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Nonparametric estimation of allocative efficiency using indirect production theory: Application to container ports in Norway

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Abstract
Adaption to prices is an important feature of productivity development. This paper proposes an extension of the StoNED model to accommodate estimation of allocative efficiency. It demonstrates how indirect production theory is suited for assessing allocative efficiency and helps alleviating the curse of dimensionality for stochastic nonparametric estimators compared to conventional measures of allocative efficiency. Furthermore, the paper elaborates on the appropriate cost of capital for the estimation of allocative efficiency. The proposed model framework is utilized to study allocative efficiency of Norwegian container ports, thereby adding to the literature on seaport terminal efficiency studies.

Keywords Indirect production theory · Stochastic Nonparametric Envelopment of Data · Allocative efficiency · Container port

1 Introduction

Optimal adaption to competitive market prices is an important, yet often neglected, feature of productivity and efficiency developments. Allocative efficiency refers to optimal allocation of inputs given corresponding prices. Koop and Diewert (1982) discuss how Farrell's (1957) efficiency terminology can be extended to account for allocative efficiency, along with scale efficiency and output mix efficiency. See Pastor et al. (2022) for a recent, comprehensive treatment on decomposing economic efficiency according to technical and allocative criteria.

Färe and Grosskopf (1990) show that it is possible to approximate shadow prices of inputs by their corresponding derivatives of the input distance function. The wedge between shadow and market prices exhibits allocative efficiency. Indirect production theory, as studied by Färe et al. (1988; 1992), provides a useful way to approach this topic, exploiting the indirect input requirement sets proposed by Shephard (1974); see also Färe and Primont (1995). In this paper, we draw on these important contributions by Färe, Grosskopf and their coauthors, proving their relevance for contemporary work on productivity and efficiency analysis.

The main advantage of the indirect approach becomes apparent when the production function is estimated using stochastic nonparametric methods such as Stochastic Nonparametric Envelopment of Data (StoNED) (Kuosmanen, 2006; Kuosmanen and Kortelainen, 2012), which are subject to the curse of dimensionality. The first contribution of this paper is to show how indirect production theory is suited for assessing allocative efficiency within the StoNED approach, in addition to demonstrating the use of indirect production theory to alleviate the curse of dimensionality compared to direct Farrell-type assessment of allocative efficiency. Indeed, this is the first study to assess allocative efficiency using the StoNED approach.

The second contribution of this paper is to elaborate on the appropriate cost of capital in the estimation of allocative efficiency. Although market prices are often applied to study allocative efficiency in context of asset composition, it is well known from the fixed capital literature that *unit user costs of capital* (Jorgenson, 1963) is the theoretically correct measure.

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Importantly, the return from alternative use of capital is not reflected by market prices alone. Unit user costs of capital also reflect capital depreciation and required return of capital for given risk levels. *Capital services* is a related concept, concerning aggregation to a common measure of capital when different assets are weighted according to their annual unit user costs. Whereas the fixed capital stock concept captures the value of the capital holding over all periods, the capital services concept expresses the total user value of capital at a given period. The concept was introduced by Jorgenson and Griliches (1967) and Christensen and Jorgenson (1969), and it is inter alia reviewed by Diewert (1980; 2005), Harper et al. (1987), Jorgenson (1989), Baldwin and Gu (2007), Hulten (1991) and OECD (2009).

The third contribution of this paper is empirical. Allocative efficiency is seldom assessed within the large stream of port efficiency literature. To our knowledge, it has not been studied in the literature focusing on container ports, despite its obvious relevance for the sector. We utilize a dataset on Norwegian container ports from 2000 to 2016 to examine allocative efficiency and the role of capital immobility. Our empirical strategy is suited for identifying productivity enhancing container port design.

The paper is organized as follows: Section 2 presents the production model, while Section 3 outlines the paper's contribution to port efficiency measurement and reviews the data used. Section 4 presents the empirical results, while Section 5 concludes.

2 Methodology

This section first introduces Farrell's (1957) decomposition of overall efficiency (OE) into components of technical efficiency (TE) and allocative efficiency (AE) and the indirect approach to measure and decompose OE drawing on Färe et al. (1988; 1992). We then discuss estimation of the cost indirect production function and the cost of capital.

2.1 Allocative efficiency

Let $\boldsymbol{x} \in \mathbb{R}_+^M$ denote a vector of inputs and $\boldsymbol{w} \in \mathbb{R}_+^M$ the corresponding input prices. We focus on the single output setting where the output is denoted $y \in \mathbb{R}_+$ and its price is denoted P. The production function $f(\boldsymbol{x})$ defines the maximum output achievable by inputs $\boldsymbol{x}$. Analogously, the revenue function $R(P, \boldsymbol{x})$ defines the maximum revenue achievable by given inputs, and the cost function $C(y, \boldsymbol{w})$ denotes the minimum cost of producing given output y subject to input prices $\boldsymbol{w}$. Recall from duality theory (Shephard, 1974; Färe and Primont, 1995) that if $f(\boldsymbol{x})$ is monotonic increasing, quasi-concave and satisfies free disposability of inputs, then the cost function $C(y, \boldsymbol{w})$ and the revenue function are equivalent representations of the technology consistent with $f(\boldsymbol{x})$.

Let $i = 1,..,N$ denote a set of decision making units; e.g., seaports. Following Farrell (1957), the output-oriented overall efficiency (OOE) of unit i can be decomposed into output technical efficiency (OTE) and output allocative efficiency (OAE) as

$$OOE_i = \frac{R(P_i, \boldsymbol{x}_i)}{P_i y_i} = \frac{f(\boldsymbol{x}_i)}{y_i} \times \frac{R(P_i, \boldsymbol{x}_i)}{P_i f(\boldsymbol{x}_i)} = OTE_i \times OAE_i \tag{1}$$

Remark 1: *In the single output case,* $R(P_i, \boldsymbol{x}_i) = P_i f(\boldsymbol{x}_i)$, *implying* $OAE_i = 1$.

Analogously, the input-oriented overall efficiency (IOE) of unit i can be decomposed into input-oriented technical efficiency (ITE) and input-oriented allocative efficiency (IAE) as

$$IOE_i = \frac{C(y_i, \boldsymbol{w})}{\boldsymbol{w}'\boldsymbol{x}_i} = \frac{1}{D_i(y_i, \boldsymbol{x}_i)} \times \frac{C(y_i, \boldsymbol{w})}{\left(\frac{\boldsymbol{w}'\boldsymbol{x}_i}{D_i(y_i, \boldsymbol{x}_i)}\right)} = ITE_i \times IAE_i \tag{2}$$

where $D_i(y_i, \boldsymbol{x}_i) = \sup_\gamma\{\gamma : y_i \leq f(\boldsymbol{x}_i/\gamma)\}$ is known as the (direct) input distance function.

We refer to OOE and IOE as *direct* approaches to measure and decompose overall efficiency. Note that the input- and output-oriented measures and decompositions are not identical in general. The conditions under which they coincide can be stated as follows.

Proposition 1: *Assume that the technology represented by functions* $f(\boldsymbol{x})$, $R(P, \boldsymbol{x})$, $C(y, \boldsymbol{w})$ *exhibits constant returns to scale* (CRS). *Then* $IOE_i = 1/OEE_i$ *if and only if* $IAE_i = 1$.

Proof: The equivalence of technical efficiency measures $ITE_i = 1/OTE_i$ under CRS (i.e., linear homogeneity of $f(\boldsymbol{x})$, $R(P, \boldsymbol{x})$, $C(y, \boldsymbol{w})$) has been proven in terms of the input and output distance functions by Färe and Lovell (1978), Proposition 3. The equivalence of the overall efficiency measures $IOE_i = 1/OOE_i$ follows directly from Remark 1.

2.2 Indirect approach to allocative efficiency

Besides the direct OOE and IOE approaches described in the previous section, there are also indirect approaches studied by Färe et al. (1988;1992). For the sake of brevity, we focus on the cost indirect output approach. The cost *indirect* production function (Shephard, 1974; Färe and Primont, 1995) is defined as:

$$f(\boldsymbol{w}, C) = \sup_{y,\boldsymbol{x}}\{y : f(\boldsymbol{x}) \geq y, \boldsymbol{w}'\boldsymbol{x} \leq C\} \tag{3}$$

We can utilize $f(\boldsymbol{w}, C)$ to measure cost-indirect overall efficiency (CIOE) of unit i as

$$CIOE_i = \frac{y_i}{f(\boldsymbol{w}, C_i)} = \inf_{\theta, \boldsymbol{x}}\left\{\theta : \frac{y_i}{\theta} \leq f(\boldsymbol{x}), \boldsymbol{w}'\boldsymbol{x} \leq C_i\right\} \tag{4}$$

Note that CIOE is also known as the cost indirect output distance function in the literature (confer Färe and Primont, 1995). CIOE can be further decomposed into technical and cost-indirect allocative efficiency (CIAE) components as follows

$$CIOE_i = \frac{y_i}{f(\boldsymbol{x}_i)} \times \frac{f(\boldsymbol{x}_i)}{f(\boldsymbol{w}, C_i)} = \frac{1}{OTE_i} \times CIAE_i \tag{5}$$

Note that the output-oriented technical efficiency (OTE) is the same as in the direct decomposition of OOE. However, the indirect measure of allocative efficiency is not identical to IAE in general. The conditions under which these two measures coincide can be stated as follows:

Proposition 2: *$CIAE_i = IAE_i$ if and only if the production function $f(\boldsymbol{x})$ exhibits CRS.*

Proof: Färe and Primont (1995), proposition (4.1.9), prove that $CIOE_i = IOE_i$ if only if the technology exhibits CRS. The equivalence of technical efficiency measures $ITE_i = 1/OTE_i$ under CRS follows from Proposition 1, implying that $CIOE_i = ITE_i \times CIAE_i$ under CRS. Consequently, $IOE_i = CIOE_i \Leftrightarrow ITE_i \times IAE_i = ITE_i \times CIAE_i \Leftrightarrow IAE_i = CIAE_i$ under CRS.

While the indirect approach is equally valid as the direct approach from a theoretical point of view, according to our experience, the direct approach remains more widely used in empirical applications. One potential explanation might relate to estimation: While the direct approach to measure overall efficiency only involves straightforward computation of revenue or cost ratios, CIOE requires estimation of the cost-indirect revenue function.

2.3 Estimation

Thus far, we have implicitly assumed a deterministic setting where any deviation of the observed output from the production frontier is attributed to technical efficiency (OTE). We next relax this assumption by postulating a more general stochastic frontier model in the case of panel data with time periods t = 1,…,T

$$y_{i,t} = f(\boldsymbol{x}_{i,t})e^{\varepsilon_{i,t}} \tag{6}$$

where $\varepsilon_{i,t} = v_{i,t} - u_i$, the random variable $v_{i,t}$ is a symmetric error term and $u_i > 0$ is a time-invariant inefficiency term. Note that in this setting, we have $\text{OTE}_\text{i} = e^{-u_i}$.

Resorting to the indirect approach described in Section 2.2, we can estimate the relevant components in three stages. In the first stage, we apply a panel data variant of Convex Nonparametric Least Squares (Kuosmanen and Kortelainen, 2012) or CNLS for short to estimate the production function. The following CNLS problem is computed using quadratic programming (QP):

$$\begin{aligned}
&\min_{\alpha,\beta,\varphi,\varepsilon} \sum_{t=1}^{T}\sum_{i=1}^{N} \varepsilon_{i,t}^2 \\
&s.t. \\
&\ln y_{i,t} = \ln \varphi_{i,t} + \varepsilon_{i,t},\ \forall i, t \\
&\varphi_{i,t} = \alpha_{i,t} + \beta'_{i,t}\boldsymbol{x}_{i,t},\ \forall i,\ t \\
&\varphi_{i,t} \leq \alpha_{h,s} + \boldsymbol{\beta}'_{h,s}\boldsymbol{x}_{i,t},\ \forall i,\ t,\ h,\ s \\
&\beta_{i,t} \geq 0,\ \forall i,\ t
\end{aligned} \tag{7}$$

where i and h as well as t and s are aliases that index the same set of seaports and time periods, respectively. Further, $\boldsymbol{\beta}$ defines the marginal products of inputs, which are constrained to be non-negative to ensure monotonicity (cf., the second set of inequalities in Eq. 7). The first set of inequalities are known as Afriat inequalities and ensure that the estimated production function is concave. Finally, the slope coefficients $\boldsymbol{\alpha}$ allow estimating the production function under variable returns to scale. Constraining them to zero would effectively impose constant returns to scale.

In the second step, we predict technical efficiency using Schmidt's and Sickles' (1984) approach for panel data analysis. This procedure implies: (i) Calculating the average residual for each unit i in the sample (i.e., $\bar{\varepsilon}_i = \frac{\sum_t \hat{\varepsilon}_{i,t}}{T}$, where $\hat{\varepsilon}_{i,t}$ is obtained by solving Eq. 7); (ii) Identify unit h with the maximum average residual (i.e., $\bar{\varepsilon}_h = \max\{\bar{\varepsilon}_i\}$), to be used as the benchmark with $u_h = 0$; and (iii) Estimate technical efficiency by taking the exponent of the difference between each port's average residual and the maximum residual, that is,

$$\widehat{OTE}_i = \exp(-(\bar{\varepsilon}_i - \bar{\varepsilon}_h)) \tag{8}$$

In the third step, we utilize the fact that the output-oriented Data Envelopment Analysis (DEA) problem can be stated as a sign-constrained CNLS problem (Kuosmanen and Johnson, 2010). Given the estimated coefficients $\hat{\alpha}_{i,t}, \hat{\boldsymbol{\beta}}_{i,t}$ from the first step, we estimate the cost indirect production function (3) by solving the following linear programming problem:

$$\begin{aligned}
&\hat{f}(\boldsymbol{w}, C_{i,t}) = \max_{\tilde{y}_{i,t}, \tilde{\boldsymbol{x}}_{i,t}} \tilde{y}_{i,t} \\
&s.t. \\
&\hat{\alpha}_{i,t} + \hat{\boldsymbol{\beta}}'_{i,t}\tilde{\boldsymbol{x}}_{i,t} \geq \tilde{y}_{i,t},\ \forall i,\ t \\
&C_{i,t} \geq \boldsymbol{w}'\tilde{\boldsymbol{x}}_{i,t},\ \forall i,\ t
\end{aligned} \tag{9}$$

Applying Eq. (5), we have $\widehat{CIAE}_{i,t} = \frac{\hat{f}(\boldsymbol{x}_{i,t})}{\hat{f}(\boldsymbol{w}, C_{i,t})}$ and $\widehat{CIOE}_{i,t} = \widehat{CIAE}_{i,t}/\widehat{OTE}_{i,t}$.

As part of our empirical investigation, we explore the economic implications of some inputs being (quasi)fixed, whereas others are freely adjustable. Our distinction among short- and long run allocations is similar to Färe et al. (1989), who classify inputs into (quasi)fixed and variable inputs. Using DEA, Färe et al. (1989) estimate maximal output (a) by keeping (quasi)fixed inputs at their current levels in the short run and (b) by making (quasi)fixed inputs decision variables in the long run. By comparing the two solutions, the long-run growth potential can be estimated.

In our treatment, we let $\boldsymbol{x}\in\{\boldsymbol{x}^{A}, \boldsymbol{x}^{B}\}$, where $\boldsymbol{x}^{A}$ and $\boldsymbol{x}^{B}$ denote immobile and mobile fixed assets, respectively. The former is here regarded (quasi)fixed, while the latter is regarded variable inputs. In our application to seaports, immobile capital refers to the persistent inputs area and quays, while mobile assets refer to tradeable handling machines and cranes. We let the availability of immobile fixed assets be bounded upwards by $\bar{\boldsymbol{x}}_i^{A}$, which corresponds to adding the constraint $\boldsymbol{x}^{A} \leq \bar{\boldsymbol{x}}_i^{A}$ to problem (8). In principle, we impose that $\bar{\boldsymbol{x}}_i^{A}$ equals the current levels of immobile assets per port, to prevent their expansion.

2.4 Curse of dimensionality

The problem that the number of explanatory variables is "too large" compared to the number of observational units and therefore reduces the discriminatory power and accuracy of the efficiency measurement is known as *curse of dimensionality*. A standard approach to circumvent this problem is to reduce the dimensionality of the model, for example, by aggregating multiple variables into a single metric.

In a recent paper, Zelenyuk (2020) explores price-based aggregation of inputs and outputs to circumvent the curse of dimensionality. We will here briefly demonstrate that CIOE can be similarly viewed as an approach to mitigate the curse of dimensionality, compared to direct approaches.

Denote the predicted outputs of the CNLS estimator by $\widehat{y}_{i,t} = y_{i,t}/exp\left(\widehat{\varepsilon}_{i,t}\right)$ where $\widehat{\varepsilon}_{i,t}$ denotes the residuals obtained as the optimal solution to (7). Applying duality theory, we can now re-express the linear programming problem (8) equivalently as

$$\begin{aligned} \widehat{f}\left(\boldsymbol{w}, \boldsymbol{C}_{i,t}\right) &= \max_{\theta,\lambda,\widetilde{\boldsymbol{x}}} \theta \\ & s.t \\ \theta \widehat{y}_{i,t} &\leq \sum_s \sum_h \lambda_{h,s} \widehat{y}_{h,s} \\ \widetilde{x}_{i,t,k} &\geq \sum_s \sum_h \lambda_{h,s} x_{h,s,k}, \forall k \\ \sum_s \sum_h \lambda_{h,s} &= 1 \\ C_{i,t} &\geq \sum_k w_k \widetilde{x}_{i,t,k} \end{aligned} \tag{10}$$

In this formulation, inputs $\widetilde{\boldsymbol{x}}_{i,t}$ are jointly optimized with the output distance function. Slacks for the input constraints can consequently be set to zero in optimum. By substituting the second set of inequalities (i.e., the input constraints) in (9) into the fourth constraint, we obtain the reduced formulation:

$$\begin{aligned} \widehat{f}\left(\boldsymbol{w}, \boldsymbol{C}_{i,t}\right) &= \max_{\theta,\lambda} \theta \\ & s.t \\ \theta \widehat{y}_{i,t} &\leq \sum_s \sum_h \lambda_{h,s} \widehat{y}_{h,s} \\ C_{i,t} &\geq \sum_k w_k \sum_s \sum_h \lambda_{h,s} x_{h,s,k} \\ \sum_s \sum_h \lambda_{h,s} &= 1 \end{aligned} \tag{11}$$

Denoting $C_{h,s} = \Sigma_k w_k x_{h,s,k}$, we can simplify (10) further by writing

$$\begin{aligned} \widehat{f}\left(\boldsymbol{w}, \boldsymbol{C}_{i,t}\right) &= \max_{\theta,\lambda} \theta \\ & s.t \\ \theta \widehat{y}_{i,t} &\leq \sum_s \sum_h \lambda_{h,s} \widehat{y}_{h,s} \\ C_{i,t} &\geq \sum_s \sum_h \lambda_{h,s} C_{h,s} \\ \sum_s \sum_h \lambda_{h,s} &= 1 \end{aligned} \tag{12}$$

These formulations demonstrate that the indirect approach effectively aggregates all inputs into a single input using input prices as weights. This can substantially reduce the dimensionality of the model when the number of inputs is large and is consequently a potential response to the curse of dimensionality in nonparametric estimators.

2.5 Capital services

Optimal allocation of input factors will ultimately depend on the unit user costs of capital. The concept of unit user costs of capital was developed by Jorgenson (1963) and reflects the alternative capital return. For each capital form, the unit user costs of capital correspond to the sum of required return and depreciation rates, less the capital price increase adjusted for depreciation. As volumes will be measured in different units, we also adjust for each asset k's share of total assets.

Formally let $\boldsymbol{w} \in \mathbb{R}_+^{\boldsymbol{M}}$ be a vector of unit user costs of capital. Assuming time-invariant weights between capital forms, the unit user cost of capital w_k for asset form k is defined:

$$w_k = (r + \delta_k - \pi_k(1 - \delta_k))s_k \tag{13}$$

where r is required return on capital. For asset k, we further have that δ_k is the depreciation rate, π_k is the rate for annual expected price growth and s_k is the share of total assets in fixed prices.

Table 1 Overview over model specifications in port efficiency studies since 2010

Aggregation level	Barros (2012)	Chang (2013)	Cheon et al. (2010)	Chin and Low (2010)	Cullinane and Wang (2010)	De Oliveira and Cariou (2015)	Hung et al. (2010)	Iyer and Nanyam (2021)	Munisamy and Singh (2011)	Mustafa et al. (2021)	Nguyen et al. (2016)	Nguyen et al. (2020)	Odeck and Schøyen (2020)	Pérez et al. (2020)	Rødseth et al. (2023)	Schøyen and Odeck (2017)	Serebrisky et al. (2016)	Simões and Marques (2010a)	Simões and Marques (2010b)	Song and Cui (2014)	Suárez-Aleman et al. (2016)	Wiegmans and Witte (2017)	Wu and Goh (2010)	Yuen et al. (2013)
Port studies	X	X									X			X				X	X					
Terminal studies			X		X	X	X	X	X	X		X	X		X	X	X			X	X	X	X	X
Estimation procedure																								
DEA	X	X	X	X	X	X	X	X	X	X	X	X				X		X	X	X	X	X	X	X
FDH																			X					
SFA											X		X	X			X				X	X		
StoNED															X									
Efficiency measure																								
Economic efficiency	X		X		X	X	X		X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Environmental efficiency		X		X																				
Output																								
Bulk	X[4]													X				X	X					
Cargo handled		X									X			X				X	X	X				
Container capacity flows	X			X																		X		
Container throughput			X		X		X	X	X	X		X	X		X	X	X	X	X		X	X	X	X
Container transit						X											X							
Delays in handling ship cargo	X																							
Gaseous emissions		X[1,2]		X																				
Vessels	X	X																						
Input																								
Berth			X			X	X		X	X[4]	X	X	X	X		X	X				X		X	X
Bilateral trade flow				X																				
Cargo handling machines					X[4]	X[1]	X[1]	X	X		X		X		X	X					X	X[1]	X	X[1]
Energy consumption		X																						
Frequency of shipping services				X																				
Labor	X	X												X[1]				X[1]	X[1]	X		X		
Port area	X	X	X		X[3]	X	X	X	X		X	X	X		X	X	X				X	X	X	X
Quay cranes			X			X		X	X	X	X	X	X	X	X	X	X[4]			X	X	X	X	X
Quay length	X	X			X[3]	X	X	X			X	X	X	X	X	X	X			X	X	X	X	X
Port facilities								X	X	X	X[1]							X[4]	X[4]			X[4]		

Table 1 (continued)

Aggregation level	Barros (2012)	Chang (2013)	Cheon et al. (2010)	Chin and Low (2010)	Cullinane and Wang (2010)	De Oliveira and Cariou (2015)	Hung et al. (2010)	Iyer and Nanyam (2021)	Munisamy and Singh (2011)	Mustafa et al. (2021)	Nguyen et al. (2016)	Nguyen et al. (2020)	Odeck and Schøyen (2020)	Pérez et al. (2020)	Rødseth et al. (2023)	Schøyen and Odeck (2017)	Serebrisky et al. (2016)	Simões and Marques (2010a)	Simões and Marques (2010b)	Song and Cui (2014)	Suárez-Aleman et al. (2016)	Wiegmans and Wiitte (2017)	Wu and Goh (2010)	Yuen et al. (2013)
Contextual variables																								
Competitive environment						X						X					X[1]				X[1]		X[1]	X[1]
Foreland market access						X[2]									X[6]						X			
Hinterland market acess						X								X[5]	X						X			X
Port size						X															X			

(1) Partially covered, (2) negative output, (3) variable applied as output, (4) applied as two variables, (5) applied as three varaibles and (6) applied as four variables Data envelopment analysis (DEA), free disposable hull (FDH), stochastic frontier analysis (SFA) and stochastic nonparametric envelopment of data (StoNED)

Capital services correspond to aggregation of capital stocks over types of assets, applying the annual user costs of capital as weights (i.e. $C_i = \boldsymbol{w}'\boldsymbol{x}_i$ for port i). By such aggregation, alternative capital usage is accounted for without naïve aggregation of capital volumes based on relative capital values.

3 Application to seaport efficiency

In this section, we first provide a brief review of the port efficiency literature. We then introduce the data applied in our empirical investigations alongside descriptive statistics.

3.1 Literature review

Attainment of ambitious policy and managerial objectives to strengthen the role of maritime transport hinges on improving port productivity and efficiency. Ex ante studies on port design typically build on forward-looking simulation and optimization rather than empirical observations (e.g. Thoresen, 2010). Ex post evaluation on the other hand hinges on data on realized port activities and port efficiency measurement, which consequently has become a key topic in maritime economics (see e.g. Gonzalez and Trujillo (2009) or; Pallis et al. (2010; 2011) for overviews up to 2010s and the preceding references for later contributions).

Production analysis of ports dates back to Roll and Hayuth, (1993). Works on seaport efficiency can broadly be classified into two strands; *port studies* and *terminal* studies. We apply the following distinction: *Port studies* focus on joint production of multiple cargoes, and port inputs are typically collected from accounting data. *Terminal studies* do, on the other hand, focus on the handling of a single cargo type – typically containers – and frequently utilize input variables that characterize physical infrastructure and layout of the port. Multi-output cost functions are commonly applied by port studies, while production functions are preferred in terminal studies.

Authors of port studies often argue in favor of a multi-output model specification, while authors of terminal studies put more weight on input heterogeneity. For instance, Jara-Diaz et al. (2006, p. 67) state that ‘what is known as port operations really encompass a large number of smaller operations, most of which form a successive links of a chain in which the weakest link is the one that determines the strength of the chain as a whole.’

In an early contribution, Dowd and Leschine (1990) argue that the productivity of a container ports depends on efficient use of land, labor and capital. Sachish (1996) finds that labor represents 53 percent of the total port expenditure, while buildings and cargo-handling and other equipment account for 42 percent.

Bichou (2011, p. 7) do on the other hand argue that 'modern container-terminal systems are designed and operated in terms of three main operating sites; the quay, the yard, and the gate.' A similar argument is made inter alia by Notteboom et al. (2000). Terminal studies typical exclude labor for which data is often not available. However, Marconsult (1994) finds that there is a fixed relationship between the number of quay cranes and the number of dock workers at container terminals, implying that quay cranes may proxy the number of workers. The use of physical attributes in port production functions has been thoroughly discussed and justified by Cullinane and Wang (2006). It has become a conventional approach in the terminal efficiency literature. Among the early seminal contributions on container ports, Cullinane et al. (2006) compare DEA and Stochastic Frontier Analysis (SFA) to analyze technical efficiencies of 57 container terminals in 28 ports.

In Table 1, we provide an overview over studies in the port efficiency literature. As the literature is large, and we are mostly interested in the recent progress, we focus on studies from 2010. We refer to Simoes and Marques (2010a), Wu and Goh (2010) and Barros (2012) for reviews of earlier studies.

Our mapping of the literature clearly illustrates that terminal studies dominate the recent port efficiency literature, and DEA is found to be the most common estimation method. Preferred model specifications typically involve a wide range of inputs, suggesting that allocative efficiency is important. For container ports, immobile and mobile fixed assets dominate selected inputs, while labor is typically proxied by mobile assets.

While decomposition of efficiency scores into technical and allocative efficiencies is common in the productivity and efficiency literature in general, this approach is seldom studied in the port literature. There are notable exceptions, particularly among studies concerned with Spanish ports. Baños-Pino et al. (1999) investigate allocative efficiency and overutilization of quasi-fixed inputs. Rodriguez-Alvarez et al. (2007) study technical and allocative efficiencies of ports in Las Palmas, Spain. Both studies address allocative efficiency by considering the ratios between shadow prices of production and market prices. Other efficiency studies from Spain that take allocative efficiency into consideration include Díaz-Hernández et al. (2014) and Hidalgo-Gallego et al. (2022). Studies from other countries and regions include Barros (2003) in Portugal, Wang et al. (2013) in United States, and Zheng and Yin, (2015) in China.

While allocative efficiency has received some attention by seaport studies in general, we have not come across any *terminal* efficiency studies assessing allocative efficiency. By advancing this field, our study also contributes to the research field of port design by undertaking an empirical analysis of maximal container throughput subject to port characteristics, including port layout and equipment. It can indeed be viewed as an ex post study of port design. Ex post studies of infrastructure investment are paramount for understanding the success rate of analytical tools used in the planning process.

3.2 Port data

For our empirical investigation, we scrutinize the eight largest container ports in Norway, applying quarterly data from 2010 to 2016. Five ports are located in the Oslo Fjord Region, while three ports are located in the Western/Southern Norway, confer Fig. 1.

In the following, we estimate and decompose cost-indirect overall efficiencies of Norwegian container ports using the approach outlined in Section 2.3. In the implementation of our empirical design, we follow a baseline specification with one output and four inputs, which is standard within the container terminal literature. The four inputs may alternatively be replaced by capital services as a sole input variable (cf. subsection 3.3). Note that while the direct approach is output-oriented, the indirect approach applied here is neither purely input-oriented nor output-oriented, but a hybrid of both (cf. subsection 2.2 in general and proposition 2 in particular).

Container throughput ($y_{i,t}$) is obtained by processed data from Statistic Norway's quarterly port statistic and is applied as the only output. Immobile fixed capital inputs ($\boldsymbol{x}_{i,t}$) comprise quay length in meters and port area in square meters, while mobile fixed capital comprise the numbers of quay cranes and handling machines. The input variables are collected from the ports under investigation. The dataset has previously been used and accounted for in Rødseth et al. (2020; 2023).

3.3 Construction of capital services

To construct capital services, as operationally defined in Eq. (13) in subsection 2.5, we need data on depreciation rates, expected price growth and share of asset volumes by type of asset, as well as data on required return on capital.

Depreciation rates for each type of asset k, δ_k, are collected from Holmen (2022). He uses processed capital data from the Norwegian national accounts based on the National Enterprise Register. According to these data, depreciation rates for service activities related to water transportation are about 1.95 percent for real estate (including land area) and 14.25 percent for machinery and trucks/carriers.[1] These rates are roughly in line with

[1] Based on the depreciation rate δ, the life span L can approximated by the formula, $L = 2/\delta$. Thus, the life spans of real estate and machinery and equipment for service activities in water transportation are around 102 and 14 years respectively.

Fig. 1 Map of South Norway, where red dots indicate ports in our sample. Source: Rødseth et al. (2018)

depreciation and amortization found in the ports' financial reports.

For each asset k, the expected rate for capital price growth, π_k, is set equal to the actual growth from 2010 and 2016. Price data for quay cranes and handling machines are collected from Statistics Norway (e.g. Statistics Norway, 2023). Among disaggregate national account assets, we let 'machinery and equipment for other industries' and 'vans, trucks, crane trucks, tractors, etc.' represents quay cranes and handling machines. For quay length and port area, we estimate the annual price growth for the study period based on deflators for harmonized real estate prices obtained from the consultancy Eiendomsverdi (Holmen, 2022). The weighted average annual price growth rates over the study period is 1.26 percent for handling machines and quay cranes and 6.35 percent for quay length and port area.

The distribution of asset volumes, reflected by s_k in Eq. (10), are approximated based on disaggregated Norwegian national accounts data (cf. Statistics Norway 2023 for further documentation).[2] This data source suggests that quay cranes and handling machines represent 10.78 percent of the fixed capital stock and quay length and port area represent 89.22 percent of the fixed capital stock. The estimates are quality assured by reviewing the ports' annual financial reports.[3] Quay length and port area do in principle proxy volumes for the same fixed capital. Furthermore, we do not have any a priori reason to believe that one of them is more important than the other. Accordingly, we let them represent 44.61 percent of the capital volume each. Although there are more handling machines than quay cranes, annual reports and port statistics suggest that their capital values are about equal. Thus, we let them represent 5.39 percent of the capital volume each.

At last, we approximate the required return on capital, r, based on relevant estimates of weighted average cost of capital (WACC). Data from Damodaran (2020) suggest that the WACC for the maritime industry and the transportation industry are 5.68 and 4.41 percent, respectively. These estimates are also roughly of the same magnitude as WACC estimates for other Norwegian infrastructure industries (The Norwegian Communications Authority, 2020; The Norwegian Energy Regulatory Authority, 2020). Thus, we assume that the required return on fixed capital is 5 percent.

3.4 Descriptive statistics

Summary statistics for outputs and inputs are provided in Table 2. Note that handling machines and container throughput fluctuate less than the other variables in relative terms.

Table 3 reports a piecewise correlation matrix for the output, the inputs and time. Note that handling machines, capital services and container throughput are strongly correlated. Correlations between quay length and other variables are relatively weak, except for the correlation with port area.

4 Empirical results

This section examines how seaport productivity and efficiency vary over time, regions and port size. We estimate the production models using GAMS, assuming variable returns to scale. We report the distribution of efficiency estimates ranging from 0 to 1, where 1 indicates that the port under consideration is efficient.

4.1 Overall efficiency

We refer to Section 2.3 for details about the computation of cost-indirect overall efficiency and its decompositions. CIOE and associated technical and allocative efficiency scores are summarized in Table 4. Allocative efficiency scores are comparable to technical efficiency scores on average but vary slightly more. Note that both the median and minimum are substantially higher for technical compared to allocative efficiencies.

Overall, we find ample potential for improving port efficiency from both better capacity utilization and better

[2] This data and associated meta-data can be made available upon request to Statistics Norway's national accounts section.

[3] The financial statements concerning the ports in this study are largely available online and otherwise accessible upon requests to port authorities.

Table 2 Summary statistics for outputs and inputs

Variable	Mean	Standard deviation	Median	Minimum	Maximum
Container throughput (TEUs)	16,610.1	13,612.0	13,109.0	1,009.0	57,751.0
Quay length (m)	417.8	228.2	385.0	140.0	875.0
Port area (m^2)	64.9	37.7	65.0	10.0	140.0
Quay cranes (no)	2.1	1.0	2.0	1.0	4.0
Handling machines (no)	6.2	6.0	5.0	2.0	24.0
Capital services* (mNOK)	186.6	131.4	142.1	62.8	552.8

* Average fixed prices, 2010–2016

strategies for capital investment. Figure 2 presents overall efficiency scores by port. It shows that efficiency scores vary substantially over ports, and that ports in the Oslo Fjord Region outperform ports in Western/Southern Norway in general. Overall efficiency scores for the port of Drammen fluctuate considerably, while they are persistent in the case of Moss, Oslo and Kristiansand.

4.2 Allocative efficiency and other production properties

Figure 3 shows that allocative efficiencies are close to identical to corresponding technical efficiencies for half of the ports in the sample. For the other cases, Drammen and Ålesund have higher technical than allocative efficiencies, while the opposite is the case for Oslo and Borg. There are no clear systematic patterns with regards to how differences between allocative and technical efficiencies vary with efficiency levels or among the two port regions.

Figure 4 presents the relationship between allocative efficiency and port size. The latter is here defined in terms of the *average* container throughput per port over the period under consideration, and the widths of the bars represent the share of each port's average throughput relative to the total industry throughput.

The largest port (i.e. the port of Oslo) is also the most allocative efficient. Moreover, large ports tend to be more efficient than smaller ports. The exception is Ålesund, which is second least allocative efficient, despite of being the third largest port in the sample.

4.3 Allocative efficiency and capital immobility

Ports' abilities to adjust their assets depend on the type of assets, particularly in the short run. Whereas inputs of mobile assets such as handling machines and quay cranes are relatively flexible and easy to adjust in the short run, inputs of immobile assets represented by quay length and port area are more persistent and less adjustable.

Drawing on Färe et al.'s (1989) contribution, we estimate allocative efficiency both with and without an expansion constraint for immobile assets (cf., Section 2.3 for a comprehensive discussion of the estimation strategy). Our results – presented by Fig. 5 – show that expansion constraints have a negligible impact on allocative efficiencies for most of the ports. The exception in Kristiansand, which becomes allocative efficient when expansion constraints are applied. This is likely due to land scarcity in Kristiansand, where the terminal is located in the city center and therefore has limited possibility for further expansion.

Table 3 Piecewise correlations between outputs, inputs and time

Variable	1.	2.	3.	4.	5.	6.
1. Container throughput	1.000					
2. Quay length	0.286	1.000				
3. Port area	0.657	0.710	1.000			
4. Quay cranes	0.792	0.173	0.438	1.000		
5. Handling machines	0.966	0.333	0.669	0.811	1.000	
6. Capital services	0.932	0.564	0.773	0.778	0.975	1.000
7. Quarter	0.058	0.165	0.076	0.001	0.037	0.067

4.4 Development of allocative efficiency

Finally, we consider the development of allocative efficiency over time. As shown by Fig. 6, three out of the eight container ports exhibit persistent allocative efficiencies. While allocative efficiency of the port of Drammen increased over our study period, allocative efficiencies of Larvik and Borg decreased in the same period. Risvika and Ålesund show more fluctuation in allocative efficiencies over the study period.

5 Conclusions

Indirect production theory offers a fruitful avenue for investigating allocative efficiency in frontier productivity analyses. Despite its applicability, this approach has hitherto only been exploited in the frontier literature to a modest extent. We hope this paper can raise awareness of the important contributions of Färe et al. (1988, 1992), thereby fostering its use in preceding research on productivity and efficiency measurement.

Table 4 Main results for average technical productivity

Statistic	Mean	Standard deviation	Median	Minimum	Maximum
Overall efficiency	0.618	0.196	0.608	0.210	0.894
Allocative efficiency	0.762	0.168	0.776	0.384	1.000
Technical efficiency	0.799	0.151	0.852	0.549	1.000

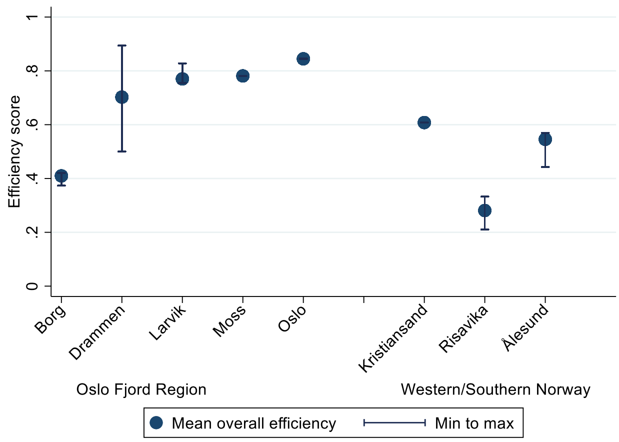

Fig. 2 Overall efficiency per port. Mean (dots), interval from minimum and maximum (interval line)

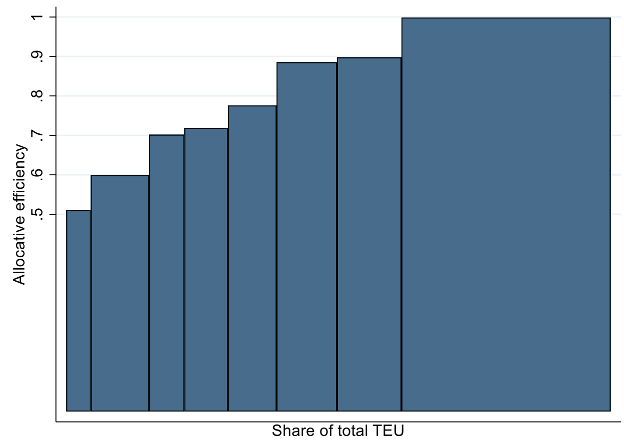

Fig. 4 Average allocative efficiency and port size

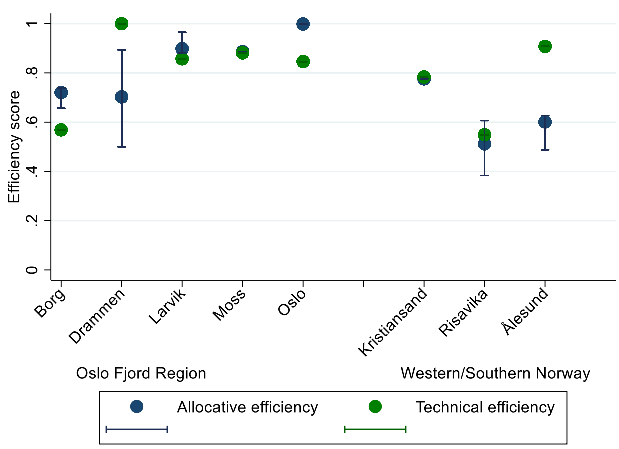

Fig. 3 Technical and allocative efficiency per port. Mean (dots), interval from minimum and maximum (interval line)

Within the context of indirect production theory, our paper explores the use of unit user costs of capital in measuring allocative efficiencies of container ports. This is valuable, as it enables consideration of that the return from alternative capital usage is not reflected by market prices alone. We show how alternative user values can be handled by the concept of capital services, where annual user costs of different types of capital are applied as weights. This approach leads to new insights for port managers, especially by providing an ex post assessment of investments in port capital. While studies guiding port design are predominantly based on simulation and optimization, the complementary approach presented herein provides additional decision support by enabling cross-checks of the success rate of analytical tools used in the planning process. Through learning, new cost-effective investment strategies can be developed to mitigate allocative inefficiencies in port development and investments.

We demonstrate the virtues of the proposed approach by an empirical application to eight Norwegian container ports in the period from 2010 to 2016. Our empirical investigation suggests that not all port investments have been productivity enhancing. Overall, we find potentials to improve returns to capital both by mitigating technical and allocative efficiencies.

It appears ambiguous whether allocative or technical inefficiencies are most severe within the Norwegian port sector. Allocative efficiency appears closely correlated with port size, which may suggest that larger ports attract better managers or have developed better investment plans. However, we also find indications of overcapacities in Norwegian container ports: By carrying out efficiency measurement with and without expansion constraint for port area and quay length, we reveal that investment in immobile assets hamper efficiency in only one out of the eight ports investigated. This is likely due to the incentive structure of the port sector in Norway, where publicly owned ports traditionally have been required to use extracted revenues for investments and port development.

Seemingly, there is a productivity gap between Western/Southern and Eastern Norwegian ports, which can relate to differences in market access (e.g. Rødseth et al. 2023). Further investigations into the causes of this gap can lead to better plans for port structure and development, to increase the competitiveness of the Norwegian port sector.

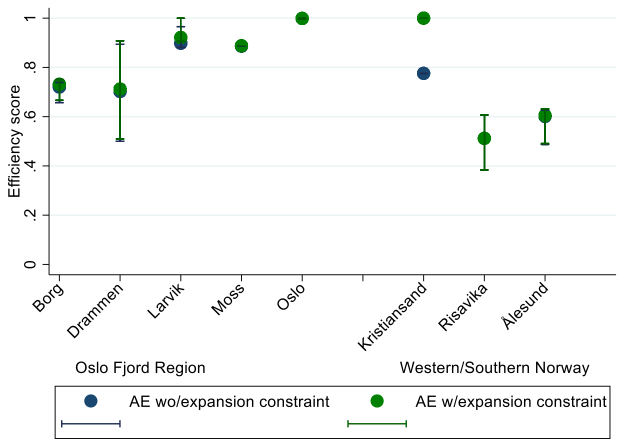

Fig. 5 Allocative efficiency (AE) estimated with (denoted w) and without (denoted wo) potential for expansion of port area and quay length. Mean (dots), interval from minimum and maximum (interval line)

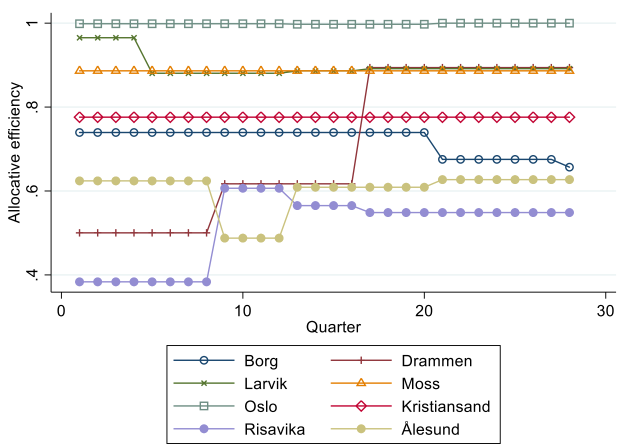

Fig. 6 Intertemporal development of allocative efficiency

As part of our study, we demonstrate how indirect production theory helps alleviating the curse of dimensionality of nonparametric estimators compared to conventional efficiency measurement: Using mathematical analysis, we demonstrate that the indirect approach effectively aggregates all inputs into a single input using input prices as weights. This proves that the indirect approach can be valuable for nonparametric analysis by substantially reducing the dimensionality of the production model when the number of inputs or outputs is large. We consequently foresee that indirect production theory could play an important role in efficiency measurement subject to big data.

In future research, we aim for further exploration of allocative efficiency using the StoNED approach, for example involving more complex applications and testing of assumptions on the assets' adjustability and endogeneity. We thank Rolf and Shawna and their co-authors for their contributions on indirect production theory, which constitute crucial building bricks for our current work.

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Compliance with ethical standards

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