Marit Econ Logist (2018) 20:112–130
https://doi.org/10.1057/s41278-017-0061-0

ORIGINAL ARTICLE

A regional perspective of port performance using metafrontier analysis: the case study of Vietnamese ports

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Published online: 23 January 2017

Abstract Previous studies have not considered one important aspect of port efficiency; seaports in different groups operate under different technologies. This study examines the technical efficiency (TE) of 43 ports in Vietnam and their influential factors using metafrontier analysis. The results show that cargo handling facilities and information technology are the most important inputs for ports, despite their varying contribution to port performance across regions. Land is important for the TE of ports in the North, whereas the cargo storage capacity is important to ports in the Central areas, and information technology is important to ports in the South. The majority of Vietnamese ports are operating under increasing returns to scale. On the other hand, each region needs a different approach. For example, in ideal situations, ports in the North could reduce berth length by up to 57% without affecting throughput. National and regional reference networks are developed to identify the leading ports at the regional and national levels and their connections with other ports.

Keywords Vietnam · Seaports · Technical efficiency · Metafrontier · Data envelopment analysis · Stochastic frontier analysis

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Introduction

Numerous studies have assessed the issue of port efficiency. As the literature review in the next section reveals, they have focused mostly on identifying the important factors affecting port efficiency and their effects on efficiency. To this end, most studies have used either data envelopment analysis (DEA) or stochastic frontier analysis (SFA) models. Both models have commonly attempted to compare productivity differences across seaports in a country or internationally. In addition, some studies have examined how productivity differences are associated with certain policy variables or characteristics of the ports, such as privatization and governance structures (e.g., Liu 1995; Barros and Athanassiou 2004; Cullinane and Song 2003; Cullinane et al. 2006; Pagano et al. 2013; Yuen et al. 2013), port size and hub nature (e.g., Coto-Millan et al. 2000; Notteboom et al. 2000; Cullinane et al. 2006; Schøyen and Odeck 2013), and the degree of competition (e.g., Yuen et al. 2013).

The current literature on port economics, however, has not considered one important aspect: how seaports in different regions may be subject to different technologies, which can contribute to variations in their performance. As noted by Hayami (1969), and Hayami and Ruttan (1970, 1971), such analysis needs to be based on a metafrontier or "meta-production function" concept, defined by Hayami and Ruttan (1971, p. 82) as "the envelope of commonly conceived neoclassical production functions." According to Battese and Rao (2002, p. 87), the meta-production function concept is a theoretically attractive notion in that "all producers in different groups (countries, regions, etc.) have potential access to the same technology." This approach enables an estimation of comparable technical efficiencies for firms operating under different technologies. In particular, it enables an estimation of the technology gaps of firms under different technologies, or groups within an industry, relative to those available to the industry overall. To capture cargo handling technology, earlier studies, reviewed below, have mostly used the quantity of cargo handling equipment as an input, e.g., number of cranes and straddle carriers, rather than quality. In this study, as explained in detail below, both cargo handling and communication technology (ICT) equipment are used to capture cargo handling technologies used by ports in different regions.

The current study examines the efficiency of the Vietnamese seaports, taking into account their individual technologies, i.e., especially how port efficiency varies across the three regions and how the ports can improve their efficiency by learning from each other. Metafrontier analysis is novel in examining the efficiency of ports within a region and with reference to the entire sector in the maritime literature. To examine the efficiency of Vietnamese seaports in three regions of Vietnam and evaluate the technology gap between each individual group and the entire sector, the study builds upon the framework of O'Donnell et al. (2008). Along a coastline of more than 3260 km in Southeast Asia, Vietnam has 166 terminals belonging to 49 seaports (Vinashipping 2008). This leads to a high level of competition between ports, with an average distance between two ports of only 67 km. The seaports are divided into three regions, the North, the South, and the Central, having their own economic and social characteristics. Seaports face severe competition in each region due to close proximity. Ports in each region are also affected by region-specific factors, such as corporate culture and government policies and regulations. Ports can ‘learn’ not only from their competitors within their region, but also from those in other regions, whereas all regions are influenced by common factors, such as global trade, macroeconomic policies, and industry regulations.

Overall, this study contributes to the port economics literature in three ways. First, this is the first study using the metafrontier production model to address the efficiency of seaports in groups with different technologies. Second, the study uses both SFA and DEA models. The two methods complement each other and can provide a more comprehensive view on port performance than each individual method. Only few earlier studies have used both models in the literature (e.g., Cullinane et al. 2006; Panayides et al. 2009) and even these do not consider technology differences across regions. Last, this study is one of few works on the Vietnamese port industry, intended to attract more academic attention in the future due to the country’s rapidly developing economy and its important role in the maritime transportation network in Southeast Asia. There are no studies on the Vietnamese port efficiency other than that of Nguyen et al. (2015). Their study is limited in addressing port efficiency with a technology gap between groups.

The paper is organized as follows. The next section reviews the relevant studies on port efficiency. The following two sections explain the analytical methods and dataset, and present and discuss the results, respectively. Finally, the paper concludes and provides further research directions.

Literature review

This section is limited to the literature review of studies on port efficiency, particularly those using DEA and SFA. More comprehensive reviews can be found in Schøyen and Odeck (2013), Panayides et al. (2009), González and Trujillo (2009), Cullinane and Wang (2006), and Barros (2006).

Regarding the applicability and popularity of DEA and SFA, the former has attracted a relatively larger number of studies, even though it has been used in port economics only recently. On the other hand, although SFA has been around for a longer period, its application to the port sector is not as extensive. As reported by Schøyen and Odeck (2013), there have been 36 studies on port efficiency using DEA but only 11 studies using SFA. Such a difference could be because DEA offers more flexibility and less restrictions than SFA in terms of applicability (i.e., no need to assume functional forms and economic behavior such as cost minimization or profit maximization).

Early DEA studies on port efficiency were those of Martinez-Budria et al. (1999) and Tongzon (2001). The first applied DEA to evaluate the performance of 26 Spanish ports over the 1993–1997 period. The results showed that the efficiency of ports of high complexity improves over time, but the same is not the case in medium- and low-complexity ports. Tongzon (2001) applied DEA to evaluate the efficiency of four Australian and twelve other international container ports.

Similarly, Barros (2006) and Cullinane and Wang (2006) applied DEA to panel data to observe the evolution of port efficiency over time.

DEA is also applied in different ways to identify the factors that help improve port efficiency. Barros and Athanassiou (2004) applied DEA to estimate the efficiency of Portuguese and Greek seaports and reported that the scale of operations and privatization are important factors helping ports to improve efficiency. Cullinane and Wang (2006) also found that high levels of technical efficiency are associated with scale, private sector participation, and transshipment (as opposed to gateway) ports. Yuen et al. (2013) and Wan et al. (2014) used DEA to evaluate efficiency, and efficiency scores were then incorporated into Tobit regression to further analyze the effect of various factors, such as ownership and competition, on efficiency. Yuen et al. (2013) claimed that the ownership structure and intra-port and inter-port competition affect the efficiency of Chinese ports. Interestingly, Wan et al. (2014) reported that the use of an on-dock rail facility at container terminals has a negative impact on efficiency, whereas the impact of class I rail services (large railroads with operating revenues exceeding USD 250 million in the USA) is inconclusive. Furthermore, the effects of road congestion around the port on efficiency are positive for the main ports with substantially larger container traffic (their research finding is opposite to intuition, possibly implying that there may not be any causal relationship between congestion and efficiency).

Schøyen and Odeck (2013) evaluated the technical efficiency of Norwegian container ports relative to a frontier composed of the best performing ports, among themselves and other comparable Nordic and UK ports. They found that efficiency had improved during the period studied; Norwegian ports are over-performers and under-performers with regard to technical and scale efficiency, respectively. Economies of scale were found to be important for improving port efficiency, as the ports reviewed were too small for the tasks they perform. De Oliveira and Cariou (2011) evaluated the efficiency of bulk terminals using DEA and found a strong correlation between efficiency level and the annual throughput.

Most DEA studies on port efficiency have not considered the undesirable or bad outputs (e.g., air pollution, noise, and accidents) in the models, except for a few, such as Chang (2013) who developed an environmental efficiency assessment model using a slacks-based measure DEA and applied it to Korean ports. Their approach provides useful information to port managers, such as excess inputs and shortages in outputs for each port, in both economic and environmental aspects, if they are willing to learn from best practices.

Regarding the SFA approach, there are only few reports in the literature, focusing on the effects of port governance, size, and hub-port characteristics on efficiency. They examine how port efficiencies are affected by port ownership structures, particularly privatization, economies of scale, or by the hub or feeder status of a port. As for the governance variable, Liu (1995) applied SFA to examine the effect of ownership on port performance using panel data from 28 UK ports covering the period, 1983–1990. The results do not confirm the effects of ownership on port performance. However, positive relationships between privatization and efficiency have been reported by other SFA studies. Cullinane and Song (2003) applied SFA to estimate the technical efficiency of Korean ports and evaluated the effects of private sector ownership on efficiency using both cross-section and panel data. Their results indicate that private participation and deregulation in the port sector have a positive effect on technical efficiency. Pagano et al. (2013) also used SFA to assess the financial performance of ports and evaluate the effects of port privatization in Panama. The authors compare the effectiveness of the Panama privatized ports with the US ports of different levels of privatization. The results again demonstrate the savings and effectiveness gains from the privatized ports.

The findings of other studies, interested in port size, location, and hubbing nature, are mixed. Notteboom et al. (2000) estimate container terminal efficiency using the Bayesian stochastic frontier over 40 container terminals: 36 European and four Asian ones. Their results reveal a slightly superior performance of northern European container terminals compared to southern ones. Furthermore, terminals in hub ports are on average more efficient than those in feeder ports. Coto-Millan et al. (2000) used SFA to assess the economic efficiency of Spanish ports using the panel data of 27 Spanish ports over the 1985–1989 period. In contrast to Notteboom et al. (2000), here the relatively larger ports in the study were more inefficient. González and Trujillo (2008) used a similar method to study the effect of port reforms on Spanish container ports. Although the reform program in Spain led to technological progress, it is unclear if it increased technical efficiency.

Although both DEA and SFA are the most popular methods used to evaluate port efficiency, very few studies have applied both methods and compared their performance (Panayides et al. 2009). Such comparison could provide a test for the robustness of their results under different assumptions associated with each method. Cullinane et al. (2006) applied both DEA and SFA and compared the results of the two methods. A strong correlation was observed between the efficiency scores obtained from the two methods. Nguyen et al. (2015) compared the efficiencies of Vietnamese ports among SFA, standard DEA, and bootstrapped DEA. The results show that, while the efficiency scores obtained from the three methods provide useful and consistent measures of port efficiency, they also differed significantly. In particular, SFA efficiency scores tend to be higher than DEA and bootstrapped DEA efficiency scores. Moreover, as bootstrapped DEA efficiency scores are not affected by the random nature of economic variables, they are more reliable (Nguyen et al. 2015).

Compared with the maritime literature, other areas of work have developed a new technique toward capturing technology differences among different groups of producers. Hayami (1969) and Hayami and Ruttan (1970, 1971) report that such analysis, to account for technology differences, be based on a metafrontier or “meta-production function,” defined as “the envelope of commonly conceived neoclassical production functions” (Hayami and Ruttan 1971, p. 82). Battese and Rao (2002, p. 87) supported the meta-production function as a theoretically attractive approach in that all producers in different groups have potential access to the same technology. Battese et al. (2004) presented a metafrontier production model and showed that the model enables an estimation of the comparable technical efficiencies for firms operating under a range of technologies. Moreover, O’Donnell et al. (2008) developed a framework to estimate a metafrontier using non-parametric and parametric methods.

This literature review showed that although many studies have compared port performance across different time periods or regions, no attempt has been made to study the technical efficiency of ports in different groups that may not have the same technologies. This study fills the gap in the maritime literature by developing metafrontier models with both DEA and SFA and applying them to Vietnamese ports.

Methodology and data

One of the key assumptions in benchmarking the efficiency of firms is that they are homogenous, i.e., ports provide same services, use similar technologies, and operate under the same market conditions and business environment. Therefore, a comparison of the efficiency of firms operating in different regions is problematic. One way to overcome this issue is to construct a metafrontier that envelops the individual frontiers of all regions.

This study follows the approach by O'Donnell et al. (2008) to construct a metafrontier and calculate the distance between the group frontiers and the metafrontier using the concept of the *distance function*. In particular, such functions measure the distance from an actual observation to the technological frontier in an input–output space. To define the distance functions, one must first define the production technology, which is the set of all feasible input–output combinations. A meta-production technology T is defined as

$$T = \{(x, y){:}x \text{ can produce } y\} \tag{1}$$

where $x \in \mathbb{R}_+^K$ is a vector of inputs and $y \in \mathbb{R}_+^M$ represents a vector of outputs. A metafrontier is defined as the boundary of the output (or input) set in the meta-production technology T. For example, the output set for an input vector $\mathbf{x}$ can be represented as

$$P(x) = \{y{:}(x, y) \in T\} \tag{2}$$

O'Donnell et al. (2008) referred to the boundary of this output set as the output "metafrontier." A meta output distance function (D_O) is defined as follows (for more on DEA and distance functions, see Cooper et al. 2007):

$$D_\text{O}(x, y) = \underset{\phi}{\text{Max}}\{\phi \geq 1, (x, \phi y) \in P(x)\} \tag{3}$$

Equation (3) is interpreted as the maximum amount of outputs that a firm can produce from a given set of inputs. A firm is fully efficient if $D_\text{O}(x, y) = 1$.

Similarly, the above concept can be applied to construct "group frontiers." In particular, technology group k ($k = 1, 2,\ldots, K$), output sets, and distance functions are defined, respectively, as follows:

$$T^k = \{(x, y){:}x \text{ can produce } y \text{ by all firms in group } k\} \tag{4}$$

$$P^k(x) = \{y:(x, y) \in T^k\} \tag{5}$$

$$D_O^k(x, y) = \underset{\phi}{Max}\{\phi \geq 1, (x, \phi y) \in P^k(x)\} \tag{6}$$

As mentioned previously, a firm is technically efficient if it has a distance function equal to unity. Therefore, the technical efficiency of a firm at the metafrontier and group frontier can be represented, respectively, by the distance functions:

$$\mathrm{TE}(x) = D_O(x, y) \tag{7}$$

$$\mathrm{TE}^k(x) = D_O^k(x, y) \tag{8}$$

The gap in technology between the metafrontier and group frontier is defined simply as the ratio of technical efficiencies between the two frontiers. This measure is referred to in the literature as the meta-technology ratio (MTR):

$$\mathrm{MTR}^k(x, y) = \frac{D_O(x, y)}{D_O^k(x, y)} = \frac{\mathrm{TE}(x, y)}{\mathrm{TE}^k(x, y)}. \tag{9}$$

Because the metafrontier envelops all group frontiers, the technical efficiency scores of the group frontiers are generally higher than those based on the metafrontiers. This ratio is interpreted as the extent to which a firm can further improve its production by moving from being efficient at the group frontier (a.k.a., 'the best') to being efficient at the metafrontier (a.k.a. 'best-of-the-best'). If a firm achieves MTR = 1, it is fully efficient in both frontiers, while MTR = 0.8 implies that the firm can further increase its outputs by 20% by moving from the group frontier to the metafrontier.

The DEA and SFA approaches were used to measure the regional differences in operational efficiency of seaports in Vietnam. While DEA requires no assumption on functional form, SFA can consider random noise and measurement errors, which are likely to occur in data of any country, including Vietnam. Each of these approaches is presented briefly below.

Data envelopment analysis

The calculation of the technical efficiency (TE) for any ith firm requires solving a linear programming problem to measure the distance from its input–output structure to the frontier as follows:

$$\begin{aligned} D_O\{x_i, y_i\} &= Max\{\phi \geq 1, (x,\ \phi y \in p(x)|Y\lambda \geq y_i, x_i \geq X\lambda \quad \lambda \geq 0,\ \phi \geq 1\} \\ i &= 1, 2, \ldots, N, \end{aligned} \tag{10}$$

where ϕ is a scalar, λ is a vector of constants, representing the weights used to construct the weighted outputs/inputs achievable for the firm to be fully efficient, X and Y are, respectively, the matrix of inputs and matrix of outputs of all firms under investigation, and x_i and y_i are the vectors of inputs and outputs, respectively, of the ith firm. Because DEA is deterministic, the metafrontier is guaranteed to envelop all group frontiers. Therefore, to calculate the MTR using DEA, one can simply calculate the TE of the firm using the group frontier and the metafrontier.

Stochastic frontier analysis

The SFA for firm i of the group k frontier model is represented as

$$y_i = f(x_{1i}, x_{2i}, \ldots, x_{ni}; \beta^k)\mathrm{e}^{V_i^k - U_i^k} \tag{11}$$

where y_i and x_{1i}, x_{2i},…,x_{ni} represent the output and inputs, respectively, V_i^k is the random noise, and U_i^k is the non-negative inefficiency component. Similarly, the *deterministic* metafrontier for all groups (countries, states, or regions) in the sample is represented by

$$y_i^* = f(x_{1i}, x_{2i}, \ldots, x_{ni}; \beta) \tag{12}$$

where y^* is the metafrontier output and β is the set of metafrontier parameters that satisfies the following constraint:

$$\beta x_i \geq \beta^k x_i \tag{13}$$

The metafrontier is constructed by solving the following linear programming problem:

$$\min_{\beta} \sum_{i=1}^{N} [f(x;\beta) - f(x;\beta^k)] \tag{14}$$

$$\text{s.t. } \ln f(x,\beta) \geq \ln f(x,\beta)^k \tag{15}$$

Because the estimated group coefficients β^k are fixed and the functional form is log-linear, the above problem can be expressed equivalently as follows:

$$\min_{\beta} \sum_{i=1}^{N} x'\beta \tag{16}$$

$$\text{s.t. } x_i'\beta \geq x'\beta^k \tag{17}$$

Because there are only eight observations available for the northern group, a parsimonious approach to functional selection is necessary. The Cobb–Douglas production function is selected for estimation of the group frontiers and the metafrontier, because it requires only five parameters (respective to the input variables) to be estimated. The use of a more flexible functional form, such as a translog function, is not possible because the number of parameters is larger than the number of observations. (For details of comparing the Cobb–Douglas and translog production functions, readers are referred to González and Trujillo (2009)). In addition, it was assumed that the inefficiency term follows a half-normal distribution (Greene 2008), as this is the most used one in the literature, while other distributions tend to overestimate the efficiency scores (González and Trujillo 2009).

Dataset

The dataset covers 43 seaports and it was compiled from database provided by the Vietnam Seaports Association (2015). In the numerous studies on port efficiency, the more frequently used input and output variables are as follows: the cargo throughput, as the output variable, and berth length, terminal areas, warehouse capacity, and cargo handling equipment as the input variables. Although labor is an important input variable in production theory, unfortunately labor data were not available in our case. Thus, we have chosen cargo handling equipment as a proxy for labor under the assumption that labor employed by a port varies proportionately with its cargo handling equipment (see González and Trujillo 2009; Park and De 2004; Cullinane and Wang 2006; Notteboom et al. 2000; Tongzon and Heng 2005; de Oliveira and Cariou 2011; Nguyen et al. 2015; Schøyen and Odeck 2013). In addition, the capacity of information and communication technology (ICT) affects the production of contemporary ports due to the critical role that ICT plays in port operations (Nguyen et al. 2015). Based on the above, the total port throughput (hereinafter "throughput"), i.e., the amount of cargo in tons handled by the port, is the dependent variable. Five input variables were used in this study including port infrastructure, land, cargo storage facility, cargo handling facility, and information technology (hereinafter "infrastructure," "land," "cargo storage facility," "cargo handling facility," and "information technology," respectively).

To construct the metafrontier and calculate the distance between group frontiers and the metafrontier, the ports in this study were divided into three groups/regions, namely the North, the Central, and the South, corresponding to the three official administrative regions of Vietnam, each with its own distinctive economic characteristics. In particular, the North relies more on the export of bulk mineral commodities, whereas the Central has small ports with relatively minor trade, functioning as ports to handle transitional cargoes. The South relies more on the export of high-valued, agricultural products and is also more active in terms of trade, partly because of its close proximity to countries in the center of Southeast Asia, including Singapore, Thailand, Malaysia, Indonesia, and the Philippines. The gross regional products of the North and the South regions are also significantly larger than those of the Central region and so are their levels of income per capita.

Table 1 lists the descriptive statistics of the variables, as well as the substantial differences between ports in terms of their inputs and outputs. The *t* tests comparing the means of the input and output variables in the regions do not show a significant difference in the port inputs, but find a 5% significant difference in the port throughput across the regions. On average, throughput level in the North is the largest, followed in order by the South and Central regions. Moreover, the correlation test revealed significant differences between the input and output variables, thereby confirming the monotonicity condition between them as expected, thus justifying our variable selection.

Table 1 Descriptive statistics of the variables

Variable name	Mean	Min	Max	Mean by region		
				North	Central	South
Throughput (ton)	3020	30	25,232	6613	940	3261
Infrastructure (m)	623	76	2975	900	514	599
Land (m^2)	257	12	4527	186	169	362
Cargo storage facility (m^2)	19	0	195	26	8	24
Cargo handling facility (ton)	766	10	5534	933	508	912
Information technology (no)	67	4	650	83	29	90

Results and discussion

Table 2 lists the SFA average technical efficiency scores of ports in the three regions and the effect of each input variable on throughput. SFA of all ports indicates that cargo handling facility and information technology are the most important determinants of Vietnamese port performance. In particular, a 1% increase in cargo handling capacity leads to a 0.73% increase in total throughput. Although information technology cannot be measured directly, the value of its coefficient (0.39), which is smaller than that of the cargo handling facility variable, indicates that the latter is more important to Vietnamese ports' efficiency. Interestingly, the effect of infrastructure (indicated by berth length) and land (indicated by land area) is insignificant. This suggests that ports have not been able to use these inputs effectively (hence they have not had a significant effect on port throughput).

The result of group frontier analysis indicates that the role of inputs in port operations varies across the regions. For ports in the North, land appears to be an

Table 2 Technical efficiency and meta-technology ratio by SFA

	All ports	North	Central	South
Infrastructure	0.05 (0.23)	0.08 (0.17)	0.16 (0.4)	0.28 (0.23)
Land	0.04 (0.18)	0.61** (0.24)	−0.04 (0.22)	−0.19 (0.24)
Cargo storage facility	−0.1 (0.1)	−0.21** (0.09)	0.63** (0.28)	−0.02 (0.15)
Cargo handling facility	0.73*** (0.17)	−0.31 (0.36)	0.54** (0.27)	0.65*** (0.17)
Information technology	0.39* (0.22)	0.67 (0.53)	−0.28 (0.29)	0.41* (0.22)
Constant	0.83** (0.37)	0.98*** (0.11)	−0.5 (1.41)	0.14 (2.03)
Sample size	43	8	16	19
Average technical efficiency score				
Regional/own frontier	0.97	0.87	0.99	0.99
Metafrontier	0.51	0.65	0.42	0.54
Meta-technology ratio	0.43	0.81	0.17	0.49

All variables are in natural log

Standard errors are in parentheses; significant levels are *** 1%, ** 5%, and * 10%

important input with an elasticity of 0.6, whereas the effect of warehousing for ports in this region appears to be odd, as indicated by the negative sign of the coefficient. This could be because ports in the North mainly handle bulk cargo, particularly coal, whereas ports relying on warehouses tend to focus more on high-value logistics services and may have relatively smaller total port throughput compared to those specialized in bulk cargo handling. On the other hand, the warehousing and cargo handling capacities are important to ports in the Central areas, while cargo handling capacity and information technology are important to ports in the South. As indicated by the value of the coefficient for the Central ports, the cargo storage facility (0.63) is slightly more important than the cargo handling facility (0.54). For the South ports, however, the cargo handling facility (0.65) is significantly more important than information technology (0.41).

The last three rows of Table 2 show the regional technology and meta-technology of the three regions. The average MTR estimated by SFA (0.43) suggests that Vietnamese ports can increase their throughput by 57% by learning from the best practices at national level, rather than at regional level. The North comprises the most efficient ports. Moving from regional frontier to the metafrontier only improves their output by 19%. Interestingly, the MTR of ports in the Central is only 0.17 suggesting that they can improve their efficiency by 87% by learning from nationally efficient ports (on the metafrontier). This suggests that special support and intervention are needed in the Central ports to upgrade the level of their performance to the national level. The results provided in Table 2 also indicate that the South ports on average can double their throughput by learning the best practices from other ports in the country.

Table 3 lists the results of metafrontier analysis using DEA. The results are consistent but not identical to those obtained from SFA. The dissimilarity between SFA and DEA is because the former allows for the stochastic nature of variables, whereas the latter does not. On the other hand, the consistency in the SFA and DEA results confirms that the North ports have the highest average metafrontier ratio and represent the most efficient group in the country. The MTR (0.88) means that a 12% increase in throughput can be achieved by learning from the best practices of ports in all regions. The Central ports have the lowest level of technical efficiency on average, with a MTR of 0.43, indicating that they can increase their outputs by 57% by learning from the national best practices. Similarly, the average MTR of 0.67 in the South ports indicates that the ports in this region rank second in the nation on average.

The above analysis indicates a strong need for Vietnamese ports to improve their efficiency. On the other hand, to determine how ports can achieve this objective, further analysis is required to decompose their overall technical efficiency into scale efficiency and (pure) technical efficiency. In addition, analysis of the input slacks and returns to scale is applied to identify the specific inputs that each region should target to improve its own technical efficiency. This is supported by the use of the slack-to-mean ratios. Table 4 lists the measures of scale efficiency and pure technical efficiency, slacks of input variables, and measures of production scale by DEA models. The most important factor contributing to the efficiency of ports in the North and Central areas is their operational scale, with the values of 0.73 and 0.66, respectively, while pure technical efficiency (0.65) is the dominant factor for the

Table 3 Technical efficiency and meta-technology ratio by DEA

Criteria	Mean	SD
All ports		
Regional frontier	0.83	0.27
Metafrontier	0.54	0.36
Meta-technology ratio	0.62	0.35
The North		
Own technical efficiency	0.67	0.30
Metafrontier efficiency	0.59	0.29
Meta-technology ratio	0.88	0.17
The Central		
Own technical efficiency	0.81	0.31
Metafrontier efficiency	0.39	0.35
Meta-technology ratio	0.43	0.32
The South		
Own technical efficiency	0.92	0.20
Metafrontier efficiency	0.65	0.38
Meta-technology ratio	0.67	0.35

Table 4 Determinants of the inter-regional technology disparities

Criteria	Metafrontier			Regional frontier		
	North	Central	South	North	Central	South
Overall efficiency	0.41	0.19	0.34	0.41	0.68	0.67
Technical efficiency	0.59	0.39	0.65	0.67	0.81	0.92
Scale efficiency	0.73	0.66	0.62	0.65	0.84	0.74
Slack of infrastructure	517.03	257.32	272.39	469.73	117.63	24.63
Slack-to-mean ratio	0.57	0.50	0.45	0.52	0.23	0.04
Slack of land	91.56	111.74	275.99	92.36	2.65	3.81
Slack-to-mean ratio	0.49	0.66	0.76	0.50	0.02	0.01
Slack of cargo storage facility	21.97	3.98	16.67	15.96	1.35	0.44
Slack-to-mean ratio	0.85	0.50	0.69	0.61	0.17	0.02
Slack of cargo handling facility	533.71	133.72	488.32	608.22	130.41	0.00
Slack-to-mean ratio	0.57	0.26	0.54	0.65	0.26	0.00
Slack of information technology	26.25	1.79	45.24	26.54	4.77	0.92
Slack-to-mean ratio	0.32	0.06	0.50	0.32	0.16	0.01
Decreasing returns to scale	0.13	0.00	0.11	0.13	0.06	0.26
Most efficient scale	0.13	0.00	0.11	0.13	0.38	0.32
Increasing returns to scale	0.75	1.00	0.79	0.75	0.56	0.42

ports in the South. Therefore, to improve on efficiency, ports in the North and Central would need to improve their pure technical efficiency, while ports in the South would need to improve their scale efficiency.

The input slacks listed in Table 4 indicate the amounts of inputs that can be reduced without affecting port throughput in ideal situations (assuming no effect on ship waiting time). For example, the ports in the North can reduce berth length by as much as 517 m on average without affecting throughput. On the other hand, the values of the input slacks are not helpful for comparative analysis when the ports in the three regions are substantially different in their size (see Table 1). Therefore, it is imperative to rely on the input slack-to-mean ratios when analyzing the slack variables. The input slack-to-mean ratios of the metafrontiers reported in Table 4 indicate that the North can improve the efficiency of its ports by targeting port infrastructure (0.57), cargo storage facility (0.85), cargo handling facility (0.57), and information technology (0.32). Note the large difference between the input slack-to-mean ratios of the South's regional frontier and the national (meta)frontier. This explains the potential benefits that the South can gain by learning from the national best practices, despite its ports doing relatively well.

The DEA results also reveal the role of ports in regional and national networks. In this study, two measures, namely the peer counts and peer weights obtained from the DEA, were used to develop peer (reference) networks. A 'peer' refers to an efficient port that can play the role of a model for inefficient ports, guiding them to improve their operational efficiency. The 'peer count' refers to the number of times a port is referred to as the 'model' for other ports to study, in order to improve their efficiency. The 'peer weight' refers to the relative importance of a port among all the peers. For example, a peer weight of one means that there is only a single peer (reference port), while set peer weights of 0.5, 0.3, and 0.2 refer to three peers with the first peer having the highest weight (0.5) followed in order by the second (0.3) and third (0.2) peers. Figures 1 and 2 show the peer reference network developed based on this information and the Gephi graphic tool (Bastian et al. 2009). The arrows in the figure show the peer ports, which inefficient ports can learn from in order to improve their efficiency. The thickness of the arrows represents the weight of a peer (i.e., a thicker arrow indicates a higher weight and hence a higher level of importance).

Figure 1 shows that the most influential ports at national level are Cam Pha in the North, Quang Binh in the Central, and Cac Cui and Thuong Cang Vung Tau in the South. For example, Cam Pha is referred to as the peer for 28 other ports in the country, the relative figures of Cac Cui, Thuong Cang Vung Tau, and Quang Binh were 18, 15, and 9, respectively. The possible reason for Cam Pha being so efficient is that it is specialized in handling bulk cargo, particularly of coal exports with fairly standardized technology. Therefore, its throughput is very large while it does not depend on cargo storage facility (warehouses). Cac Cui is located in the Can Tho Province, which is the center of the Mekong Delta region. The main reason for the high efficiency of this port is believed to be its specialization in handling bulk cargo, i.e., rice exports. The same reason explains why Tra Noc-Can Tho, another port in the same province, is quite efficient in the national peer network. The efficiency of Thuong Cang Vung Tau could be because this port is relatively new and is expected to benefit from cargo handling equipment of more advanced technology. On the other hand, Quang Binh port is the entrance point for several provinces in Central Vietnam; its strategic location could play a role in

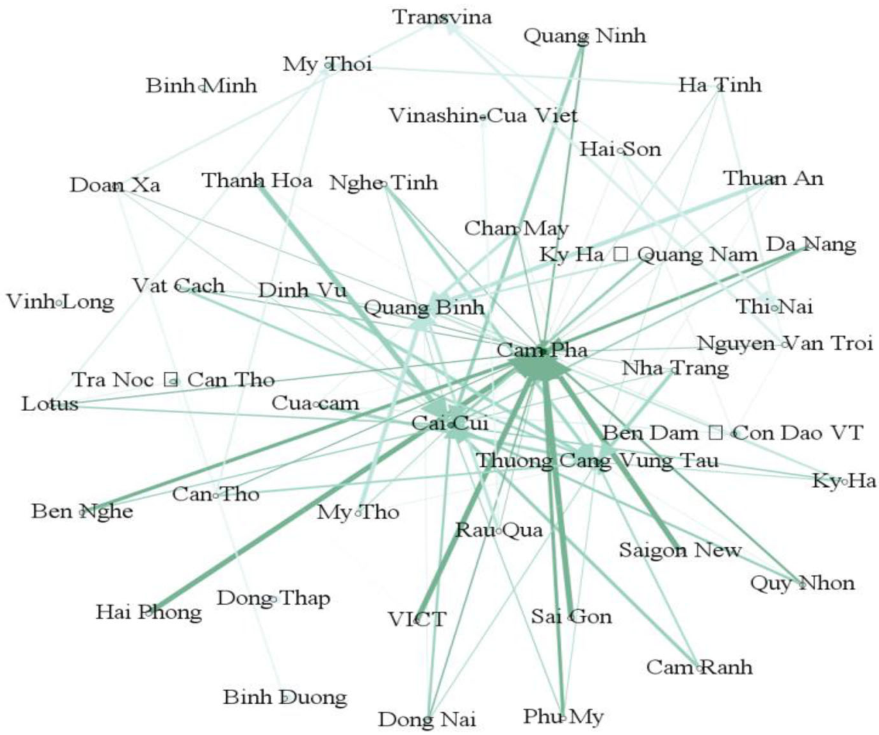

Fig. 1 Peer network at the national level

improving its efficiency. The metafrontier also shows a strong level of connections with only three standalone ports: Binh Minh, Vinh Long, and Dong Thap. The DEA results show that all these ports are technically efficient (they are on the production frontier). Therefore, one possible explanation is that the input–output structures of these ports are unique and it would be difficult for other ports to adopt their operational structures.

As shown in Fig. 2, the regional peer networks for the North and the Central regions show a similar picture with Cam Pha and Quang Binh being relative influential ports. The two regions are also highly connected, where the input–output structure of the most efficient ports can be applied to inefficient ports in their regions. One noticeable difference is that Quy Nhon is inefficient at the national level and needs to learn from the experience of Cam Pha and Cac Cui to improve its operational efficiency. At the regional level, however, Quy Nhon is efficient and plays the role of a peer for Da Nang, Nghe Tinh, Ky Ha, and Thuan An, despite its weight for the last two ports being relatively small. The regional peer network for the South shows a substantially different picture. The ports in this region are much less interconnected, with more than 50% being efficient by default (they are the peer for only themselves). On the other hand, Cac Cui and Tra Noc-Can Tho remain influential ports in the region.

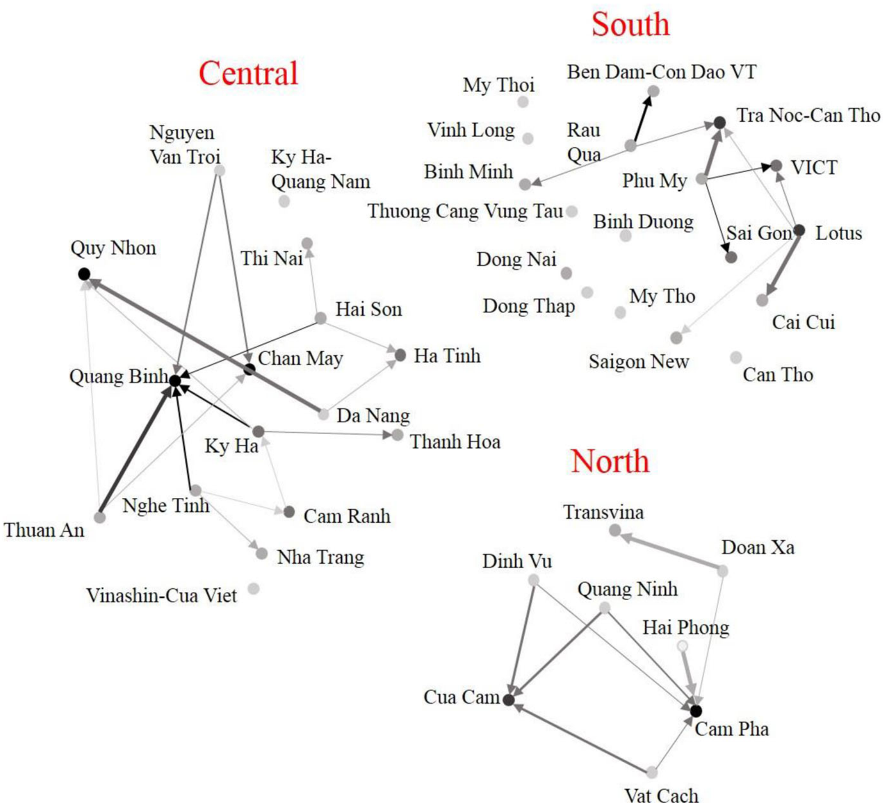

Fig. 2 Peer networks at the regional level

Implications and conclusion

Implications

A number of managerial implications and future research needs can be drawn from the findings of the metafrontier analysis in the previous section. To begin with the managerial implications, *economies of scale* is a key factor, influential to the Vietnamese port efficiency and their efficiency disparity. The ports in the North are most efficient because of their larger average size (see Table 1). On the other hand, technical efficiency issues facing the Central ports are attributed to their much smaller size compared to those in both the North and the South. This suggests that ports can improve their efficiency if they can operate with the economies of scale through investment and expansion. Given the limited government resources and constrained demand, ports can rely on different measures to achieve this objective. One is to restructure the sector, e.g., mergers and acquisitions. This allows ports to gain economies of scale through resource sharing. This option would be feasible because of the close proximities between ports in Vietnam. The many albeit small ports in the Central should be able to benefit from this measure. Another measure is port reform (González and Trujillo 2008; Lacoste and Douet 2012), especially toward commercialization and corporatization that can help ports improve their competitiveness and respond better to changes in market demand (Bandara et al. 2013).

Second, although the ports in each region appear to be relatively efficient within their own group, they can gain substantial benefits by learning from national best practices, which will help improve pure technical efficiency. In particular, the ports in the Central and South should be able to improve their efficiency by learning from those in the North. The ports in the South are already highly efficient and the regional frontier has relatively very low input slack-to-mean ratios. On the other hand, these ratios are much higher when benchmarked against metafrontier models with other ports, particularly those in the North.

Third, decomposition of the overall technical efficiency into scale efficiency and pure technical efficiency indicates that ports can improve their technical efficiency by targeting specific input variables, given a port's service profile. This suggests that port development strategies should vary across the regions. In particular, the North ports should focus more on handling bulk and break bulk cargo instead of investing in cargo storage; the Central ports should focus on scale efficiency and pure technical efficiency, by restructuring and investing more in cargo storage facilities and information technology rather than in land and infrastructure; the South ports should pay attention on value-adding services, such as warehousing, logistics, and promotion of port clusters.

Fourth, the peer reference networks presented in the previous section show how ports in the same group can form clusters led by the most efficient ones. Ports in the same clusters can not only learn from each other in the same region, but also cooperate and coordinate to gain even more comprehensive and sustainable benefits and support economic development in the region. In the North, Cam Pha has been identified as the most technically efficient port. Given its location near Quang Ninh coal mine and the favorable conditions of access to and from the ocean, Cam Pha can play the leading role in the port cluster in the North, supported by Hai Phong as the second largest port. In the Central region, given its high efficiency in the region, Qui Nhon can play a leading role in the Central's port cluster. In the South, while Sai Gon remains one of the key ports in the region, the port cluster features many other ports that are also important to the economic development of the region; in the Southeast are Vung Tau, Cai Mep, Phu My, Long Son ports, etc. and on the Southwest are Can Tho-Tra Noc, Can Tho, My Thoi, Cai Cui, etc.

As regards research implications, two suggestions can be drawn from this study for further research. First, although this is the first study on port efficiency using metafrontier models, further studies should be conducted in other countries separately or combined with the Vietnamese data.

Second, various forms of SFA and DEA approaches can be attempted using the metafrontier models. This study used the Cobb–Douglas production function due to the lack of data, as mentioned previously. However, when sufficient data exist, so as to use other production function forms, requiring an estimation of more parameters, such as the translog production form, the results will be compared to that of Cobb–Douglas one, as the results of SFA can be sensitive to any used functional form of production. In addition, other distributions can be used for the inefficiency term, Ui, instead of the current half-normal distribution, e.g., exponential distribution.

Conclusions

This study has used the metafrontier production model to address seaport efficiency in groups of ports with different technologies. The findings indicate that technology plays an important role in the efficiency of Vietnamese ports as a whole (Table 2). However, its contribution is only significant to ports in the South but not in the North and Central. Port infrastructure, land, cargo storage facility and cargo handling equipment, and information technology are all important to ports but at different levels of significance. Although Vietnamese ports are operating with increasing returns to scale, their efficiency varies across the regions and their performance can be improved by learning from best practices in other ports. To improve on performance, restructuring and reform could be considered as valid options. Investments in infrastructure, cargo handling equipment, storage facility, and information technology could also help improve efficiency. On the other hand, investments should take into account the nature of the cargo and the role of the port in the region. For example, although land is important to the technical efficiency of the ports in the North, cargo storage capacity is important to the ports in the Central region, and information technology is important to the ports in the South. The results of this study imply that port reform can have an extensive and long-term positive impact on the ports in all regions, even though this point could be open to further discussion. Development of port clusters/networks, led by the more efficient ports, is among the measures recommended to improve port efficiency.

This study has some limitations. First, it focuses only on technical efficiency. Therefore, the effects of factors, such as competition and port pricing on port performance, were not taken into account. Second, the study did not consider the role of value-adding services, which are increasingly important for modern ports. Third, different governance models could not be addressed because most ports in Vietnam are state-owned enterprises, and the government plays a key role in port performance. Moreover, it would be interesting to evaluate the trend in the efficiency and network relationship of Vietnamese ports using panel data. Future research can address these limitations.

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