Efficiency Measurement Using the Stochastic Frontier Analysis and Data Envelopment Analysis Methods: An Application to the Vietnamese Ports

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Abstract
This study examines the efficiency of the Vietnamese sea ports. Vietnam’s effort in economic reform, attracting foreign investment and active participation in globalisation has resulted in its international trade value exceeding its GDP. This contribution of international trade to the country’s economic growth would not be possible without the support from the maritime transport industry with more than 50 ports along the 3260km coastline. Thus, managing port efficiency is not only important to Vietnamese ports to stay competitive in the market and manage their resources efficiently, but also vital to the national economy. This study seeks to apply both well known data envelopment analysis (DEA) and stochastic frontier analysis (SFA) methods to evaluate the Vietnamese ports’ efficiency. The analysis results show that, while the efficiency indexes obtained from the two methods provide useful and consistent measures of Vietnamese ports’ efficiency, they are significantly different. Based on these, further analysis is conducted to gain more insights into the application and methodological issues of efficiency measurement methods.

Key words: Vietnam, maritime transport, efficiency measurement, data envelopment analysis, stochastic frontier analysis
1. Introduction

For most countries in the world, the trend in globalisation including foreign trade, investment and outsourcing has made most countries in the world more dependent on trade. For countries in transition such as like Vietnam, economic growth is even more dependent on trade. However, since more than 90% of trade is carried by sea, Vietnam is dependent on sea transport as much as it is on international trade. This is not to mention that the country is located in Southeast Asia and has a long coastline of more than 3260 km, which are favourable conditions for international maritime services as well as national coastal shipping.

Be it for international coastal shipping, Vietnam sea ports incur the main cost in maritime transport and international logistics and therefore play a pivotal role in national trade competitiveness and economic development. The Vietnamese sea port industry attracts a lot of attention from policy makers as well as research because there are currently 166 of seaports of all sizes in Vietnam, belonging to 49 port clusters (Vinashipping, 2008), which imply an average distance of less than 20km between ports along the coastline. Seaports also play a critical role in helping the maritime sector to compete with other modes of transport and provides sufficient infrastructure for intermodal transport and logistics (Nguyen and Nguyen, 2008). The very high density of ports along the coastline suggests intense competition especially between regional ports; in 2007, the total port throughput was about 134 million tonnes, of which 96 million tonnes, equivalent to 71%, was contributed by the ten largest ports, and this leaves a port throughput of 38 million tonnes shared among the remaining ports, which is far from what is needed by regional ports to be operationally efficient. Thus, efficiency is of paramount important to the port sector. As far as seaport development is concerned, the main issues are about not only how to allocate limited resources between many ports, most of which are state-owned, but also whether demand for regional ports is sufficient to justify their intensive investments.

The current paper seeks to assess the efficiency of Vietnamese sea ports. Due to the multiple-product nature of ports and its social economic roles, the performance of a port cannot be measured simply by looking at its monetary indicators such as profit, revenue or cargo throughput. Thus, to achieve this objective, the relevant efficiency measurement methods, namely stochastic frontier analysis (SFA) and data envelopment analysis (DEA), will be applied. Although both methods have been widely used in efficiency measurement, they are based on completely different approaches. SFA is essentially an econometric method, while DEA is a linear programming method. The former is based on a parametric approach, while the latter is non-parametric approach. The use of both methods therefore not only allows for an extensive analysis of Vietnamese port efficiency but also provides an insight into how the two methods perform, especially due to the fact that there have been so far only few studies using both methods to evaluate sea port efficiency.

The paper is organised as follows; the next section provides a review of the literature on the application of SFA and DEA to the port sector and presents an analytical methods for Vietnamese seaport efficiency measurement and the data set, section 3 presents the results of analysis and section 4 is conclusion.
2. Analytical methods of Vietnamese seaport efficiency measurement:

Stochastic frontier analysis method

SFA was proposed by Aigner, Lovell and Schmidt (1977), Schmidt (1985) and has recently been applied extensively to the analysis of sea port efficiency by many, including but not limited to Tongzon and Wu (2005), Cullinane and Song (2006), Trujillo and Tova (2007), and Cullinane (2010).

To exactly understand how the SFA method works, we define an “IDEAL” production frontier function for a port, which, unlike other production functions, has a special structure of the error term comprising of two parts as specified in the following equations:

\[
\ln y = \beta_1 + \sum \beta_k \ln x_k + \epsilon
\]

\[
\ln y = \beta_1 + \sum \beta_k \ln x_k - u + \nu, u \geq 0, \nu \sim N[0, \sigma^2] \tag{2}
\]

The first part of the error term, \( u \geq 0 \), reflects the gap between the observed and theoretical throughput level of the port, and the second part, \( \nu \sim N[0, \sigma^2] \), is a white noise. The above structure shows that \( u \) is a measure of inefficiency and needs to be estimated. Moreover, since the log linear function is used, \( u \) is a measure of the percentage of the firm that fails to achieve the frontier (ideal output level).

Aigner, Lovell, and Schmidt (1977) suggested the following “half-normal” and the “exponential” models. Let:

\[
\varepsilon = \nu - u
\]

\[
\lambda = \sigma_u / \sigma_v \tag{4}
\]

\[
\sigma = (\sigma_u^2 + \sigma_v^2)^{1/2} \tag{5}
\]

\[
\theta = 1 / \sigma \tag{6}
\]

and \( \phi(z) \) and \( \Phi(z) \) be the distribution function and cumulative distribution function (probability to the left) of the standard normal variable \( z \). In the “half-normal” model, the density and likelihood functions and estimated inefficiency respectively are:

\[
\ln h(\varepsilon_i | \beta, \lambda, \sigma) = \left[ -\ln \sigma - \left( \frac{1}{2} \right) \log \frac{2}{\pi} - \frac{1}{2} \left( \frac{\varepsilon_i}{\sigma} \right)^2 + \ln \Phi \left( -\frac{\varepsilon_i \lambda}{\sigma} \right) \right] \tag{7}
\]

\[
\ln L = -n \ln \sigma - \frac{n}{2} \ln \frac{2}{\pi} - \frac{1}{2} \sum_{i=1}^{n} \left( \frac{\varepsilon_i}{\sigma} \right)^2 + \sum_{i=1}^{n} \ln \Phi \left( -\frac{\varepsilon_i \lambda}{\sigma} \right) \tag{8}
\]

\[
E[u | \varepsilon] = \frac{\sigma \lambda}{1 + \lambda^2} \left[ \phi(z) \right] - z, \quad z = \frac{\varepsilon \lambda}{\sigma} \tag{9}
\]

The inefficiency measure \( u \) for the half-normal model can be estimated using equation (9) and the efficiency measure is (1-u).

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1 This and next section present the SFA and DEA methods for sea ports. However, both methods can be applied to any sector.

2 The following presentation is adapted from Greene (2008).
In the “exponential” model, the density and likelihood functions and estimated inefficiency respectively are:

\[
\ln h(\varepsilon_i | \beta, \theta, \sigma_v) = \left[ \ln \theta + \frac{1}{2} \theta^2 \sigma_v^2 + \theta \varepsilon_i + \ln \Phi \left( -\frac{\varepsilon_i}{\sigma_v} - \theta \sigma_v \right) \right] \tag{10}
\]

\[
\ln L = n \ln \theta + \frac{n}{2} \theta^2 \sigma_v^2 + \theta \sum_i^n \varepsilon_i + \sum_i^n \ln \Phi \left( -\frac{\varepsilon_i}{\sigma_v} - \theta \sigma_v \right) \tag{11}
\]

\[
E[u | \varepsilon] = z + \sigma_v \frac{\phi(z/\sigma_v)}{\Phi(z/\sigma_v)}, \quad z = \varepsilon - \theta \sigma_v \tag{12}
\]

Inefficiency measure \( u \) for the exponential model can be estimated using (12) and efficiency measure is also (1-u).

**Data envelopment analysis method**

Unlike SFA that relies on regression analysis of a production function and hence the functional specification, data envelopment analysis does not require functional specification. In data envelopment analysis (DEA), efficiency of a port is measured by benchmarking its actual output against the frontier that “envelops” all ports included in the study\(^3\). DEA also allows for both constant returns to scale (CRS) proposed by Charnes, Cooper and Rhodes (1978) as well as variable returns to scale (VRS) proposed by Banker, Charnes and Cooper (1984). The linear programs for both CRS and VRS can be described as follows\(^4\).

DEA linear program for CRS is specified as follows:

Min: \( \theta, \lambda_1, \lambda_2, \ldots, \lambda_n \)

Subject to:

\[
\theta x_{10} - (x_{11} \lambda_1 + x_{12} \lambda_2 + \ldots + x_{1n} \lambda_n) \geq 0
\]

\[
\theta x_{20} - (x_{21} \lambda_1 + x_{22} \lambda_2 + \ldots + x_{2n} \lambda_n) \geq 0
\]

\[
\ldots
\]

\[
\theta x_{m0} - (x_{m1} \lambda_1 + x_{m2} \lambda_2 + \ldots + x_{mn} \lambda_n) \geq 0
\]

\[
y_{10} - (y_{11} \lambda_1 + y_{12} \lambda_2 + \ldots + y_{1n} \lambda_n) \leq 0
\]

\[
y_{20} - (y_{21} \lambda_1 + y_{22} \lambda_2 + \ldots + y_{2n} \lambda_n) \leq 0
\]

\[
\ldots
\]

\[
y_{s0} - (y_{s1} \lambda_1 + y_{s2} \lambda_2 + \ldots + y_{sn} \lambda_n) \leq 0
\]

\[
\lambda_1, \lambda_2, \ldots, \lambda_n \geq 0
\]

The above can be rewritten in the matrix-form as:

Min: \( \theta, \lambda \)

Subject to:

\[\theta x_o - X\lambda \geq 0\] \tag{14}

\[Y\lambda \geq y_o\] \tag{15}

\[\lambda \geq 0\] \tag{16}

\(^3\) See González and Trujillo (2009) and Cullinane (2010) for a review of and comparison of the SFA and DEA methods.

\(^4\) This presentation of the CRS and VRS models were adapted from Cooper, Tone and Seiford (2007).
\[ \lambda \geq 0 \]

Where \( \lambda = (\lambda_1, \lambda_2, \ldots, \lambda_n)' \) and \( X \) and \( Y \) are the input and output matrixes respectively:

\[
X = \begin{pmatrix}
    x_{11} & x_{12} & \cdots & x_{1n} \\
    x_{21} & x_{22} & \cdots & x_{2n} \\
    \vdots & \vdots & \ddots & \vdots \\
    x_{m1} & x_{m2} & \cdots & x_{mn}
\end{pmatrix}, \quad
Y = \begin{pmatrix}
    y_{11} & y_{12} & \cdots & y_{1n} \\
    y_{21} & y_{22} & \cdots & y_{2n} \\
    \vdots & \vdots & \ddots & \vdots \\
    y_{o1} & y_{o2} & \cdots & y_{on}
\end{pmatrix}
\]

DEA linear program for VRS in matrix form is specified as follows:

Min: \[ \theta \] \[ \theta \theta \theta \lambda \]

Subject to: \[ \theta x_o - X \lambda \geq 0 \] \[ (17) \]
\[ Y \lambda \geq y_o \] \[ (18) \]
\[ i' \lambda = 1 \] \[ (19) \]
\[ \lambda \geq 0 \] \[ (20) \]

Note that the only difference between the CRS and VRS models is the constraint (19), which is: \( \Sigma \lambda = 1 \). Due to its flexibility and independence on functional specification, DEA has been relatively widely in sea port efficiency studies including but not limited to Park and De (2004), Barros (2006), Cullinane and Wang (2006), Rios and Gastaud (2006), González and Trujillo (2009), Panayides, Maxoulis, Wang and Ng (2009), and Cullinane (2010).

The data set includes 43 largest ports, of which 18 are multi-function ports that handle both bulk and container cargo. The data were collected from the Vietnam Seaports Association (2010) with the following variables:

- Total throughput (THROUGHPUT) (tons)
- Container throughput (TEU) (TEUs)
- Berth length (BERTH) (m)
- Total areas (AREA) (thous sqm)
- Warehouse area (WAREH) (thous sqm)
- Cargo handling equipment capacity (EQUIP) (tons)
- Number of computer (PCS) (pcs)

Because all 43 ports handle bulk cargo and only 18 ports handle containers, cargo throughput will be analysed using both SFA and DEA. Container throughput is analysed using only DEA because of the small sample size not allowing for effective regression analysis. In addition, due to the unavailability of data for the labour variable, the number of personal computers is used as a proxy for this variable. The use of the number of computers as a proxy for the labour variable would essentially ignore port plain labour with little skills and knowledge that is used in ship loading and unloading. It is expected that the use of the proxy would not cause substantial bias to the results of efficiency analysis. In addition, this variable can also be regarded as an indicator of the port’s investment in IT technology.

3. Analysis Results

Table 1 shows the correlation matrix for the input and throughput variables. As expected, there is strong correlation between warehouse area (WAREH) and total area (AREA) (0.842), cargo handling equipment capacity (EQUIP) and berth length (BERTH) (0.842), cargo handling equipment capacity (EQUIP) and total area (AREA) (0.769), berth length (BERTH) and number of computers (PCS) (0.808), cargo handling equipment capacity (EQUIP) and warehouse area (WAREH) (0.721), number of computers (PCS) and berth length (BERTH)
(0.808), number of computers (PCS) and total area (AREA) (0.817), number of computers (PCS) and warehouse area (WAREH) (0.765), and number of computers (PCS) and cargo handling equipment capacity (EQUIP) (0.920). Strong correlation between many variables suggests that the regression analysis will be subject to a strong collinearity problem. It is interesting to note that the throughput variable (the dependent variable) has strong correlation only with the number of computers, which however has strong correlation with all variables.

Table 1: Correlation matrix

|     | BETH  | AREA  | WAREH | EQUIP  | PCS   | THROUGHTPUT |
|-----|-------|-------|-------|--------|-------|-------------
| BETH| 1     |       |       |        |       |             |
| AREA| 0.534 | 1     |       |        |       |             |
| WAREH| 0.575 | 0.842 | 1     |        |       |             |
| EQUIP| 0.842 | 0.769 | 0.721 | 1      |       |             |
| PCS  | 0.808 | 0.817 | 0.765 | 0.920 | 1     |             |
| THROUGHTPUT| 0.632 | 0.572 | 0.514 | 0.686 | 0.772 | 1           |

For the reference purposes Table 2 reports the OLS results of the estimation of the production (log linear) function which are comparable with the results obtained from the maximum likelihood method applied to both the half-normal and exponential models, which are shown in Tables 3 and 4 respectively. As shown in Tables 2 to 4, all variables have the expected (positive) signs. Due to the presence of the multi-collinearity problem, the first four variables are not significant but become significant when the other variables are removed from the regression. The regression results reported in Tables 2-4 consistently suggest that the cargo handling equipment variable (LNEQUIP) has the strongest influence on port throughput as the dependent variable with the coefficient values of 0.749, 0.725 and 0.811 in OLS, MLE for the half-normal and exponential models respectively. It has also been consistently shown that the number of computer (LNPCS) also have a very strong effect on port throughput with its coefficient value being 0.348, 0.355 and 0.283 in Tables 2, 3 and 4 respectively. As noted earlier that this variable has strong correlation with all variables therefore it is not surprising to see that this variable appears to be insignificant in the regression results reported. In fact, this variable becomes strongly significant when other variables are removed from regression. Because cargo handling equipment can be well regarded as a capital stock variable, and as mentioned earlier, the number of computers has been used as a proxy for labour and is also an indicator of investment in IT technology, the two variables together would represent the standard variables in the production function.

It is also evident from the regression results reported in Tables 2-4 that although all other variables including berth length (LNBERTH), total area (LNAREA), and warehouse area (LNWAREH) have a positive effect on port throughput, their effect varies between 0.01 and 0.1, which is quite modest compared to those of cargo handling equipment (LNEQUIP) and number of computers (LNPCS). Despite the presence of a strong collinearity problem, the value of R-square of 0.616 indicates a good fit of the production function given the data set.
Table 2: OLS results

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>St. error</th>
<th>t-statistics</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.880</td>
<td>1.109</td>
<td>0.793</td>
<td>0.433</td>
</tr>
<tr>
<td>LNBERTH</td>
<td>0.035</td>
<td>0.234</td>
<td>0.148</td>
<td>0.883</td>
</tr>
<tr>
<td>LNAREA</td>
<td>0.019</td>
<td>0.198</td>
<td>0.098</td>
<td>0.922</td>
</tr>
<tr>
<td>LNWAREH</td>
<td>0.053</td>
<td>0.135</td>
<td>0.392</td>
<td>0.697</td>
</tr>
<tr>
<td>LNEQUIP</td>
<td>0.749</td>
<td>0.174</td>
<td>4.305</td>
<td>0.000</td>
</tr>
<tr>
<td>LNPCS</td>
<td>0.348</td>
<td>0.196</td>
<td>1.770</td>
<td>0.085</td>
</tr>
</tbody>
</table>

R-square: 0.661. Adjusted R-square: 0.616. Number of observations: 43.

Table 3: MLE results for the half-normal model

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>St. error</th>
<th>t-statistics</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>1.169</td>
<td>93.193</td>
<td>0.013</td>
<td>0.990</td>
</tr>
<tr>
<td>LNBERTH</td>
<td>0.010</td>
<td>0.203</td>
<td>0.050</td>
<td>0.960</td>
</tr>
<tr>
<td>LNAREA</td>
<td>0.016</td>
<td>0.251</td>
<td>0.062</td>
<td>0.950</td>
</tr>
<tr>
<td>LNWAREH</td>
<td>0.073</td>
<td>0.145</td>
<td>0.505</td>
<td>0.614</td>
</tr>
<tr>
<td>LNCAPAC</td>
<td>0.725</td>
<td>0.136</td>
<td>5.323</td>
<td>0.000</td>
</tr>
<tr>
<td>LNPCS</td>
<td>0.355</td>
<td>0.241</td>
<td>1.470</td>
<td>0.142</td>
</tr>
</tbody>
</table>

SIGMA: 0.848483. LAMBDA: 0.058123. Number of observations: 43.

Table 4: MLE results for the exponential model

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>St. error</th>
<th>t-statistics</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.153</td>
<td>92.763</td>
<td>0.002</td>
<td>0.999</td>
</tr>
<tr>
<td>LNBERTH</td>
<td>0.076</td>
<td>0.206</td>
<td>0.369</td>
<td>0.712</td>
</tr>
<tr>
<td>LNAREA</td>
<td>0.084</td>
<td>0.230</td>
<td>0.366</td>
<td>0.714</td>
</tr>
<tr>
<td>LNWAREH</td>
<td>0.065</td>
<td>0.144</td>
<td>0.452</td>
<td>0.651</td>
</tr>
<tr>
<td>LNCAPAC</td>
<td>0.811</td>
<td>0.121</td>
<td>6.729</td>
<td>0.000</td>
</tr>
<tr>
<td>LNPCS</td>
<td>0.283</td>
<td>0.232</td>
<td>1.221</td>
<td>0.222</td>
</tr>
</tbody>
</table>

THETA: 41.461. SIGMAV: 0.830. Number of observations: 43.
Table 5 reports the results of port efficiency measurement provided by both SFA and DEA methods. In particular, the first column shows the identification number of the port, the second and third columns show the result of stochastic frontier analysis of the half-normal and exponential models, and the last two columns show the result of data envelopment analysis under the constant returns to scale (CCR model) and variable returns to scale (BBC model) assumption respectively. In general, the results of the half-normal and exponential models in SFA are very close, while those of the CCR and BBC models in DEA are consistent though not as close as in SFA. In addition, the BBC models’ efficiency measures tend to be larger than those of CCR model.

Many differences between the results of the two methods are worth noting. First, most efficiency levels estimated by SFA being around 0.96 tend to be much higher than those estimated by DEA, most of which are less than 0.5. Second, despite very high efficiency levels, no ports have been found to be efficient (with the efficiency level of one) by SFA. In contrast, many ports have found to be efficient. This is expected since the DEA method must identify efficient ports so that they can be used as benchmarks to evaluate the efficiency of other ports. Third, there are more efficient ports under the BBC model (variable returns to scale) than the CCR model (constant returns to scale). This is expected because of the difference between the two models’ assumptions.

Next, the output of efficiency analysis in Table 5 are then plotted in Figures 1-3 to get more insights into the results of SFA and DEA. Figure 1 shows the plots of the efficiency measures provided by the half-normal and exponential models in SFA, which indicates a very high level of consistency. Figures 2 and 3 show the plots of the half-normal model (SFA) and the CCR model (DEA), and the plots of the exponential model (SFA) and the CCR model (DEA) respectively. Both Figures 2 and 3 indicate significance correlation between the results of SFA and DEA. It is also clear from the figures that the outliers are largely associated with the efficient ports (with the efficiency level of one) identified by DEA. Since those efficient ports play a key role in benchmarking, having those outliers are inevitable and this provides an explanation of the difference between the two methods.

As noted earlier, there are 18 ports handling both bulk cargo and containers, whose efficiencies are analysed separately using DEA because of the small sample size insufficient for SFA. Table 6 reports the efficiency levels of these 18 container ports using both CCR and BBC models for constant returns to scale and variable returns to scale respectively. Compared with the efficiency levels found by benchmarking against the full sample of 43 ports, these efficiency levels of container ports are generally significantly higher. In addition, despite there being only 18 ports covered in the analysis, there are more efficient ports. This may also indicate that DEA results can be sensitive to the choice of variable; there are two output variables used to get the results in Table 6 compared to only one output variable used in efficiency computation shown in the previous Tables 2-5.

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5 See, for example, Cooper, Tone and Seiford (2007) for detailed explanation.
Table 5: Efficiency measures estimated by the SFA and DEA methods for 43 sea ports

<table>
<thead>
<tr>
<th>Port ID</th>
<th>Half-normal model</th>
<th>Exponential model</th>
<th>CCR model</th>
<th>BBC model</th>
<th>Half-normal model</th>
<th>Exponential model</th>
<th>CCR model</th>
<th>BBC model</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>0.963816104</td>
<td>0.977952873</td>
<td>1</td>
<td>1</td>
<td>0.963816104</td>
<td>0.977952873</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>37</td>
<td>0.960292027</td>
<td>0.975302427</td>
<td>0.214436351</td>
<td>0.79977806</td>
<td>0.960292027</td>
<td>0.975302427</td>
<td>0.214436351</td>
<td>0.79977806</td>
</tr>
<tr>
<td>5</td>
<td>0.960664188</td>
<td>0.975667649</td>
<td>0.209065664</td>
<td>0.550887762</td>
<td>0.960664188</td>
<td>0.975667649</td>
<td>0.209065664</td>
<td>0.550887762</td>
</tr>
<tr>
<td>38</td>
<td>0.960604681</td>
<td>0.975650574</td>
<td>0.208719087</td>
<td>0.521797717</td>
<td>0.960604681</td>
<td>0.975650574</td>
<td>0.208719087</td>
<td>0.521797717</td>
</tr>
<tr>
<td>41</td>
<td>0.961094704</td>
<td>0.976116581</td>
<td>0.21914705</td>
<td>0.219264888</td>
<td>0.961094704</td>
<td>0.976116581</td>
<td>0.21914705</td>
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</tr>
<tr>
<td>40</td>
<td>0.961143759</td>
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<td>0.224380669</td>
<td>0.22500581</td>
<td>0.961143759</td>
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<td>0.224380669</td>
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<td>25</td>
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<td>0.976210622</td>
<td>0.26444515</td>
<td>0.26455897</td>
<td>0.961297404</td>
<td>0.976210622</td>
<td>0.26444515</td>
<td>0.26455897</td>
</tr>
<tr>
<td>6</td>
<td>0.961367174</td>
<td>0.976362524</td>
<td>0.416193879</td>
<td>0.677071286</td>
<td>0.961367174</td>
<td>0.976362524</td>
<td>0.416193879</td>
<td>0.677071286</td>
</tr>
<tr>
<td>2</td>
<td>0.960715929</td>
<td>0.97571002</td>
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Figure 1: Inefficiency measures of the half-normal and exponential models
Figure 2: Efficiency measures of the half-normal model and the CCR model

Figure 3: Efficiency measures of the exponential model and the CCR model
4. Implications and Conclusion

The efficiency measures provided by SFA and DEA are highly correlated consistent. This is consistent with Cullinane’s (2010) and González and Trujillo’s (2009) observation that the two approaches when using the same data set produce outputs which are reasonably correlated and that one of these two approaches dominates the other.

The analysis results provide evidence confirming the relationship between the two entirely different approaches to efficiency measurement, one being parametric (econometric) and the other being non-parametric (linear programming). Although the efficiency measures are consistent, they can be significantly different. The differences between the results of the two approach are at least because DEA must identify and use efficient ports as the benchmark to compute the efficiency levels of other ports. However, such efficient ports are however not confirmed by SFA.
Due to the inability of the SFA method to handle multiple products, the DEA method was used to evaluate the efficiency of sea ports that produce more than one product/service. However, it appears that the results provided by this method may be sensitive to the choice of variables.

It is interesting to note that, when checking the size of those ports found to be on the frontier, we found the efficiency levels of Vietnamese seaports are not related to the size of the ports or any other explanatory variables.

The above findings provide some insight into the differences between the two approaches to efficiency measurement. Further insights may also be gained by controlling for the effect of the noise in the DEA, which has not been accounted for in the study. Thus, further research can apply bootstrap DEA and compare the results obtained with those provided by SFA. Future research may also cover the role of other variables and externalities of sea ports.

References


