douglas functional form, considering cross-sectional data. The results show that the most significant factors influencing efficiency are cargo handling technologies, information technology, land and cargo storage capacity. In [40], the authors have applied the BC1995 model with a trans-logarithmic functional form to analyze the efficiency and productivity of 20 Brazilian terminals using panel data for the 2008–2017 period, concluding that private terminal operators are more efficient than public ones. To conclude, both methods, DEA and SFA, have certain advantages and drawbacks but both of them have been frequently used for technical efficiency levels estimation. Taking into account all the above-mentioned approaches, it is reasonable that the parametric approach i.e., SFA, will be applied in this paper due to its adaptability to characteristics of the defined problem.

3. Materials and Methods

3.1. Theoretical Specification of the Stochastic Frontier Model

As stated above, to estimate the frontier and to measure terminals efficiency, numerous powerful approaches (deterministic and/or stochastic) have been introduced and adopted retaining the same ultimate objective: to acquire the estimated results accurately and as efficiently as possible. In that sense, the SFA approach is the most commonly implemented. The stochastic frontier analysis presents a parametric method based on econometric techniques for estimating technical efficiency, where the production function must be specified [20,40]. The production frontier shows the maximum quantity of output that can be obtained for a given combination of inputs [22]. Specifically, the efficiency of a given port/terminal corresponds to the distance between its observed and theoretical behavior [14]. However, the deviations from the frontier may not be fully under the control of terminals. In that case, SFA is used to calculate the inefficiencies of terminals based on different distribution assumptions, so that different terminals may have different efficiencies [17].

The stochastic frontier model was originally introduced in [41], but a more reasonable error structure than a purely one-sided one has been simultaneously constructed and presented in [42,43]. The proposed error structure consists of two error terms: random error term, defined as statistical error and inefficiency term i.e., inefficient behavior. Inefficiency, in that case, reduces the maximum feasible output due to circumstances or occurrences beyond the control of the port/terminal operator [5,16]. Furthermore, the expanded stochastic frontier model BC1992 was found to be the most suitable and will be applied in this paper [44]. Stochastic frontier model BC1992 presents the groundwork for the application on (un)balanced panel datasets ($t = 1, 2, 3, \ldots, T$), taking into account time-varying effects assumed to be distributed as a truncated normal random variable. The specification of proposed model can be written as follows [44]:

$$Y_{it} = \beta x_{it} + (v_{it} - u_{it}); i = 1, 2, 3, \ldots, N;\ t = 1, 2, 3, \ldots, T, \tag{1}$$

where Y_{it} represents the production of the i^{th} port/terminal at the t^{th} time period; x_{it}: refers to a $kx1$ input vectors of the i^{th} port/terminal at the t^{th} time period; β is an unknown parameters vector that has to be estimated. The main feature of the BC1992 model is the assumption imposed over the random error term i.e., statistical noise v_{it}, that helps to disentangle statistical noise from the residual term representing inefficiency u_{it}. In that case, v_{it} is assumed to be independent and two-sided identically distributed such as $N\left(0,\ {\sigma_v}^2\right)$ and is independent of u_{it}, a term associated with the inefficiency that measures the shortfall of production Y_{it} from its maximum frontier [18,30]. Inefficiency term u_{it} is assumed to be independent and one-sided identically distributed as truncations at zero of the $N\left(\mu,\ {\sigma_u}^2\right)$ distribution and it can be specified as:

$$u_{it} = u_i\, exp(-\eta(t - T)), \tag{2}$$

where η is an unknown scalar parameter [44]. The method of maximum likelihood estimation is proposed for simultaneous calculation of the stochastic frontier model parameters. The likelihood function is expressed in terms of variance parameters. In that order, parametrization proposed in [45] was used to replace ${\sigma_v}^2$ and ${\sigma_u}^2$ with $\sigma^2 = {\sigma_v}^2 + {\sigma_u}^2$ indicating that $\gamma = {\sigma_u}^2/\sigma^2$. In that case, ${\sigma_v}^2$ is the variance of the random noise term, ${\sigma_u}^2$ is the variance of the inefficiency term, and σ^2 is the variance of the total error term. The γ parameter varies between 0 and 1. If γ is closer to 1 the deviations from the frontier are caused by the inefficiency and if γ is close to 0 then the deviations from the frontier are mostly due to the random error i.e., statistical noise.

Furthermore, when the assumptions are established, the technical efficiency levels of the i^{th} port/terminal in the t^{th} time period, relative to the potential output, defined by the frontier function for a given input vector, can be estimated. These estimates are determined using the following equation:

$$TE_{it} = exp(-u_{it}). \tag{3}$$

Presenting the stochastic frontier for determining the level of terminals' technical efficiency, it is necessary to specify the functional form of the production function. The selection of the most appropriate functional form has been the subject of numerous studies [46–49]. Accordingly, we have chosen the Cobb-Douglas and the trans-logarithmic functional forms since they turn out to be the most appropriate. These two functional forms introduced in [50,51], are respectively shown in (4) and (5):

$$lnY_{it} = \alpha_0 + \sum_{i=1}^{N} \beta_{it} lnx_{it} + v_{it} - u_{it}, \quad (4)$$

$$lnY_{it} = \alpha_0 + \sum_{i=1}^{k} \beta_{it} lnx_{it} + \sum_{i=1}^{k} \sum_{j=1}^{k} \beta_{ijt} lnx_{it} lnx_{jt} + v_{it} - u_{it}. \quad (5)$$

The main difference between these two functional forms is that the trans-logarithmic functional form is more flexible than the Cobb-Douglas, as it does not require assumptions regarding production constant elasticities or elasticities of substitution between inputs and allows the data to indicate the real curve of the function rather than imposing a priori assumptions [40,48,52].

Finally, the method of the one-sided generalized likelihood ratio-test was used to test model specifications i.e., the presence of technical inefficiency effects u_{it} under both, the null and alternative hypotheses. The generalized likelihood ratio-test can be expressed as follows:

$$LR = -2\{ln[L(H_0)] - ln[L(H_1)]\}, \quad (6)$$

where $L(H_0)$ and $L(H_1)$ are the values of the likelihood function under the null hypothesis H_0 and the alternative H_1, respectively. In this case, if H_0 is true, this LR statistics has an asymptotic distribution which is a mixture of χ^2 distribution.

3.2. Definition of Output/Input Variables

An acceptable stochastic frontier model specification for port/terminal time-varying technical efficiency estimation must be based on a reasonable relationship between output and the right combination of statistically significant input variables. The main limitation of each parametric, and consequently of implemented approach, is the availability, accuracy and veracity of input and output data, especially when time-varying efficiency analysis is considered.

According to numerous studies conducted on productive output variable determination, it is reasonable that container throughput Y proved to be the most relevant and widely used one in technical efficiency levels estimation [16,32,39,47,53,54]. Container throughput, expressed in a twenty-foot equivalent unit (TEU), in the best way, represents the total amount of containers handled on terminals i.e., container handling activity, considering the handling of imports, exports, empty containers and trans-shipments. Moreover, container throughput is closely related to the need for cargo-related facilities and services since it is the main indicator for comparing and ranking terminals among themselves, in particular when assessing their relative size, level of investment and/or activity [19,55].

Determining the appropriate combination of input variables that in the best way describes dependencies with the respect to the container throughput is covered in numerous studies, wherein [30,56] authors' summarized discussion is presented. In general, the main idea is to define such a combination of input variables that will reflect actual terminal production as accurately as possible [56]. With this in mind, it was decided that basic economic inputs, such as capital and labor, could satisfy the requirements for conducting a quality analysis at the port/terminal level. However, it was found that the availability and quality of these data is a very sensitive question, especially from a stakeholder's perspective. To avoid usage of assumed and questionable quality data and to reduce potential errors, an alternative approach was introduced in [57] where authors concluded that port/terminal output depends on the efficient use of three data categories: land, equipment and labor. These data categories are a reliable substitute for basic economic data and in the best way describe the dependencies with output variable and, on the other hand, represent physical characteristics of terminals.

Therefore, we have introduced five first-order input variables in our model. The variables presenting the main indexes and reflecting the land data category are quay length QL and container stacking area SA. QL represents the total length of the quay in meters where vessels can be berthed to perform loading/unloading operations, while SA represents the gross yard size of port/terminal where containers can be stacked, expressed in square meters [23,32,53,54,58,59]. Alongside mentioned variables, we have also considered another input variable—berth water depth WDb, closely related to quay length, that represents the average depth along the port/terminal quay in meters, indirectly determining the size of the vessel that can be berthed alongside the quay [11,13,33,40,60]. The introduced variable, which is the most appropriate proxy for the aforementioned equipment data category, is quay cranes QC, representing the number of units used for container handling in ship-to-shore and shore-to-ship relations [16,32,37]. The final first-order input variable associated with both, the equipment and labor data categories, is yard equipment YE. YE presents a number of equipment used to handle containers in the container stacking area such as RTG cranes (rubber tier gantry crane), RMG cranes (rail mounted gantry crane), straddle carriers, reach stackers, forklifts, etc. In [18,19,54,55,58,61,62] the authors have declared that the yard equipment is the best substitute for labor data category, in cases when data is not accessible from the available sources since there is a fairly firm correlation between those two variables.

In order to obtain more reliable estimations, suggestions provided by numerous studies on port/terminal efficiency analysis indicate that, besides first-order input variables, it is necessary to determine control variables in the model. Control variables should in the best way represent universal or specific external influences, exogenously affecting port/terminal throughput and ultimately, efficiency [23,32,63]. Introducing control variables into the model is also important to explain a significant share of port throughput independent of input allocation. In that sense, we have defined variables that best represent demand proxies such as Gross Domestic Product GDP, International Trade IT, and Port Liner Shipping Connectivity Index $PLSCI$. GDP (in constant EUR) was collected via United Nations Conference on Trade and Development (UNCTAD) and measures the size of the economy of a country where the port/terminal is located [64]. IT (in constant EUR) was also collected via UNCTAD, and represents the degree to which countries where terminals are located export/import merchandise from the rest of the world [65]. $PLSCI$, provided by EUROSTAT, measures how well countries are connected to the global shipping network by taking into account the number of scheduled ship calls per week, the annual capacity deployed in TEUs, the number of regular liner shipping services, the average size of vessels in TEUs, etc. [65]. Final control variable is the public/private participation in ownership structure PPo. The values of this dummy variable can range from 0 to 1. The specific variable values are determined according to Table 2, where the relationships between the functions and the sectors are presented.

Table 2. Public/private sector participation in terminal ownership.

NAPA Terminal	Regulator	Landowner	Operator	Value/Function
Rijeka	Public	Public	Private	0.33
Koper	Public	Public	Public	0.00
Trieste	Public	Public	Private	0.33
Venice	Public	Private	Private	0.66
Ravenna	Public	Public	Private	0.33

Source: Adapted by authors according to [9].

Since we perform a time-varying technical efficiency level estimation based on panel data with very short time resolution, it is important to set time trend Tt variable that in the best manner captures the overall changes in productivity over the observed periods of time.

3.3. Testing Area Description and Econometric Models Specification

Testing of the proposed model, based on defined output and the combination of input variables, is conducted on the sample of terminals situated in a narrow geographic region representing the main connections of a transport corridor as a gateway for a particular container traffic region. Defined criteria for selecting testing area is very interesting since these terminals present each other competition. In some cases, this can impose negative effects for specific gravitational regions that are unique for some terminals and consequently cause absolute changes in the existing logistic services.

The described scenario occurred very often between terminals situated in the Mediterranean region. Therefore, we have singled out an example of terminals situated in narrow North-Adriatic geographical region. Furthermore, we took a sample of medium-sized terminals that constitute a significant component of the main national ports of border countries such as Croatia (Rijeka), Slovenia (Koper) and Italy (Trieste, Venice, Ravenna). It is also important to note that selected terminals are not multi-purpose but specially equipped for handling exclusively containerized cargo.

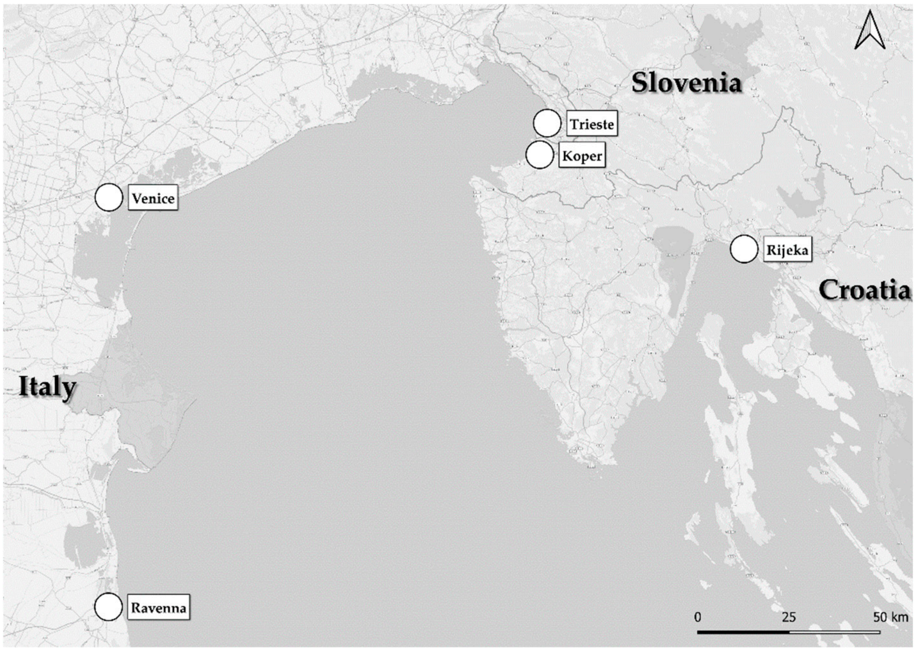
Total quantities of containerized cargo associated with selected terminals presenting main connections of the North-Adriatic transport corridor are irregularly distributed. This fact can be confirmed by the evidence that selected ports i.e., terminals are organized into a North Adriatic Port Association (NAPA) whose basic function is to prevent or decrease the overall influence of individual ports on the North-Adriatic transport corridor. Due to the high significance of the North-Adriatic transport corridor, as the main European Gateway for Far-East container traffic with destinations in Central and Eastern Europe, it is very important to estimate the technical efficiency levels and compare differences within selected NAPA terminals [66].

The locations and intermediate distances between NAPA terminals are shown in Figure 1a,b, respectively.

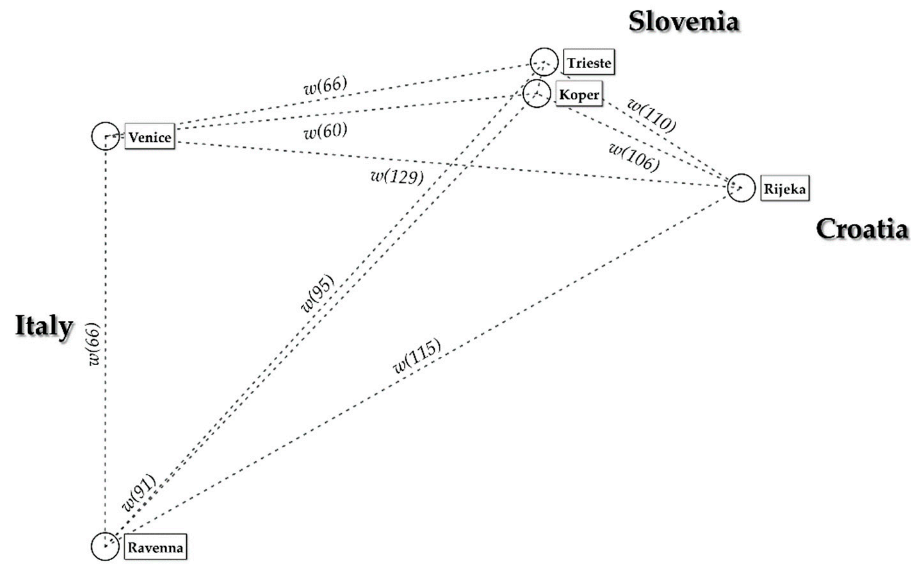
For the selected sample of NAPA terminals, we have defined an observation dataset for the 2010 to 2019 time period with a quarterly time resolution. Decision on short time resolution is vital to get a detailed insight into the technical efficiency levels because of the fluctuations in overall production caused by influences of external events during the yearly period. Based on the defined observation period, we have collected, validated, and prepared a dataset related to each combination of output and relevant input variables. Research datasets were collected based on the official reports provided by terminal operators and/or port authorities, statistical yearbooks, etc. Descriptive statistics on a balanced panel dataset of output and input variables associated with the NAPA terminals (quarterly time resolution) are presented in Table 3.

Considering the idea presented in [19], we have introduced an additional sample of larger terminals located in a broader Mediterranean region. In that case, the introduction of an additional dataset for terminals has important implications for further model development, particularly in ensuring the robustness of the overall estimation. Subsequently added terminals are situated in the ports of the Western (Port of Barcelona and Valencia), Central (Port of Genoa and Gioia Tauro), and Eastern (Port of Piraeus and Thessaloniki) the Mediterranean and possess extensive outputs (greater than 1,000,000 TEU/quarter) as well as associated inputs compared to the NAPA terminals. Descriptive statistics on a balanced panel dataset of output and input variables for the basic and additionally introduced terminals that will be used for further analysis procedures are shown in Table 4.

Furthermore, we have conducted sensitivity analysis to determine the most relevant stochastic frontier model specification based on a particular combination of input variables according to several interconnected sequences showed in Figure 2.



(a)



(b)

Figure 1. (**a**) Model testing area—NAPA terminals; (**b**) Network model of NAPA terminals with intermediate distances expressed through weights in nautical miles.

Table 3. Descriptive statistics of NAPA terminals dataset.

Variable Classification	Variables	Unit	Mean	Median	Std. Deviation	Minimum	Maximum
Output	CTCont. Throughput	TEU	104,153.51	85,254.50	66,050.95	17,798.00	280,637.00
Input	QLQuay Length	Meters	722.92	649.00	203.66	300.00	1,072.00
	SAStacking Area	Sq. meters	120,472.00	104,450.00	49,730.42	60,400.00	208,000.00
	WDbWater Depth	Meters	13.58	14.04	2.72	10.00	18.00
	QCQuay Cranes	No.	6.12	7.00	2.20	2.00	10.00
	YEYard Equipment	No.	74.38	64.00	28.69	37.00	131.00

Table 4. Descriptive statistics of NAPA and additionally introduced terminals dataset.

Variable Classification	Variables (Unit)	Unit	Mean	Median	Std. Deviation	Minimum	Maximum
Output	CTCont. Throughput	TEU	270,172.95	161,644.50	276,494.73	17,798.00	1,342,400.00
Input	QLQuay Length	Meters	1063.16	921.00	523.38	300.00	2847.00
	SAStacking Area	Sq. meters	224,819.41	172,000.00	148,093.66	60,400.00	496,100.00
	WDbWater Depth	Meters	14.40	14.94	2.66	10.00	19.50
	QCQuay Cranes	No.	9.72	8.00	6.23	2.00	31.00
	YEYard Equipment	No.	106.36	100.00	53.42	37.00	233.00

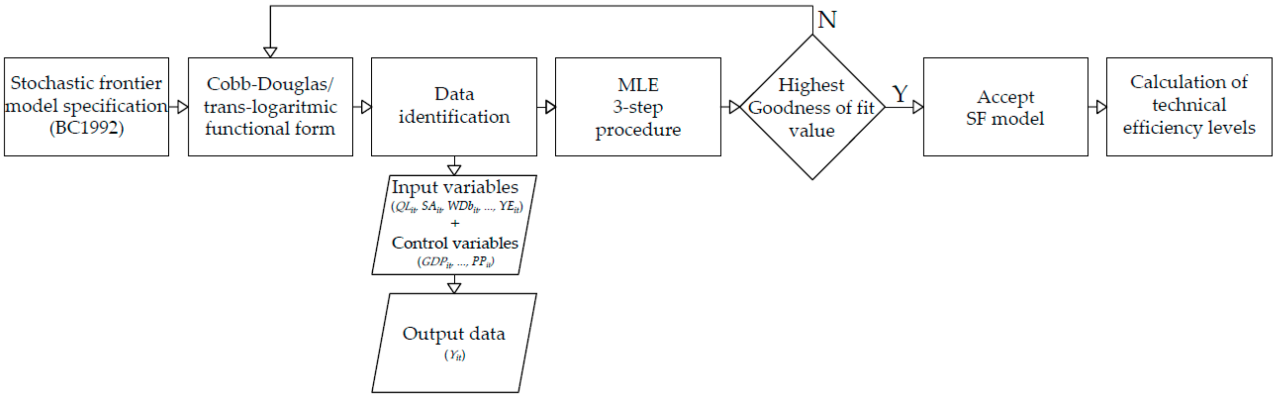


Figure 2. Procedure sequences of sensitivity analysis.

The idea behind the conducting of sensitivity analysis is to determine the model specification consisting of the appropriate combination of input variables based on the specific functional form that describes relationships between selected input variables and output variable. Evaluation of the proposed model is conducted by goodness-of-fit parameter calculation, representing the log-likelihood and/or coefficient of determination. In the second sequence of conducting sensitivity analysis, a Cobb-Douglas or trans-logarithmic functional form was selected. The third sequence relates to testing different combinations of proposed input variables. For such model specifications, in further sequence, the unknown coefficients are estimated using the three-step maximum likelihood estimation method incorporated with version 4.1 of the 'FRONTIER' software [67]. In the first step, the ordinary least squares (OLS) method was used to estimate the initial values of the unknown coefficients. Then, a two-step grid search of γ is performed using the OLS estimates over the parameter space of γ. In the third and final step, the values selected by the grid search are used as initial values in an iterative procedure using the David-Fletcher-Powell Quasi-Newton algorithm to obtain the final values of the unknown coefficients. Finally, if the goodness-of-fit parameter value is not the highest, the procedure sequences are repeated all over again with different combinations of input variables and with different functional forms. This iterative procedure is repeated until the model with a particular combination of input variables and with the highest log-likelihood value is obtained.

The performed sensitivity analysis has resulted in selecting the final stochastic frontier model specifications for which the highest goodness-of-fit values are obtained. Model specifications by Cobb-Douglas and trans-logarithmic functional forms based on presented first-order and control input variables are given in (7) and (8), respectively:

$$\begin{aligned} ln(CT_{it}) &= \alpha_0 + \beta_1 ln(QL_{it}) + \beta_2 ln(SA_{it}) + \beta_3 ln(WDb_{it}) + \beta_4 ln(QC_{it}) + \\ &+ \beta_5 ln(YE_{it}) + \beta_6 Tt_t + \theta_1 ln(GDP_{it}) + \theta_2 ln(IT_{it}) + \theta_3 ln(PLSCI_{it}) + \\ &+ \theta_4 PPo_{it} + v_{it} - u_{it};\ i = 1, 2, \ldots, N;\ t = 1, 2, \ldots, T, \end{aligned} \tag{7}$$

$$\begin{aligned} ln(CT_{it}) &= \alpha_0 + \beta_1 ln(QL_{it}) + \beta_2 ln(SA_{it}) + \beta_3 ln(WDb_{it}) + \beta_4 ln(QC_{it}) + \\ &+ \beta_5 ln(YE_{it}) + \beta_6 Tt_t + \beta_7 [ln(QL_{it})]^2 + \beta_8 [ln(SA_{it})]^2 + \beta_9 [ln(WDb_{it})]^2 + \\ &+ \beta_{10} [ln(QC_{it})]^2 + \beta_{11} [ln(YE_{it})]^2 + \beta_{12} ln(QL_{it}) ln(SA_{it}) + \\ &+ \beta_{13} ln(QL_{it}) ln(WDb_{it}) + \beta_{14} ln(QL_{it}) ln(QC_{it}) + \beta_{15} ln(QL_{1it}) ln(YE_{it}) + \\ &+ \beta_{16} ln(SA_{it}) ln(WDb_{it}) + \beta_{17} ln(SA_{it}) ln(QC_{it}) + \beta_{18} ln(SA_{it}) ln(YE_{it}) + \\ &+ \beta_{19} ln(WDb_{it}) ln(QC_{it}) + \beta_{20} ln(WDb_{it}) ln(YE_{it}) + \\ &+ \beta_{21} ln(QC_{it}) ln(YE_{it}) + \theta_1 ln(GDP_{it}) + \theta_2 ln(IT_{it}) + \theta_3 ln(PLSCI_{it}) + \\ &+ \theta_4 ln(PPo_{it}) + v_{it} - u_{it};\ i = 1,2,3,\ldots,N;\ t = 1,2,3,\ldots,T, \end{aligned} \tag{8}$$

where:

- CT_{it}: container throughput of the i^{th} terminal in t^{th} time period,
- QL_{it} : quay length of the i^{th} terminal in t^{th} time period,
- SA_{it} : stacking area of the i^{th} terminal in t^{th} time period,
- WDb_{it} : water depth of the i^{th} terminal in t^{th} time period,
- QC_{it} : quay cranes of the i^{th} terminal in t^{th} time period,
- YE_{it} : yard equipment of the i^{th} terminal in t^{th} time period,
- Tt_t: time trend,
- GDP_{it}: country output in t^{th} time period in which i^{th} terminal is situated,
- IT_{it}: quantity of traded merchandises (import and export) of the country in period t^{th} in which i^{th} terminal is situated,
- PPO_{it}: dummy variable which quantifies public/private participation in the ownership structure of the i^{th} terminal in the t^{th} time period,
- $\alpha_0;\ \beta_0, \ldots, \beta_{21};\ \theta_1, \ldots,\ \theta_3$: vector of unknown parameters,
- i : each analyzed terminal,
- t : each analyzed time period,
- v_{it}: random error term which is identically distributed $N(0,\ \sigma_v{}^2)$ and independent from u_{it},
- u_{it}: the technical inefficiency term which is identically distributed as truncations at zero of the $N(\mu,\ \sigma_u{}^2)$.

Finally, regarding the orientation of the model, we could choose between output and input-oriented ones. The main difference between these two approaches is that in an input-oriented model, the main objective is to minimize the defined inputs to achieve a given level of output, while in output-oriented models, the main objective is to maximize the level of output for a given set of inputs [46]. Both approaches are widely used in the studies. For example, in [13,56,60,68] authors have implemented an output-oriented model where the main argument was that terminals can affect output by using different trade policies and market strategies, but infrastructure changes are very difficult to implement over short periods of time. Contrariwise, in [9,10,16,32] authors have used an input-oriented approach where they found that terminals are usually able to approximately predict the container throughput in the short and medium-term due to the relatively stable customer base of shipping lines. Ultimately, input-oriented models are closely related and more relevant to operational, i.e., short-term planning issues, whereas output-oriented models are more related to long-term planning issues and strategy for an increase of the demand. Given the specific situation in the selected testing area and our interest to investigate how efficiently NAPA terminal inputs are used, we chose an output-oriented model as more convenient in this particular case to investigate efficiency levels of development. Particularly, whether the inputs of the NAPA terminals are fully utilized and whether production at these terminals is maximized by using the available inputs.

4. Results

Table 5 shows the maximum-likelihood estimates for the two selected stochastic frontier model specifications based on NAPA and additionally introduced terminals over the time period from 2010 to 2019 with a quarterly time resolution. Along with the estimated coefficients, the standard errors are presented in parentheses representing the robustness of the estimation. Thus, the Model 1 ($CD_{Spec.}$) and Model 2 ($TL_{Spec.}$) columns show the estimates with the Cobb-Douglas and trans-logarithmic model specifications presented in (7) and (8), respectively, where control variables, i.e., demand proxies and public-private ownership participation dummy are included.

Table 5. Maximum likelihood estimates of the selected stochastic frontier model specifications.

Variables		Model 1 ($CD_{Spec.}$)	Model 2 ($TL_{Spec.}$)
α_0	Constant	3.7335 *** (1.2465)	4.8314 (4.3176)
β_1	$\ln(QL)$	0.4240 *** (0.1361)	0.5823 *** (0.1002)
β_2	$\ln(SA)$	0.7849 *** (0.0829)	0.8467 *** (0.1267)
β_3	$\ln(WDb)$	0.5288 *** (0.1600)	0.2830 ** (0.1279)
β_4	$\ln(QC)$	0.1506 (0.1045)	0.3249 * (0.1957)
β_5	$\ln(YE)$	0.6735* * (0.2618)	0.4713 *** (0.1073)
β_6	Tt	0.1841 *** (0.0461)	0.2113 * (0.1091)
β_7	$\ln(QL)^2$		0.2520 *** (0.0579)
β_8	$\ln(SA)^2$		−0.0019 (0.0208)
β_9	$\ln(WDb)^2$		0.1918 *** (0.03386)
β_{10}	$\ln(QC)^2$		−0.1995* ** (0.03663)
β_{11}	$\ln(YE)^2$		−0.2971 *** (0.1034)
β_{12}	$\ln(QL)\ln(SA)$		0.1050 * (0.0613)
β_{13}	$\ln(QL)\ln(WDb)$		−0.6294 *** (0.0554)
β_{14}	$\ln(QL)\ln(QC)$		0.3138 *** (0.0423)
β_{15}	$\ln(QL)\ln(YE)$		0.0758 (0.0767)
β_{16}	$\ln(SA)\ln(WDb)$		−0.0128 (0.0362)
β_{17}	$\ln(SA)\ln(QC)$		−0.0916 ** (0.0363)
β_{18}	$\ln(SA)\ln(YE)$		−0.4069 *** (0.0587)
β_{19}	$\ln(WDb)\ln(QC)$		0.1003 * (0.0546)
β_{20}	$\ln(WDb)\ln(YE)$		0.1217 (0.0797)

Table 5. *Cont.*

Variables		Model 1 ($CD_{Spec.}$)	Model 2 ($TL_{Spec.}$)
β_{21}	$\ln(QC)\ln(YE)$		0.3234 *** (0.0732)
θ_1	$\ln(IT)$	−0.0077 (0.0312)	−0.0069 (0.0127)
θ_2	$\ln(GDP)$	0.2763 *** (0.1332)	0.2981 *** (0.1086)
θ_3	$\ln(PLSCI)$	0.3340 *** (0.1400)	0.3471*** (0.1212)
θ_4	PPo	0.4465 ** (0.2199)	0.4559 ** (0.2271)
σ^2		0.8549	0.9463
γ		0.8025	0.7411
R^2		0.6525	0.8699
Log-likelihood		53.3940	118.5438
LR value		132.3914	134.1543

*** Significant at 1%; ** Significant at 5%, * Significant at 10%.

For brevity, we will discuss only the estimates obtained with a trans-logarithmic specification. The reason, as mentioned in Section 2, is that the trans-logarithmic functional form has been proved by many studies, as a more flexible structure than the Cobb-Douglas, easy to calculate and to allow the imposition of the homogeneity condition. However, the main reason is that Model 2 ($TL_{Spec.}$) shows higher values of the goodness-of-fit parameters. Therefore, the goodness of fit for this model, evaluated by R^2, is very high. This means the selected inputs satisfactorily explain approximately 86.99% of the variations in the model output thus representing the most appropriate model for further analysis and efficiency levels estimation.

The observed likelihood ratio test value (134.15) is greater than the critical value of the mixed chi-squared distribution implying the rejection of the null hypothesis $H_0 : \beta_1 = \cdots = \beta_{21} = \theta_1 = \cdots = \theta_4 = 0$ and acceptance of the alternative hypothesis $H_1 : \beta_1 = \cdots = \beta_{21} = \theta_1 = \cdots = \theta_4 \neq 0$. This test also indicates the selected model can be considered as a good model to represent the production technology and to estimate the technical efficiency levels. Therefore, we can also accept the alternative hypothesis $H_1 : \sigma^2 \neq 0$, which implies the existence of technical inefficiency effects. Thus, in terms of the parameter value associated with the disturbance term, the model shows a desirably higher variance of the inefficiency u_{it}. than the random error term v_{it}. This can be evaluated through γ, which is significantly different from zero ($H_1 : \gamma \neq 0$) and represents the ratio of the variance of the inefficiency term ${\sigma_u}^2$ of the total disturbance in the model σ^2. γ value implies that 74.11% of the variability of production in NAPA terminals is caused by technical inefficiency and the rest of 25.89% is associated with the random error term, i.e., statistical noise. Therefore, we can conclude there are inefficiencies in the production of NAPA terminals and the inefficiency component must be included in a model. Estimated coefficients of first-order input variables, related to the production effects, present the expected signs showing that the increase in any productive factor will lead to an increase in the value of production. Moreover, they are statistically significant with a reliability level of at least 95% (see Table 5).

Further analysis shows that the size of the container stacking area SA has the greatest impact on the production levels of NAPA terminals, indicating a 1% increase in the size of the stacking area leads to a 0.84% increase in container throughput during the observed period of time. Contrarily, the value of yard equipment YE is almost half smaller than the value of container stacking area, revealing that a 1% increase in yard equipment could lead to a 0.47% increase in terminal throughput level. The quay length QL and the number of quay cranes QC positioned along the quay also have a significant, but smaller impact on the throughput levels. This means that a 1% increase in quay length QL and number of quay cranes QC leads to a 0.58% and 0.33% increase in throughput level, respectively—providing important evidence for ensuring the right amount of space and equipment necessary for berthing and adequate loading/unloading of larger vessels. The final variable, which also has a positive impact on throughput levels, is quayside water depth WDb of terminals implying a negligible impact on the throughput level.

Moreover, the estimated coefficient of the time trend Tt is significant and has a positive value, indicating the technological progress of NAPA terminals is increasing over the observed time periods. Concerning the additionally introduced variables into the model specification, the international trade IT of a country where a particular NAPA terminal is located shows a negative sign and is not significantly different from zero. On the other hand, Gross Domestic Product GDP and Port Liner Shipping Connectivity Index $PLSCI$ are significantly different from zero and have a positive impact on throughput levels. The interpretation of these results can be related to the assertion that NAPA terminals, located in smaller economies, concentrate all their container traffic in one or few national ports. This consequently affects the number of regular liner services, the size and number of scheduled vessels, average size of transport units of NAPA terminals, etc. The dummy variable, indicating the participation of the public/private ownership structure PPo, in NAPA terminals has the highest positive impact on the throughput levels and globally implies that terminals with higher private sector participation tend to be more efficient. This is particularly evident in cases where terminals are owned and operated by liner shipping companies that can influence demand and, ultimately, throughput levels more easily by offering better conditions and higher privileges to their customers.

The estimates of technical efficiency levels, for each NAPA terminal, in quarterly time periods, evaluated by Model 2 ($TL_{Spec.}$) are presented in Table 6, where we have also included the results obtained for some additionally introduced large-size terminals exclusively for comparison purposes. Estimated values of technical efficiency levels can vary between 0 and 1. If the technical efficiency level is equal to 0, then the observed terminal is inefficient, and conversely, if the technical efficiency is equal to 1, then the observed terminal is efficient.

Table 6. Estimated technical efficiency levels evaluated by Model 2 ($TL_{Spec.}$).

Time Period (Year)	Time Resolution (Quartal)	Rijeka	Koper	Trieste	Venice	Ravenna	Piraeus	Genova	Barcelona
2010	Q1	0.4110	0.8724	0.6459	0.3743	0.6680	0.4372	0.5410	0.6551
	Q2	0.4280	0.8778	0.6589	0.3916	0.6804	0.4541	0.5565	0.6679
	Q3	0.4450	0.8830	0.6716	0.4087	0.6925	0.4708	0.5716	0.6804
	Q4	0.4618	0.8880	0.6839	0.4258	0.7042	0.4873	0.5864	0.6925
2011	Q1	0.4784	0.8928	0.6959	0.4428	0.7156	0.5036	0.6009	0.7042
	Q2	0.4949	0.8975	0.7076	0.4596	0.7266	0.5197	0.6151	0.7156
	Q3	0.5111	0.9019	0.7188	0.4763	0.7373	0.5355	0.6289	0.7266
	Q4	0.5270	0.9062	0.7298	0.4927	0.7477	0.5510	0.6424	0.7373
2012	Q1	0.5427	0.9102	0.7404	0.5090	0.7577	0.5663	0.6555	0.7477
	Q2	0.5581	0.9141	0.7506	0.5250	0.7674	0.5812	0.6683	0.7577
	Q3	0.5732	0.9179	0.7605	0.5407	0.7767	0.5958	0.6808	0.7673
	Q4	0.5880	0.9215	0.7701	0.5561	0.7857	0.6101	0.6929	0.7767
2013	Q1	0.6025	0.9249	0.7794	0.5713	0.7945	0.6241	0.7046	0.7857
	Q2	0.6166	0.9282	0.7883	0.5861	0.8029	0.6377	0.7160	0.7945
	Q3	0.6304	0.9314	0.7970	0.6006	0.8110	0.6510	0.7270	0.8029
	Q4	0.6439	0.9344	0.8053	0.6148	0.8188	0.6639	0.7377	0.8110

Table 6. *Cont.*

Time Period (Year)	Time Resolution (Quartal)	Rijeka	Koper	Trieste	Venice	Ravenna	Piraeus	Genova	Barcelona
2014	Q1	0.6570	0.9373	0.8133	0.6287	0.8263	0.6765	0.7481	0.8188
	Q2	0.6698	0.9401	0.8210	0.6422	0.8336	0.6887	0.7581	0.8263
	Q3	0.6822	0.9427	0.8285	0.6553	0.8405	0.7006	0.7678	0.8336
	Q4	0.6942	0.9453	0.8356	0.6682	0.8472	0.7121	0.7771	0.8405
2015	Q1	0.7059	0.9477	0.8425	0.6806	0.8537	0.7232	0.7861	0.8472
	Q2	0.7173	0.9500	0.8492	0.6927	0.8599	0.7341	0.7948	0.8537
	Q3	0.7283	0.9523	0.8556	0.7045	0.8659	0.7445	0.8032	0.8599
	Q4	0.7389	0.9544	0.8617	0.7159	0.8716	0.7547	0.8113	0.8659
2016	Q1	0.7493	0.9564	0.8676	0.7269	0.8771	0.7644	0.8192	0.8716
	Q2	0.7592	0.9584	0.8732	0.7376	0.8824	0.7739	0.8267	0.8771
	Q3	0.7689	0.9603	0.8787	0.7480	0.8875	0.7831	0.8339	0.8824
	Q4	0.7782	0.9620	0.8839	0.7580	0.8923	0.7919	0.8409	0.8875
2017	Q1	0.7872	0.9637	0.8889	0.7677	0.8970	0.8004	0.8476	0.8923
	Q2	0.7959	0.9654	0.8937	0.7770	0.9015	0.8086	0.8540	0.8970
	Q3	0.8042	0.9669	0.8983	0.7861	0.9058	0.8165	0.8602	0.9015
	Q4	0.8123	0.9684	0.9028	0.7948	0.9099	0.8241	0.8662	0.9058
2018	Q1	0.8201	0.9698	0.9070	0.8032	0.9138	0.8315	0.8719	0.9099
	Q2	0.8276	0.9712	0.9111	0.8113	0.9176	0.8385	0.8774	0.9138
	Q3	0.8348	0.9725	0.9150	0.8191	0.9212	0.8453	0.8827	0.9176
	Q4	0.8417	0.9737	0.9187	0.8266	0.9247	0.8518	0.8877	0.9212
2019	Q1	0.8484	0.9749	0.9223	0.8339	0.9280	0.8581	0.8926	0.9247
	Q2	0.8548	0.9761	0.9257	0.8408	0.9312	0.8642	0.8972	0.9280
	Q3	0.8610	0.9771	0.9290	0.8475	0.9342	0.8700	0.9017	0.9312
	Q4	0.8669	0.9782	0.9321	0.8540	0.9372	0.8755	0.9060	0.9342

5. Discussion

The derived global results on average efficiency levels reveal that between the observed time periods from 2010 to 2019, the technical efficiency of NAPA terminals varies from 65.24% estimated for terminal Venice to 93.92% estimated for terminal Koper. In decreased order, estimated technical efficiencies of the other NAPA terminals are as follows: Ravenna (83.37%), Trieste (82.15%), and Rijeka (67.79%). Moreover, the global average efficiency result for NAPA terminals shows that they operate at a 78.49% efficiency level, while the gap indicates the efficiency levels can be improved by 21.51% with the same level of given inputs. The analysis of the quarterly time resolution results presented in Table 7 shows that the NAPA terminals' efficiency levels have a stable and positive trend, indicating quarter-to-quarter performance improvements.

Table 7. Average estimated technical efficiency levels according to quarterly time resolution.

Time Resolution (Quartal)	Rijeka	Koper	Trieste	Venice	Ravenna	Piraeus	Genova	Barcelona
Q1	0.6602	0.9350	0.8103	0.6338	0.8232	0.6785	0.7468	0.8157
Q2	0.6722	0.9379	0.8179	0.6464	0.8303	0.6901	0.7564	0.8232
Q3	0.6839	0.9406	0.8253	0.6587	0.8373	0.7013	0.7658	0.8303
Q4	0.6953	0.9432	0.8324	0.6707	0.8439	0.7122	0.7749	0.8373

This detected stable and positive trend indicates the average value of global quarterly efficiency growth of 1.28% in every quartal which can be directly linked to the continuous investment in the modernization of infrastructure and superstructure of NAPA terminals that span the North-Adriatic transport corridor. Moreover, it can be linked to the fact that NAPA terminals and other stakeholders are constantly improving quality management standards. This leads to their great connectivity with the hinterland areas, i.e., Central and Eastern European countries, and to an increase in performance levels manifested through the reduction of the time required for providing terminal activities. In this sense, NAPA terminals tend to catch up with the rhythm of the new technological tendencies in order to attract new industries and logistic services. This also implies the above-mentioned problem of very high competitiveness among each other. It can also be perceived that the highest growth in efficiency levels is associated with terminal Venice (2.14%) and Rijeka (1.94%), having the lowest global average levels of estimated efficiency. Conversely, terminals with the highest estimated efficiency levels have the lowest efficiency growth, e.g., terminal Koper (0.29%). According to Tables 6 and 7, it is interesting to note that the global average efficiency of NAPA terminals is about 2% higher than the estimated efficiency levels of an additional sample of large-size terminals.

In this direction, another intriguing implication can be drawn out considering the relationship between estimated efficiency and trends in container throughput levels (Figure 3). The assumption can be reflected in the fact that efficiency levels are very closely correlated with container throughput growth.

In Figure 3 it is evident that differences between efficiency and productivity levels are persistent, where terminals with low estimated efficiency levels show high growth in container throughput during the observation period, indicating an inverse relationship. For example, terminal Venice with an average estimated efficiency of 65.24% has been considered with the average quarterly growth of container throughput level of 5.53%. Contrariwise, terminal Koper with the highest estimated efficiency of 93.92% has an average quarterly growth of only 0.29%. Therefore, this relationship can be observed especially in the relationship of NAPA and terminals presented as an additional sample. Following the presented assumption, the most efficient terminal may not necessarily be the most productive and vice versa. Therefore, the conducted analysis implies that even the most efficient NAPA terminal, in terms of throughput levels, has space for improvement and, on the other hand, terminals with the lowest efficiency have a relatively large gap to close related to the frontier.

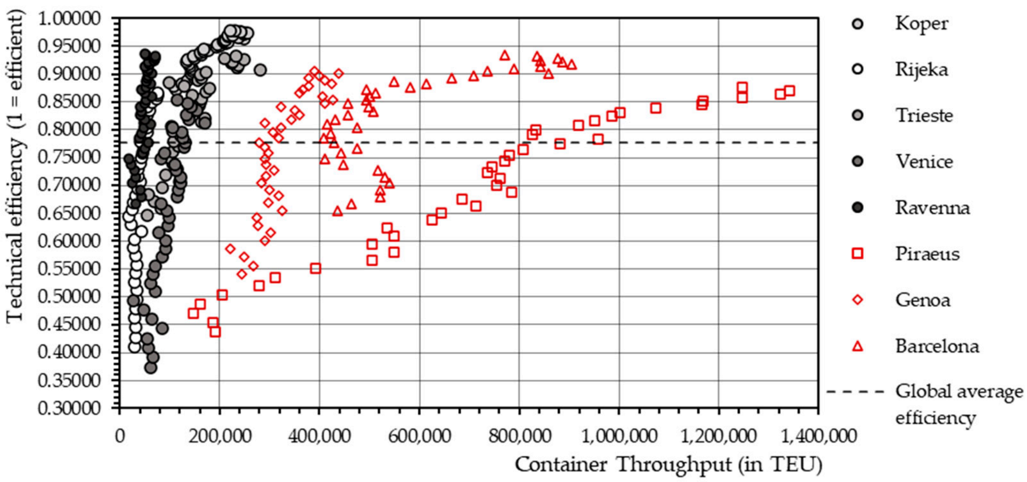


Figure 3. Technical efficiency–container throughput relationship diagram.

There are also different methods dealing with port efficiency looking from a logistic perspective, with a primary focus on quality and reliability of production process. In those cases, the efficiency may be expressed as a general cost function, aiming to optimize the resource allocation over the service time, even in a multiterminal environment [69]. Therefore, the efficiency of the terminal may be extended to observe the efficiency of the port system (e.g., NAPA port system) or the efficiency of the logistic service, where the whole logistic network could be constructed as nodes and links between transshipment points [70]. Container terminals operate in a dynamic environment where the daily decision-making process impacts the efficiency of resource utilization and therefore may impact the reliability of the service and finally the throughput. In this context, the specific approach of the simulation-based planning and optimization concept may be considered as being the digital twin method of the technologies such as the Internet of Things and artificial intelligence, that are commonly used for dealing with big data, and transforming it into information for supporting real-time terminal operation and management [71].

6. Conclusions

In this paper, we have conducted technical efficiency estimation, proposing a stochastic frontier approach based on BC1992 model specification with Cobb-Douglas and trans-logarithmic functional forms. The performance analysis of the proposed model was done using the example of interconnected terminals associated with NAPA, situated in a narrow geographical region of the Adriatic Sea thus representing the main connections of the North-Adriatic transport corridor. To sum up, the estimates obtained applying trans-logarithmic functional form have shown higher values of the goodness-of-fit parameter, indicating better, more competitive performance than in most considered cases including various combinations of first-order and additionally introduced control variables. Our research has led us to conclude there are inefficiencies in the production of NAPA terminals, therefore the inefficiency component has had to be included in a model. Likewise, the increase in any productive factor will lead to an increase in production. Further findings indicate that the SA has the greatest impact on the production levels followed by YA, QL, QC and WDb, respectively. Furthermore, we have obtained satisfactory results proving that the technological progress of NAPA terminals is increasing over the observed periods. Regarding the control variables, GDP and $PLSCI$ show a positive impact on throughput levels while IT has a negative impact. Moreover, the dummy variable PPo has the highest impact on the throughput levels, implying that terminals with higher private sector participation are more efficient. In general, the global average efficiency level of NAPA is 78.49%, varying from 65.24%, estimated for terminal Venice to 93.92%, estimated for terminal Koper. We have noticed that the global average efficiency of NAPA terminals is about 2% higher than the estimated efficiency levels of an additional sample of large-size terminals. The differences between efficiency and productivity levels are found to be persistent since terminals with low estimated efficiency levels show high growth in container throughput during the observation period, indicating an inverse relationship. Consequently, the following is concluded: the most efficient terminal may not necessarily be the most productive one and vice versa.

The main limitation of our research that can also present the base for further research is a small sample that could be supplemented with additional terminals standing out in the Mediterranean area as those with significantly larger inputs and outputs. For that sample, an integrated model should be established, separately observing the sea and landside of terminals because different practices are persistent in those areas. Regarding input variables, terminal equipment, which in our and many other studies presents labor proxy, should be separated since labor and terminal equipment variable have significant impacts on overall model performance, especially when terminal equipment is differentiated regarding equipment models and implemented technologies. Other variables that should be included are ecological and sustainably oriented ones since the inclusion of such components will certainly, nowadays, make some terminals more competitive (at least in terms of technical efficiency levels). It would also be necessary to consider an additional combination of variables (especially external ones) that will better describe the research area. By this, we mean a special set of external variables should be defined for a particular geographical area, i.e., separately for the Mediterranean region (Eastern, Central, and Western Mediterranean) and separately for traffic routes and countries in contact with the Mediterranean since different conditions prevail in different countries, although they are located nearby. By applying the proposed model, the estimated results can present a foundation for terminal monitoring to compel long-term management to take the proper decisions well before problems occur and to test the feasibility of new solutions.

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