Port efficiency and emissions from ships at berth:
Application to the Norwegian port sector

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Abstract: This paper explores how port efficiency affects the time that ships spend in port and therefore their emissions to air whilst berthed. While the literature on port productivity and efficiency measurement largely ignores this aspect, we explore the productivity measurement biases that arise when resources spent on providing swift cargo-handling are ignored. A distinction is made between ports' technical and scale efficiencies. Their impacts on environmental productivity (i.e., units of cargo handled per unit of ship emissions) are examined using Data Envelopment Analysis on a unique dataset containing information about the duration of cargo-handling operations in the 25 largest ports in Norway. The results show that adopting best practices can significantly improve environmental productivities: If all ports under consideration become technical productive, the environmental productivity of the entire sample would be 80 percent higher. Technical efficiency alone would increase average environmental port productivity by 30 percent. Enhancing traditional port productivity can also substantially improve environmental productivity.

Keywords: *Port productivity; Ship working rate; Most productive scale size; Data envelopment analysis; Air pollution*

Introduction

Policy makers in Norway and Europe view maritime freight transport as a means to achieve a more sustainable transport system and to relieve road congestion. The Norwegian Transport Plan (Meld St. 33, 2016-2017) targets a 30 percent shift from road to rail or sea for all freight transports exceeding 300 kilometers, in line with the European Union's objectives put forth in the white paper *Roadmap to a Single European Transport Area – Towards a competitive and resource efficient transport system* (European Commission, 2011).

Ports are vital components of the maritime transport chain. Their cargo-handling productivity consequently plays an important role in determining the competitiveness of maritime transport, vis à vis other transport modes. The time ships spend in port influences carriers' operating costs (Cullinane and Khanna 2000; Jansson and Schneerson 1987). Moreover, streamlining cargo-handling services can generate benefits throughout supply chains, measured in hours and days saved. Econometric estimates by Hummels and Schaur (2013) suggest that each day goods are in transit is worth 0.6 – 2.1 % of the value of the good.

There is abundant literature which, through econometric or programming techniques,[1] addresses the potential for ports to improve their performance by eliminating technical inefficiencies and exploiting scale economies. Most of these studies pay no attention to the speed of cargo-handling operations, and therefore to

[1] See Rødseth, K.L. and P. B. Wangsness. 2015a. Application of production analysis in port economics: A critical review of modeling strategies and data management, *TØI-rapport 1390/2015*. Transportøkonomisk institutt, Oslo. for a recent review.

the time ships spend at berth. The Tongzon (2001) paper stands out by considering both the quantity of cargo handled and the quality of port services. The latter is operationalized by the *ship working rate*, i.e., the number of containers (or tons of cargo) moved per working hour per ship. Notteboom et al. (2000), on the other hand, consider the speed of cargo-handling to be a potentially inappropriate indicator of efficient resource use, as resources may be left idle for long *between* ship arrivals. Wang et al. (2005) argue that high-quality ports attract more clients, thus showing a strong correlation between cargo throughput and service quality. Correspondingly, these authors propose to include only the throughput variable in port performance assessments. Most of the published papers on port performance measurement follow this approach. Perhaps the reason for this is found in De Koster et al. (2009), who argue that while outputs *should* comprise both cargo throughput *and* quality of customer services, much of the relevant data is strictly confidential. A recent paper by Suárez–Alemán et al. (2014) provides an empirical illustration showing that efficiency scores are significantly altered when one defines output as "throughput per hour" instead of "throughput" (i.e., without reference to the time dimension).

While the ship working rate can be improved by better management of cargo-handling operations, reducing the time spent at berth will ultimately be resource demanding for ports (e.g., requiring new investments in cargo-handling equipment). Consequently, studies that only emphasize *throughput* are likely to provide biased estimates of technical and scale efficiencies. In other words, if a port spends resources on improving its service quality, but valued service quality is not measured, as is the case in most studies on port performance, the port's productivity would be understated.

The ship working rate is also a key determinant of the environmental efficiency of maritime transport. Air pollution from seagoing ships consists of emissions i) in international waters, ii) in national waters and while maneuvering, and iii) while at berth (Hulskotte and Denier van der Gon 2010). Tzannatos (2010) argues that while in-port, emissions make up a small percentage of overall emissions; ports are sources of concentrated exhaust emissions. Cofala et al. (2007) find ship emissions to be the dominant source of urban air pollution in several port cities. Hence, reducing the time that ships spend at berth contributes to reducing harmful air pollution in densely populated areas, for a given cargo volume.

Rødseth et al. (2018) investigate the relationship between returns to density in container handling operations and emissions from ships at berth. Our paper extends their contribution by developing and using *frontier methods*, examining how the duration of cargo-handling is influenced when ports adopt best practices, i.e., *technical and scale efficiencies*. Data Envelopment Analysis (DEA) is applied to a unique dataset containing information on the duration of cargo-handling operations in the 25 largest ports in Norway between 2010 and 2014.

This paper unfolds as follows. The next section establishes the theoretical underpinnings of port performance analysis when the cargo-handling time aspect is considered. The following sections offer an overview of the Norwegian port sector, the construction of the dataset, and the empirical results. The final section concludes.

Theoretical underpinnings

We model cargo-handling as a production process in which a Decision Making Unit (DMU) – in our case, a port – utilizes the input vector $x \in \Re_{+}^{N}$ to handle the throughput of cargo $y \in \Re_{+}^{M}$ within a given timespan (e.g., a year). Let $b \in \Re_{+}$ denote the sum of the durations of cargo-handling operations for all ships that call at the port within the timespan under consideration.[2] The port's technical production possibilities for the period under consideration are summarized by its technology set:

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

Following standard convention, we make several assumptions about the port's production possibilities, specified in the form of axioms. We assume that the technology of the port is non-empty; closed; its output sets are bounded; it satisfies the inactivity and no free lunch axioms; and exhibits convexity and free disposability of inputs and outputs. These axioms are standard, and we do not further elaborate on them (see Färe and Primont (1995) for details). The service quality variable (i.e., the cargo-handling duration) is less common in production analysis, and its properties deserve special treatment.

[2] The total duration of cargo-handling operations does not in general coincide with the timespan under consideration. For example, when there are simultaneous cargo-handling operations taking place at multiple quays in a given year, the aggregate duration of cargo-handling operations can exceed the number of hours in that year.

Two axioms are introduced with reference to this variable. First, time is considered an essential input to processing throughput volume:

i.e., if $(x,b,y) \in T$ and $b = 0,$ then $y = 0$

That is, handling cargo is time consuming. By the *essentiality axiom*, carriers' time costs and ships' air pollution emissions at berth are required to be positive.

Second, time is considered a freely disposable input:

i.e., if $(x,b,y) \in T$ and $b' \geq b$, then $(x,b',y) \in T$

By evoking the *free disposability axiom*, we make three assumptions about the role of time in cargo-handling operations. *First*, free disposability allows managerial inefficiency in cargo-handling operations, i.e., excessive time usage in the handling of throughput. *Second*, when inputs are kept constant, the cargo-handling duration is assumed to be non-decreasing (i.e., either constant or increasing) when the cargo throughput is increased. For example, if a ship is loaded/unloaded by one quay crane on a two-minute cycle, an additional container will add two more minutes of container handling. Hence, there exists a lower level of time required to load/unload a given amount of cargo for a given input vector. *Third*, given the volume of throughput, inputs and cargo-handling duration may be *substitutes*. For example, if the port operates close to capacity, handling cargo may be very time consuming (e.g., containers must frequently be restacked because of lack of storage space). Hence, adding capacity (e.g., port area) may allow a faster handling of the current cargo throughput. The substitutability assumption is paramount as it implies that reducing the time to load/unload cargo can be costly for ports (i.e., after exhausting measures to improve port efficiency[3]), requiring the consumption of additional inputs for handling a given amount of cargo.

Our modeling of the cargo-handling duration differs from the comparable approaches of Tongzon (2001) and Suárez–Alemán et al. (2014). Tongzon models cargo throughput and ship working rate as freely disposable outputs. This axiom allows a positive throughput when the ship working rate is zero (and vice versa), which is counterintuitive, since Tongzon operationalizes the ship working rate as the number of containers moved per working hour. Suárez–Alemán et al. (2014 p. 404) argue that "time cannot be considered as an input which is totally exogenous to the production function, as it usually depends on how the other factors are combined. In the case of infrastructure, a larger or smaller capacity determines the presence or lack of congestion and, therefore, additional delays in the estimated movement time". As explained above, the production model in Eq. 1 is ideal for modeling this case, allowing the cargo-handling duration and inputs to be substitutes. Suárez–Alemán et al. propose a theoretical production model in which the inputs (or, stated differently, their marginal productivities) are functions of the

[3] The discussions about the technical trade-offs between the duration of cargo-handling operations and inputs refer to trade-offs at the boundary of the technology set. For a port located in the interior of the set (i.e., an inefficient unit) it may be possible to improve the ship working rate without changing its current input stock.

cargo-handling duration. While their framework allows substitutability among the cargo-handling duration and inputs, there is one major difference between it and the framework proposed in this paper: Our framework allows reducing cargo-handling duration by increasing one input only, keeping other inputs fixed, while Suárez–Alemán et al.'s model (potentially) requires *all* inputs to change in proportion to the change in cargo-handling duration.[4] Using the example of port congestion, their model may predict that it may not be sufficient to increase the port area to reduce congestion, but that it may also be necessary to cut staff or cargo-handling equipment. Such a rigid model structure makes their model less tractable and less useful for applied research[5].

Note that our model does not rule out that inputs are complements in cargo-handling. We consider this an empirical question rather than imposing a fixed coefficient production structure *a priori*. Using a production model comparable to Eq. 1 for container handling, Rødseth et al. (2018) find that terminal capacity (i.e., area) is more instrumental in saving ships' time at berth than transport and stacking equipment. However, the substitutability among these inputs is found to be limited. Rødseth et al. (2018) consequently conclude that stand-alone investments in an input may be insufficient to improve a port's ship working rate.

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[4] Suárez–Alemán et al. assume a single-output production process, and model the technology by the production function $f\left(x(b)\right) = \sup\left\{y:\left(x(b),y\right)\in T\right\}$. Assuming differentiability, we derive the following condition for changes in the cargo-handling duration that is consistent with a constant output: $\frac{\sum_{n=1}^{N}\frac{\partial f}{\partial x_n}\partial x_n}{\partial b} = 0$. Hence, inputs must change proportionally to ensure that the numerator equals zero if outputs are to be kept constant.

[5] Simple parametric functional forms are assumed for the input functions (i.e., inputs as functions of time) and constant returns to scale is imposed globally to obtain the model used for estimation.

So far, we have established the theoretical framework. To apply it to empirical analysis, we turn to function representations of the technology that can be estimated from data. Because we are interested in measuring the productivity of the port[6] under consideration and to examine productivity-biases resulting when resources spent on improving the ship working rate fail to be acknowledged, we prefer the Førsund and Hjalmarsson (1979) *technical productivity measure*.[7] This measure is normally presented in the one-input one-output case. We define its generalization to multiple inputs and outputs as follows:

$$TP\left(x,b,y\right)=\inf_{\mu,\theta}\left\{\frac{\mu}{\theta}:\left(\frac{x}{\theta},\frac{b}{\theta},\frac{y}{\mu}\right)\in T\right\} \qquad (2)$$

TP seeks to scale inputs, cargo-handling durations, and outputs to maximize the productivity of the port (or data point), with consideration to its current input-output mix. It equals 1 if the DMU under consideration is technically productive, and it takes a value less than 1 if the DMU is inefficient (i.e., technically unproductive).

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[6] One referee pointed out that the term "port productivity" encompasses characteristics that go beyond the ship working rate, including ship idle time and time spent on hinterland transports. We acknowledge that such aspects are relevant, but data limitations prevent us from taking them into account. We stress that previous studies (e.g., Johnson and Styhre, 2015) have shown that the cargo-handling time is frequently the dominating component of ships' time in port. It is also contingent on the port's ship working efficiency, ship type, and type of cargo being handled (Stopford, 2009), while aspects such as the time for hinterland transport may depend on factors which are not under the jurisdiction of the port (e.g., road congestion).

[7] In the initial publication, Førsund and Hjalmarsson dubbed the measure "gross scale efficiency", but later adopted the term "technical productivity".

Note that *TP* is the reciprocal of Banker's (1984) model for the assessment of the most productive scale size.

Eq. 2 is linked to Shephard's well-known (1970) *output distance function* (or equivalently, Farrell's (1957) output-oriented technical efficiency measure) that expands outputs proportionally to the production frontier for given inputs:

$$D_O\left(x,b,y\right)=\inf_{\beta}\left\{\beta:\left(x,b,\frac{y}{\beta}\right)\in T\right\} \tag{3}$$

in the sense that Eq. 2 can be solved in two steps, first with respect to y and then with respect to $\left(x,b\right)$:

$$\begin{aligned} TP\left(x,b,y\right)&=\inf_{\theta}\left\{\frac{\inf_{\mu}\left\{\mu:\left(\frac{x}{\theta},\frac{b}{\theta},\frac{y}{\mu}\right)\in T\right\}}{\theta}\right\} \\ &=\inf_{\theta}\left\{\frac{D_O\left(\frac{x}{\theta},\frac{b}{\theta},y\right)}{\theta}\right\} \end{aligned} \tag{4}$$

where $D_0\left(\frac{x}{\theta},\frac{b}{\theta},y\right)$ is the output distance function defined by Eq. 3.

The technical productivity measure projects any point in the technology to a point on its frontier consistent with constant returns to scale (CRS). This can easily be illustrated by assuming differentiability of the output distance function, as the first order condition of Eq. 4 then reads:

$$
\begin{aligned}
&\frac{-\left[\sum_{n=1}^{N}\frac{\partial D_0\left(\frac{x}{\theta},\frac{b}{\theta},y\right)}{\partial x_n}\frac{x_n}{\theta}+\frac{\partial D_0\left(\frac{x}{\theta},\frac{b}{\theta},y\right)}{\partial b}\frac{b}{\theta}+D_0\left(\frac{x}{\theta},\frac{b}{\theta},y\right)\right]}{\theta^2}=0 \\
&\Leftrightarrow -\frac{\sum_{n=1}^{N}\frac{\partial D_0\left(\frac{x}{\theta},\frac{b}{\theta},y\right)}{\partial x_n}\frac{x_n}{\theta}+\frac{\partial D_0\left(\frac{x}{\theta},\frac{b}{\theta},y\right)}{\partial b}\frac{b}{\theta}}{D_0\left(\frac{x}{\theta},\frac{b}{\theta},y\right)}=1
\end{aligned}
\tag{5}
$$

The latter expression states that the elasticity of scale, measured in terms of the output distance function (see Färe and Primont, 1995; p. 39), equals unity in optimum – which implies CRS.

We now focus on decomposing the technical productivity measure, as it can broadly be perceived as comprising both technical and scale efficiency. We do this by choosing exogenous weights for inputs for the TP-measure. Consider

$$
TE(x,b,y)=\inf_{\mu}\left\{\frac{\mu}{1}:\left(\frac{x}{1},\frac{b}{1},\frac{y}{\mu}\right)\in T\right\}=D_O(x,b,y) \tag{6}
$$

i.e., the output distance function (see Eq. 3) is our measure of technical efficiency (TE). It quantifies the potential to increase the cargo volume given the resources already employed to handle cargo. Intuitively, because Eq. 6 is a restricted version of Eq. 2, $TP\left(x,b,y\right)$ is by definition smaller or equal to $TE\left(x,b,y\right)$.[8] The ratio of the technical productivity and efficiency measures is then our indicator of scale efficiency, i.e., $TP\left(x,b,y\right)/TE\left(x,b,y\right)$, i.e., losses in productivity due to failure to adopt the most productive scale size.

Figure 1 presents the piecewise linear technology in the one-input one-output case and illustrates its function representations and technical and scale efficiencies. The frontier of the (variable returns to scale) piecewise linear technology is spanned by the two DMUs A and C, while DMU B operates in the interior of the technology set; hence, it is inefficient. The technical inefficiency of DMU B is indicated by the solid arrow from point B to the section of the frontier defined by convex combinations of DMUs A's and C's input-output mixes. TE measures how much more throughput DMU B would be capable of handling given its input endowment, had it adopted best practices. The TP-measure, on the other hand, aims to maximize the unit's productivity (i.e., the ratio of y to x). For the case at hand, the maximal productivity is indicated by the dotted line, and is only exhibited by DMU A. Hence, TP reduces both DMU B's input and output to maximize productivity (i.e., to equate DMU B with DMU A, which is technical

[8] A formal proof can be found in Banker, R.D. and R.M. Thral, 1992. Estimation of returns to scale using data envelopment analysis. *European Journal of Operational Research* 62(1), 74-84. Note that other exogenous weights for inputs or outputs will also lead to lower or equal productivity when compared to *TP*.

productive). This means that DMUs B and C are “too large”, in the sense that they operate under decreasing returns to scale (although DMU C is technically efficient). The ratio of the technical productivity measure to the technical efficiency measure is our scale efficiency measure. Mathematically, the scale efficiency measure can equally be represented by the (vertical) distance from the technology to the dotted ray through point A, as indicated by the dotted arrow of Figure 1. This will be further discussed in the Data Envelopment Analysis section.

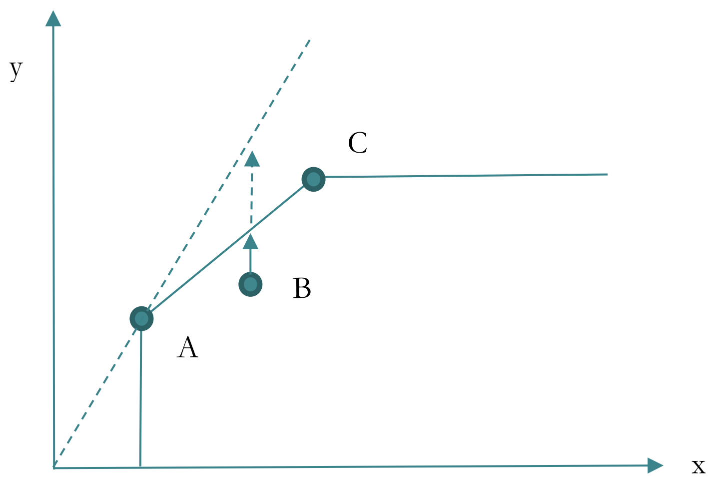

Figure 1: The technology and its function representations

Environmental productivity

Because our modeling comprises the time required to load/unload cargo, it enables us to analyze air pollution emissions due to ships at berth in the scenarios that ports become technical and scale efficient. We adopt the approach of the EPA (2009) to estimate emissions from ships at berth, for each call, as the product of i) the ship’s maximum continuous rating auxiliary power; ii) its auxiliary engine load factor; iii) the ship-specific emission factor; and iv) the number of hours spent at berth. Since the three former factors are ship-specific, we can define a vector $z \in \Re_+^K$ of ship characteristics. A general expression for the emission of a given air pollutant $e \in \Re_+$ is thus $e = g(z)b$, where $g(z)$ is the product of factors i)-iii), resulting in emissions per hour of berthing.

Let $r \in \Re_+^M$ be a vector of output weights that convert cargoes into a common metric, e.g. tons. The port's current environmental productivity can then be defined:

$$EP_0 = \frac{ry}{e} = \frac{ry}{g(z)b} \tag{7}$$

e.g., tons of cargo handled per ton of air pollution from ships during berthing. In general, this measure depends on the cargo mix and ship types that call at the port. Under technical efficiency, the environmental productivity is:

$$EP_{TE} = \frac{r\frac{y}{\beta}}{g(z)b} = EP_0 \frac{1}{TE(x,b,y)} \tag{8}$$

Correspondingly, under technical productivity:

$$EP_{TP} = \frac{r\frac{y}{\mu}}{g(z)\frac{b}{\theta}} = EP_0 \frac{1}{TP(x,b,y)} \tag{9}$$

Data envelopment analysis

We now turn to the empirical estimation of the technical productivity and efficiency measures outlined above. The port economics literature normally considers DEA or Stochastic Frontier Analysis (SFA) approaches for this purpose, and DEA appears to have become relatively more popular in recent years (Schøyen and Odeck 2013). Based on this finding, along with the fact that DEA – unlike SFA – is a nonparametric technique that does not require the selection of functional form, we prefer the DEA approach.

In recent years, a statistical approach to DEA has been introduced, based on the idea that the technology is estimated from a subset of the true but unknown technology, thereby implying that the estimated efficiency scores are downward biased in small samples. Bias correction using bootstrapping is generally seen as a remedy for this problem (Simar and Wilson 2008). However, with a (very) small sample, the same observations will frequently repeat in bootstrap samples and even the bootstrap samples themselves can repeat. Chernick (2008) therefore proposes a minimum required sample size of at least 50 observations to estimate the variability of the population data in nonparametric problems. Our dataset contains annual data for 25 ports, and we therefore refrain from using bootstrapped DEA. Instead, we apply “traditional” DEA, which is in line with most of the existing studies on port performance (Barros et al. 2010).

Assume there are *l=(1,..,L)* ports in the dataset. Each port uses inputs $x^l = \left(x_1^l,..,x_N^l\right) \in \Re_+^N$ to handle the throughput of cargo $y^l = \left(y_1^l,..,y_M^l\right) \in \Re_+^M$. The duration of cargo-handling operations is denoted $b^l \in \Re_+$. Let λ^l , *l=(1,..,L),* define the intensity variables. The variable returns to scale (VRS) estimator of the technical productivity measure for DMU *l'* is then defined:

$$TP\left(x^{l'}, b^{l'}, y^{l'}\right) = \min_{\mu,\theta,\lambda}\left\{\frac{\mu}{\theta}: \begin{array}{l} \sum_{l=1}^{L} \lambda^l y_m^l \geq \frac{y_m^{l'}}{\mu}, \quad m = 1,..,M \\ \sum_{l=1}^{L} \lambda^l b^l \leq \frac{b^{l'}}{\theta} \\ \sum_{l=1}^{L} \lambda^l x_n^l \leq \frac{x_n^{l'}}{\theta}, \quad \mathrm{n} = 1,..,N \\ \sum_{l=1}^{L} \lambda^l = 1, \quad \lambda \geq 0 \end{array}\right\} \tag{10}$$

Eq. 10 constitutes a programming problem with a nonlinear objective function. In the appendix, we show that the inverse of Eq. 10 can be obtained by the following simple linear programming problem:

$$\frac{1}{TP\left(x^{l'},b^{l'},y^{l'}\right)}=\max_{\delta,\tilde{\lambda}}\left\{\delta: \quad \begin{aligned} &\sum_{l=1}^{L}\tilde{\lambda}^{l}y_{m}^{l}\geq\delta y_{m}^{l'}, \quad m=1,..,M \\ &\sum_{l=1}^{L}\tilde{\lambda}^{l}b^{l}\leq b^{l'} \\ &\sum_{l=1}^{L}\tilde{\lambda}^{l}x_{n}^{l}\leq x_{n}^{l'}, \qquad \mathrm{n}=1,..,N \\ &\tilde{\lambda}\geq 0\right\} \end{aligned} \tag{11}$$

where $\delta=\left(\theta/\mu\right)$ and $\tilde{\lambda}=\left(\lambda/\left(1/\theta\right)\right)$.

Next, we calculate the technical productivity measure when the duration of cargo-handling operations is endogenously determined to maximize productivity:

$$TP\left(x^{l'},b,y^{l'}\right)=\min_{\mu,\theta,b,\lambda}\left\{\frac{\mu}{\theta}: \quad \begin{aligned} &\sum_{l=1}^{L}\lambda^{l}y_{m}^{l}\geq\frac{y_{m}^{l'}}{\mu}, \quad m=1,..,M \\ &\sum_{l=1}^{L}\lambda^{l}b^{l}\leq\frac{b}{\theta} \\ &\sum_{l=1}^{L}\lambda^{l}x_{n}^{l}\leq\frac{x_{n}^{l'}}{\theta}, \quad \mathrm{n}=1,..,N \\ &\sum_{l=1}^{L}\lambda^{l}=1, \quad \lambda\geq 0\right\} \end{aligned} \tag{12}$$

Since b is endogenous, it does not restrict the productivity optimization. Thus, the corresponding constraint for the duration of cargo-handling operations can safely be omitted without influencing the solution to Eq. 12. Applying the transformations of variables in the Appendix, the inverse of Eq. 12 can then be estimated:

$$\frac{1}{TP\left(x^{l'},b,y^{l'}\right)}=\frac{1}{TP\left(x^{l'},y^{l'}\right)}=\max_{\delta,\tilde{\lambda}}\left\{\delta:\begin{array}{l}\sum_{l=1}^{L}\tilde{\lambda}^{l}y_{m}^{l}\geq\delta y_{m}^{l'},\quad m=1,..,M\\ \sum_{l=1}^{L}\tilde{\lambda}^{l}x_{n}^{l}\leq x_{n}^{l'},\quad \mathrm{n}=1,..,N\\ \tilde{\lambda}\geq 0\end{array}\right\} \tag{13}$$

The model in Eq. 13 coincides with the standard approach in the port efficiency literature, where the cargo-handling duration is omitted (Suárez-Alemán et al. 2014). Eqs. 12-13 demonstrate that the standard approach (implicitly) assumes that the ship working time is allocated to maximize traditional productivity. Consequently, service and environmental qualities are neither acknowledged nor rewarded in the efficiency analysis, as the shadow price on the cargo-handling variable is zero.

Finally, we calculate the (inverse of the) technical efficiency score with the time variable included:

$$\frac{1}{TE\left(x^{l'},b^{l'},y^{l'}\right)}=\max_{\tilde{\beta},\lambda}\left\{\tilde{\beta}:\begin{array}{l}\sum_{l=1}^{L}\lambda^{l}y_{m}^{l}\geq\tilde{\beta}y_{m}^{l'},\quad m=1,..,M\\ \sum_{l=1}^{L}\lambda^{l}b^{l}\leq b^{l'}\\ \sum_{l=1}^{L}\lambda^{l}x_{n}^{l}\leq x_{n}^{l'},\quad \mathrm{n}=1,..,N\\ \sum_{l=1}^{L}\lambda^{l}=1,\ \lambda\geq 0\end{array}\right\} \tag{14}$$

where $\tilde{\beta} = (1/\beta)$.

Based on our estimates, we calculate scale efficiencies i) without the consideration of service quality $\left(TP\left(x^{l'}, y^{l'}\right)/TE\left(x^{l'}, b^{l'}, y^{l'}\right)\right)$ and ii) when the service quality output is recognized $\left(TP\left(x^{l'}, b^{l'}, y^{l'}\right)/TE\left(x^{l'}, b^{l'}, y^{l'}\right)\right)$. By definition, $TP\left(x^{l'}, \mathrm{y}^{l'}\right) \leq TP\left(x^{l'}, b^{l'}, y^{l'}\right) \leq TE\left(x^{l'}, b^{l'}, y^{l'}\right)$, and thus $\left(TP\left(x^{l'}, y^{l'}\right)/TE\left(x^{l'}, b^{l'}, y^{l'}\right)\right) \leq \left(TP\left(x^{l'}, b^{l'}, y^{l'}\right)/TE\left(x^{l'}, b^{l'}, y^{l'}\right)\right)$. Comparing the two scale efficiency scores allows us to evaluate the degree to which ignoring service and environmental qualities leads to overstatement of a port's potential to improve its productivity.

The solutions to Eqs. 11 and 13, i.e. $\delta^* = (\theta/\mu)^*$, do not readily allow identifying the cargo-handling time consistent with CRS. This can be identified by solving two additional programs:

$$\min_{\hat{\lambda},(1/\mu),(1/\theta)} \left\{ (1/\theta): \begin{array}{l} \sum_{l=1}^{L} \hat{\lambda}^l y_m^l \geq \left(\dfrac{1}{\mu}\right) y_m^{l'}, \quad m = 1,..,M \\ \sum_{l=1}^{L} \hat{\lambda}^l b^l \leq \left(\dfrac{1}{\theta}\right) b^{l'} \\ \sum_{l=1}^{L} \hat{\lambda}^l x_n^l \leq \left(\dfrac{1}{\theta}\right) x_n^{l'}, \quad \mathrm{n} = 1,..,N \\ (1/\mu) = \delta^* (1/\theta), \ \sum_{l=1}^{L} \hat{\lambda}^l = 1, \ \hat{\lambda} \geq 0 \end{array} \right\} \tag{15}$$

for Eq. 11, and

$$\min_{b,\hat{\lambda},(1/\mu),(1/\theta)} \Big\{ b: \quad \sum_{l=1}^{L} \hat{\lambda}^l y_m^l \geq \left(\frac{1}{\mu}\right) y_m^{l'}, \quad m = 1,..,M$$

$$\sum_{l=1}^{L} \hat{\lambda}^l b^l \leq b \tag{16}$$

$$\sum_{l=1}^{L} \hat{\lambda}^l x_n^l \leq \left(\frac{1}{\theta}\right) x_n^{l'}, \qquad \mathrm{n} = 1,..,N$$

$$\left(1/\mu\right) = \delta^* \left(1/\theta\right), \ \sum_{l=1}^{L} \hat{\lambda}^l = 1, \ \hat{\lambda} \geq 0 \Big\}$$

for Eq. 13.

If there are multiple solutions, the programs in Eqs. 15 and 16 will select the minimal cargo-handling durations from the VRS-technology consistent with CRS. Banker et al. (1996) note that multiple optima are unlikely in empirical analysis as their prerequisite is linearly dependent efficient observations.

Data on the Norwegian port sector

Norwegian ports handle more than 200 million tons of cargo annually, servicing both domestic and international traffic. In 2014 there were 125 publicly owned ports on the Norwegian mainland and 2 on the island Svalbard (Statistics Norway, 2015).[9] Most of these ports are small in terms of their cargo and passenger throughputs, and only 25 of them handled more than 1,000,000 tons of cargo and/or 200,000 passengers annually over the entire period for which we have data. Since these 25 ports are likely to play a lead role in the transfer of cargo from road to

[9] In addition, there are over 600 publicly owned ports related to the fishing industry (The Norwegian Coastal Administration, 2015), as well as private ports. They are not considered in this paper. Note, however, that some private terminals are included in the 25 ports under consideration in this study.

maritime transport – and because high-quality data are available for these ports only – we focus on them in the subsequent analysis. Their combined throughput amounted to 75 percent of total Norwegian port throughput, including that of private ports (Statistics Norway 2015). Moreover, our selection criterion ensures that the ports included in the production analysis are comparable in terms of their throughput. Note that our analysis focuses solely on the cargo-handling of cargo; passenger throughput is not considered.

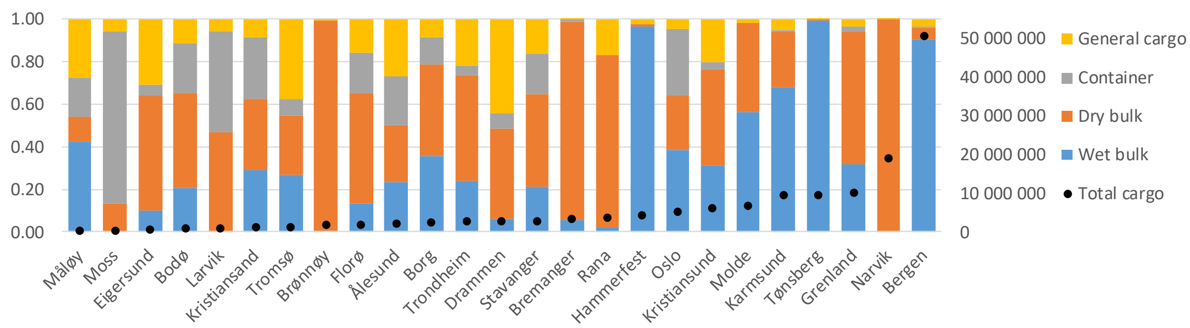

Figure 2: Cargo shares and total annual throughput volumes in tons (Average for 2010-2014)

Figure 2 presents the 25 ports' average cargo shares in terms of throughput volumes (bar charts) and total tons of cargo handled (dots) for the years 2010 to 2014. 14 of the ports handled less than 3 million tons, 6 of the ports handled between 3 and 7 million tons, 3 ports handled between 9 and 11 million tons, while 2 ports handled more than 19 million tons of cargo. Moreover, the ports range from highly specialized (e.g., Moss (containers); Brønnøy, Bremanger, Rana, and Narvik (dry bulk); Hammerfest, Tønsberg, and Bergen (wet bulk)) to multi-purpose ports (e.g., Måløy and Ålesund). The ports may thus differ substantially in terms of their exploitation of scale and scope economies.

Dry and wet bulks constitute 36 and 53 percent, respectively, of the (average) total tons of cargo handled by the 25 ports. The corresponding shares for containers and general cargo are 4 and 6 percent of the total throughput. Norway is an oil-exporting country, which explains why wet bulk is dominating the country's port throughput. Its container ports are scattered and relatively small. The vessels that call at them are consequently small and of the feeder type (Schøyen and Odeck, 2017).

A production process normally involves both inputs that are fixed and variable in the short-run. In cargo-handling, port infrastructure (e.g., area, quays) is an example of the former, while labor, energy, and cargo-handling equipment and its operation are examples of the latter. A major challenge in applied port production analyses is that high-quality data on variable inputs is lacking (Rødseth and Wangsness 2015b). For our application on Norwegian ports, we consider the technology to comprise two inputs (port area[10] and total quay length), the duration of cargo-handling operations, and four outputs (i.e., the cargo types dry bulk, wet bulk, containers, and general cargo). In general, the number of variables included in our proposed model specification (7) is high compared to the number of annual

[10] Thereby, we mean the total area comprised by the port, also including structures. We have asked the 25 ports under consideration in this study to report the overall port area in a way that is consistent with the cargo throughput reported by Statistics Norway's port statistics.

observations (25), as the DEA loses power to discriminate among efficient and inefficient ports when the dimensionality of the technology increases. Nevertheless, based on a discussion with the management of the port of Oslo, we conclude that area and quay lengths must be considered essential to ship and cargo-handling, for all types of cargo. As area and quay length are not highly correlated, omission of one of them is not justified. Jara-Diaz et al. (2006) emphasize the necessity of accounting for the diversity of cargo throughput to avoid biased estimates of marginal costs and the exploitation of economies of scale.

By excluding variable inputs, our modeling approach is unable to identify whether differences in the performance of ports relate to differences in their employment of variable (non-observable) inputs, or to managerial inefficiency (i.e., "wasting" of observable and non-observable inputs).[11] However, following the reasoning of Eqs. 12-13, this approach (implicitly) assumes that the employment of variable inputs is endogenously determined to maximize the productivity of the (observable) inputs included in the model. Färe et al. (1989) used a similar approach to measure capacity utilization, drawing on Leif Johansen's definition of capacity as the maximum amount that can be produced with given assets when variable inputs are freely accessible. Consequently, our measure of technical efficiency (i.e., Eq. 14) should be interpreted as deviation from maximal capacity utilization, as opposed to managerial efficiency. This is, in our opinion, not a drawback, as knowledge about the optimal exploitation of the current Norwegian port

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[11] See Rødseth, K.L and P.B. Wangsness. 2015b. Data availability for traditional and environmental productivity and efficiency analyses of Norwegian ports, *TØI report 1461/2015*. Transportøkonomisk instutitt, Oslo. for a formal treatment on this issue.

infrastructure is paramount when planning a large-scale shift from road to maritime transport. Moreover, adding input variables to the model would severely reduce the ability of DEA to discriminate between Norwegian ports' capacity utilizations.

Our dataset is constructed based on Statistics Norway's quarterly port statistics, which as previously noted is limited to ports that handle more than 1,000,000 tons of cargo and/or 200,000 passengers annually. We have been granted access to the (sensitive) raw data underlying the publicly available port statistics for the five years between 2010 and 2014. This has given us data on each call that involves handling of cargo in the 25 selected ports (comprising about 50 000 calls per year) for all five years. We thus have had detailed information about the throughput of different cargo types, the duration of cargo-handling operations, and ship characteristics (e.g. ship classification and gross tonnage). These data are essential to the production modeling and for estimating emissions to air from ships at berth.

The construction of the dataset can be summarized as the process of linking together separate datasets on cargo-handling with data sets on time spent in port, data cleansing, and imputing missing values for time observations for approximately 20 % of the ports of call. The process is described in detail in Rødseth and Wangsness (2015b).

Port infrastructure data was collected from publicly available sources (e.g., port websites), and was later reviewed by the ports under consideration.[12] De Koster

[12] Two of the 25 ports did not respond to our request to review the data. However, seeing that these ports do not influence our results by playing important roles in the construction of the reference

et al. (2009) and Schøyen and Odeck (2013) consider cross-checking the data with the port management to be good practice, as they often find public data to be unreliable.

We have estimated emissions to air, associated with operating the ship's auxiliary engines while cargo is loaded and/or unloaded for each call. We build these estimates from data on ships' engine power, obtained from (sensitive) ship register data provided by The Norwegian Coastal Administration. As ship register data do not cover all ships for which we have port of call data, engine power had to be imputed in some cases. We then applied parameter values for auxiliary power to propulsion power ratio, auxiliary engine load factors, and emission factors from EPA (2009) to estimate emissions to air (see the appendix in Rødseth et al. (2018) and section 6.2 in Rødseth and Wangsness (2015b) for further details).

Table 1 summarizes these estimates, aggregated to the port level, as well as the other variables included in our dataset.

Table 1: Summary statistics, port level

		Outputs				Inputs			Bad outputs		
		Wet bulk (tons)	Dry bulk (tons)	Container (TEUs)	General cargo (tons)	Time use (hrs)	Area (Sq.m)	Berth length(m)	CO_2 (tons)	NO_X (tons)	PM_{10} (tons)
2010	Mean	3 296 314	2 110 701	32 244	393 399	32 719	503 697	2 927	4 887	98	1.3
	Std Dev	8 999 063	3 525 097	43 372	472 944	29 514	556 041	2 309	6 099	123	1.6
	Median	445 412	978 345	15 754	233 932	23 582	325 000	2 185	3 442	69	0.9
	Min	0	38 923	0	3 404	1 568	3 200	140	209	4	0.1
	Max	44 862 866	17 544 312	201 893	1 898 947	136 805	2 000 000	9 922	29 582	595	7.7
2011	Mean	3 363 214	2 151 358	27 026	388 727	32 360	503 697	2 927	4 743	95	1.2

technology, and by considering the drawbacks of reducing the sample size, we decided to keep the two ports in the sample.

	Std Dev	9 516 770	3 533 968	43 370	481 294	27 557	556 041	2 309	5 697	115	1.5
	Median	348 903	1 171 149	13 467	250 376	24 067	325 000	2 185	3 569	72	0.9
	Min	0	44 474	0	2 240	2 398	3 200	140	223	4	0.1
	Max	47 466 320	17 644 114	208 799	1 984 892	135 595	2 000 000	9 922	29 235	588	7.6
2012	Mean	3 416 147	2 265 190	27 714	408 461	31 675	504 107	2 951	4 873	98	1.3
	Std Dev	9 720 445	3 867 757	41 720	572 320	29 271	555 823	2 323	6 721	135	1.8
	Median	403 377	1 129 341	15 886	246 120	25 227	325 000	2 185	3 081	62	0.8
	Min	0	56 102	0	2 724	1 439	3 200	140	217	4	0.1
	Max	48 702 632	19 363 487	202 816	2 512 938	144 175	2 000 000	9 922	34 558	695	9.0
2013	Mean	3 452 103	2 263 852	33 752	391 111	33 014	516 795	3 014	5 024	101	1.3
	Std Dev	10 082 574	3 950 470	45 520	445 647	30 214	564 489	2 403	6 904	139	1.8
	Median	360 541	1 128 836	16 383	247 953	27 140	325 000	2 185	3 356	68	0.9
	Min	0	57 270	0	3 531	1 514	6 700	305	208	4	0.1
	Max	50 526 132	19 782 351	202 469	1 625 447	148 073	2 000 000	9 922	35 301	710	9.2
2014	Mean	2 956 602	2 334 602	35 961	364 047	31 589	517 035	3 014	5 639	113	1.5
	Std Dev	7 672 327	4 191 461	47 532	405 479	29 786	564 448	2 403	7 166	144	1.9
	Median	356 378	1 275 795	20 569	257 891	19 806	325 000	2 185	3 675	74	1.0
	Min	0	38 340	0	0	1 733	6 700	305	196	4	0.1
	Max	37 987 641	21 007 961	212 724	1 603 178	137 846	2 000 000	9 922	34 547	695	9.0

We consider our dataset to give very good coverage for analyzing the productivity of the Norwegian port sector, as it comprises the most important ports – with every registered call involving cargo-handling in these ports – and most of the cargo handled by the sector. Our data and the following analysis are consistent in the use of the *port* as the DMU. In general, we respond to the criticism in De Koster et al. (2009) on current port productivity analysis by i) avoiding inconsistent use of terminals and ports as decision making units, ii) by avoiding uncritical use of public data that might be of questionable quality, and iii) by taking the quality of customer service into account through the inclusion of cargo-handling durations.

Results

We estimate the DEA models using annual data, as described in earlier sections. As a first step, we undertake two tests to identify outliers. First, we estimate super-efficiency scores (Andersen and Petersen, 1993). Several of the units in the sample receive super-efficiency scores above one, implying that they are important for constructing the reference technology. This finding is not surprising given the ratio of the number of variables to the number of observations, along with the sector's diversified cargo types, as presented in Figure 2. Moreover, the scores change over time, and units that are super-efficient in one year may be inefficient in another. However, two ports – Bergen and Florø – stand out as particularly super-efficient for the entire period between 2010 and 2014. Further examination revealed that these ports had under-reported areas and quay-lengths, and their capacity data was consequently updated prior to estimation.[13] Second, we estimate the metric of Torgersen et al. (1996) to rank efficient units by their importance as benchmarks for inefficient ones. This test shows that some ports (in particular the multi-purpose ports Kristiansund and Drammen) are important benchmarks in some years, but not for the entire period under consideration. This intertemporal variation indicates that extreme units are the product of the small sample size and the curse of dimensionality in DEA, rather than errors in measuring inputs and outputs. Dropping DMUs from the sample, based on the outlier tests, will further amplify

[13] This update had only a minor impact on the empirical results.

the problem, leaving the DEA approach incapable of differentiating among ports. Hence, we refrain from dropping units from the sample.

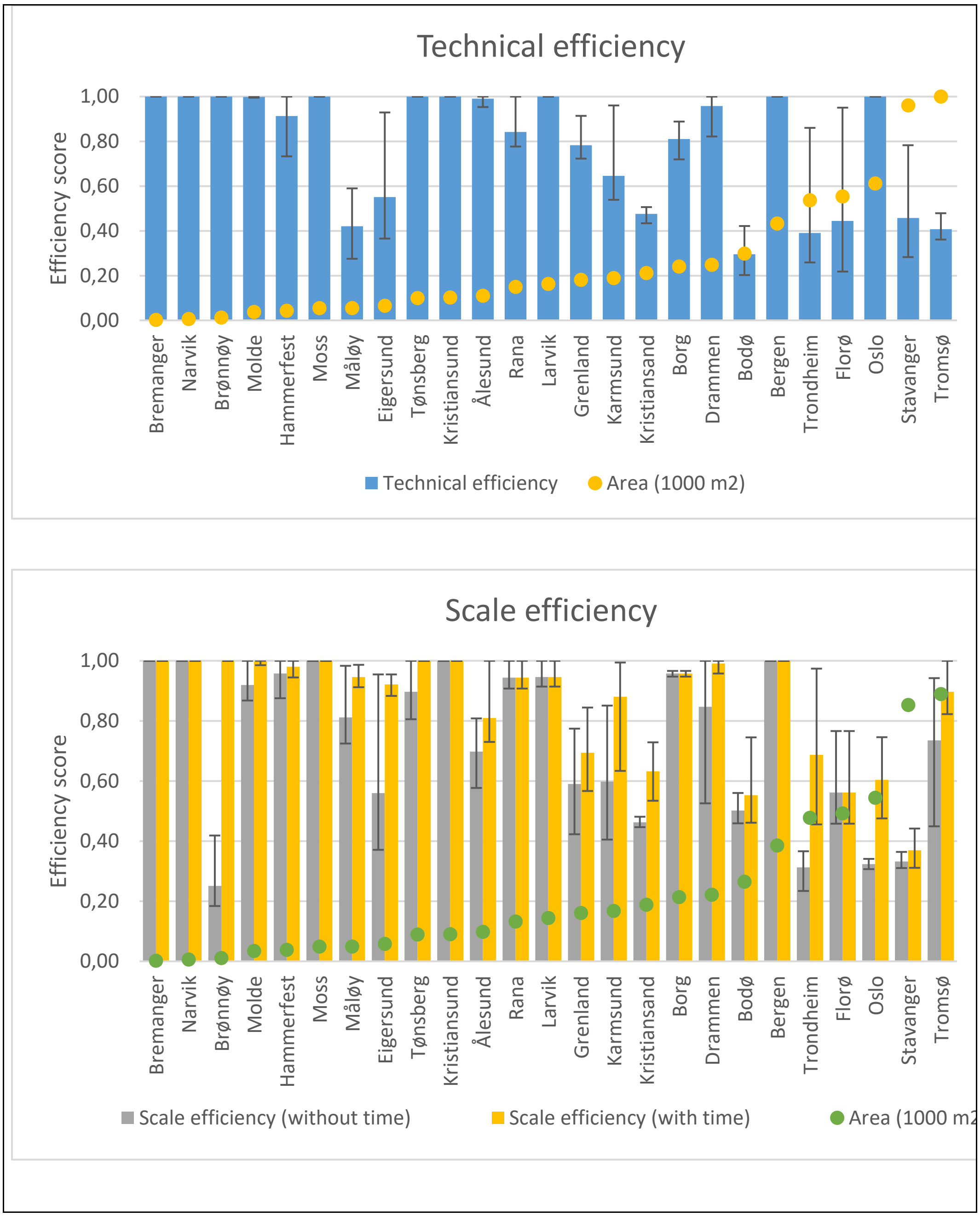

Figure 3: Technical and scale efficiencies ranked according to port capacity (Average, Min, and Max for 2010-2014)

Figure 3 reports technical and scale efficiencies, estimated for each port, for each year between 2010 to 2014. The ports are listed according to their capacities (approximated by port area). The bars indicate average port (in)efficiency over the 5-year period, while the line plots indicate the continuum between the ports' highest and lowest (annual) efficiency scores.

Figure 3 shows that technical and scale efficiencies are positively correlated, i.e., ports that currently display excess capacity have generally not adopted the most productive size. Moreover, we find that *spatially constrained ports more often operate under maximal capacity utilization* compared to spatially large ports. For example, Bremanger and Narvik are both found to be technical and scale efficient for the entire period under consideration. Spatially large ports such as Trondheim and Stavanger, on the other hand, display the opposite results, which could be an indication of overcapacity in the Norwegian port sector. This pattern is, however, not consistent over time, which probably reflects the volatility in the demand for freight transport. Note for example that Trondheim's and Florø's technical efficiency scores range from about 0.9 (almost technical efficient) to 0.25 (strongly inefficient). Our results further indicate that highly specialized ports (described above) generally operate under maximal capacity utilization. This result must be evaluated keeping in mind that efficiency scores are estimated based on a very small sample, made up of ports that are heterogeneous in terms of their cargo mix. Hence, specialized ports have few peers.

Next, we turn to the implications of accounting for cargo-handling durations in port productivity measurement. The lower panel of Figure 3 presents scale efficiencies when the duration of cargo-handling operations *is* (yellow bars) and *is not* (grey bars) included in the model. Overall, the empirical results suggest that *deviations from the most productive size* can be severely overstated when service quality is ignored. This is in particular the case for Brønnøy, which is scale efficient when the cargo-handling duration is controlled for, but becomes strongly scale inefficient when it is not. Note that the potential to improve productivity is overstated for ports in several of the largest cities in Norway (i.e., Oslo, Trondheim, Stavanger, and Kristiansand), which suggests that rapid cargo-handling is critical here.

We now return to the second core issue of this paper, namely the impact of port performance on environmental productivity. In line with Rødseth et al. (2018), we single out the local air pollutant nitrogen oxides (NO_x) due to its potent damage potential in port cities.

Figure 4 depicts aspects of Norwegian ports' environmental productivities in an overlapped bar chart, using efficiency scores for 2014. Current environmental productivities for NO_x (EP_0 - the grey bars) are displayed in the front. Behind the grey bars we show environmental productivities under *technical efficiency* with orange bars (EP_{TE}), which are taller than the grey bars when the ports are technical inefficient. Furthest in the back we show environmental productivities under *technical productivity* with light blue bars (EP_{TP}), which are taller than the grey and orange bars when the ports are scale inefficient. Hence, in the case where a port is technical productive, EP_{TP} is identical to EP_0 and only the grey bar is visible. If the port is technical efficient but scale inefficient, EP_{TE} is identical to EP_0, and the grey bar will be just as tall as the orange bar, but the light blue bar will be taller than the grey bar. If the port is neither technical nor scale efficient, then both the orange and the light blue bars are visible.

Figure 4 also shows the ports' environmental efficiencies obtained from Eqs. 13 and 16 (represented by dark blue bars), when the cargo-handling time variable is endogenously determined to maximize the ports' traditional productivities (EP_{trad}). For the visual presentation in Figure 4, the ports are sorted in ascending order according to their bulk shares, i.e., the combined tonnage of dry and wet bulk cargoes, relative to the overall tonnage handled by the port. The reason is that the speed of cargo-handling operations varies across cargo-handling methods for different types of cargo (Ghoos et al., 2004).

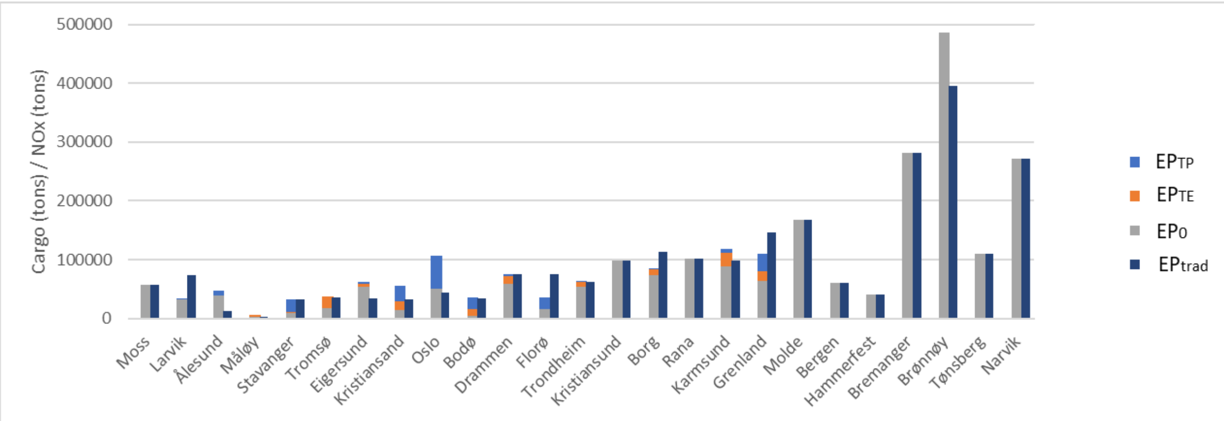

Figure 4: Environmental productivities for 2014, sorted according to the shares of bulk cargoes

The mix of cargoes and ship types appear to be of great importance for the proposed measure of environmental productivity, namely tons of cargo per emission unit. We find that the dry bulk intensive ports of Narvik, Bremanger, and Brønnøy exhibit the highest environmental productivities in the sample. These ports move large amounts of cargo with relatively low emissions because of low time usage, but also because of relatively low emissions per hour from the auxiliary engines of the observed dry bulk carriers. These ports are also found to be technical productive.

Adopting best practices can significantly improve environmental productivities. Seven of the 25 ports in the sample – Måløy, Stavanger, Tromsø, Kristiansand, Oslo, Bodø, and Florø – could have more than doubled their environmental productivities by moving to the frontier. Half of them could have doubled environmental productivity just by eliminating technical inefficiencies. If all ports became technical productive, the environmental productivity of the entire sample would become 1.8 times higher. If all ports that are technical inefficient became technical efficient, average environmental productivities would be 1.3 times higher than current environmental productivities.

Finally, we compare the environmental productivities under technical efficiency and productivity (where time is already implicitly assumed to be allocated efficiently) to the environmental productivities obtained from Eq. 16, when the time variable is allocated to maximize traditional productivity. The environmental productivities are on average 1.7 times higher than current productivities in this case, which illustrates that merely improving traditional productivity will benefit the environment. In the case of Larvik, Florø, Borg and Grenland, the environmental productivities are in fact higher when traditional productivity is maximized using Eq. 13, compared to when the time variable is included in the efficiency measurement. However, when looking at the entire sample, the environmental productivity is on average 23 percent higher when the time variable is included in the analysis compared to the case where it is ignored. This finding underlines the importance of including the swiftness cargo-handling as a variable in port productivity analysis, as it also has major implications for environmental productivities and efficiencies.

Conclusions

Does port efficiency matter for the environmental impacts of maritime transport? Our empirical results do indeed support this claim. Even efficiency improvements that do not target the port's ship working rate are found to be beneficial for the environment. Improvements in environmental productivity could come from both technical and scale efficiency adoption, but the Norwegian ports' greatest potential lies in technical efficiency improvement. This result can partly be explained by previous findings, reporting overcapacity in the Norwegian port sector (Rødseth and Killi 2014), which contributes to low capacity utilization. With the prospects for growth in maritime transport, this could be turned around in the near future.

This paper has focused on emission reductions by means of reducing the time ships spend on cargo-handling cargo. Such improvements can also benefit carriers, and thus increase Norwegian ports' attractiveness to shippers and carriers. This is a prerequisite for achieving the policy objective of shifting freight transport from road to sea. However, improving cargo-handling productivity alone may not suffice, and steps must be taken to ensure that the time benefits ships reap from swifter cargo-handling are converted into productive time rather than idle time in port. From the point of view of the environment, ancillary benefits will occur if carriers invest time benefits reaped into slow steaming between ports; see e.g., Cariou (2011).

The applicability of our approach is not limited to efficiency analysis. Future research should explore the shape of the efficient point set of the technology proposed in this paper, to identify marginal time requirements for cargo-handling of various types of cargo (i.e., the change in cargo-handling time by an infinitesimal increase in an output). First, the marginal time requirements may be useful from a port pricing perspective, facilitating differentiation of port fees according to the quantity and quality of port services provided. Second, the marginal time requirements can be combined with a monetized damage function to form estimates of marginal external air pollution costs due to ports' cargo-handling. Moreover, the concept of shadow pricing[14] allows estimating the value of time. To our knowledge, estimates of value of time from the perspective of the port – unlike from the perspective of carriers – are rare. If ports' 'value of time' are found to differ from carriers' value of time, this might suggest that port fees subject to quality premiums could be welfare enhancing.

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[14] See Rødseth, K.L., 2013. Capturing the least costly way of reducing pollution: a shadow price approach. *Ecological Economics* 92: 16-24. for a discussion of this technique.

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References

Andersen, P., and N.C. Petersen. 1993. A Procedure for Ranking Efficient Units in Data Envelopment Analysis. *Management Science* 39 (10): 1261-1264.

Banker, R.D. 1984. Estimating most productive scale size using data envelopment analysis. *European Journal of Operational Research* 17 (1): 35-44.

Banker, R.D., H. Chang, and W.W. Cooper. 1996. Equivalence and implementation of alternative methods for determining returns to scale in data envelopment analysis. *European Journal of Operational Research* 89 (3): 473-481.

Banker, R.D., and R.M. Thrall. 1992. Estimation of returns to scale using data envelopment analysis. *European Journal of Operational Research* 62 (1): 74-84.

Barros, C.P., A. Assaf, and A. Ibiwoye. 2010. Bootstrapped technical efficiency of African seaports, In: Coto-Millán, P., A.M. Pesquera, and J. Castanedo (Eds.), *Essays on Port Economics*. Physica-Verlag HD, Heidelberg: 237-250.

Cariou, P., 2011. Is slow steaming a sustainable means of reducing CO2 emissions from container shipping? *Transportation Research Part D: Transport and Environment* 16 (3): 260-264.

Chernick, M.R., 2008. *Bootstrap methods. A guide for practitioners and researchers. Second edition*. John Wiley & Sons Inc., Hoboken.

Cofala, J., M. Amann, C. Heyes, F. Wagner, Z. Klimont, M. Posch, W. Schöpp, L. Tarasson, J.E. Jonson, C. Whall, and A. Stavrakaki. 2007. Analysis of policy measures to reduce ship emissions in the context of the revision of the National Emissions Ceilings Directive. Final report. International Institute for Applied Systems Analysis, Laxenburg, Austria.

Cullinane, K., and M. Khanna. 2000. Economies of scale in large containerships: optimal size and geographical implications. *Journal of Transport Geography* 8 (3): 181-195.

EPA, 2009. Current methodologies in preparing mobile source port-related emission inventories. U.S. Environmental Protection Agency, Virginia.

European Commission, 2011. Roadmap to a Single European Transport Area – Towards a competitive and resource efficient transport system, Brussels, COM(2011) 144 final.

Farrell, M.J. 1957. The measurement of productive efficiency. *Journal of the Royal Statistical Society* 120, Part 3 (Series A, General): 253-281.

Färe, R., S. Grosskopf, and V. Valdmanis. 1989. Capacity, competiton and efficiency in hospitals: A nonparametric approach. *Journal of Productivity Analysis* 1 (2): 123-138.

Färe, R., and D. Primont. 1995. *Multi-output production and duality: theory and applications*. Kluwer Academic Publishers, Boston.

Førsund, F., and L. Hjalmarsson. 1979. Generalised Farrell measures of efficiency: An application to milk processing in Swedish dairy plants. *Economic Journal* 89 (354): 294-315.

Ghoos, H., J. Korsgaard, L. Runge-Schmidt, and H. Agerschou. 2004. Berth and terminal design in general. Storage facilities and cargo-handling systems, In: Agerschou, H. (Ed.), *Planning and Design of Ports and Marine Terminals,* Thomas Telford, London.

Hulskotte, J.H.J., and H.A.C. Denier van der Gon. 2010. Fuel consumption and associated emissions from seagoing ships at berth derived from an on-board survey. *Atmospheric Environment* 44 (9): 1229-1236.

Hummels, D.L., and G. Schaur. 2013. Time as a trade barrier. *American Economic Review* 103 (7): 2935-2959.

Jansson, J.O., and D. Schneerson. 1987. *Liner Shipping Economics*. Chapman & Hall, London.

Jara-Díaz, S.R., E. Martínez-Budría, and J.J. Díaz-Hernández. 2006. Multiple outputs in port cost functions. *Research in Transportation Economics* 16: 67-84.

Johnson, H., and L. Styhre. 2015. Increased energy efficiency in short sea shipping through decreased time in port. *Transportation Research Part A: Policy and Practice, 71:* 167-178.

De Koster, M.B.M., B.M. Balk, and W.T.I.v. Nus. 2009. On using DEA for benchmarking container terminals. *International Journal of Operations & Production Management* 29 (11): 1140-1155.

Meld. St. 33, 2016–2017. National transport plan 2018-2029. Report to the Storting (white paper).

Notteboom, T., C. Coeck, and J. Van Den Broeck. 2000. Measuring and explaining the relative efficiency of container terminals by means of Bayesian Stochastic Frontier Models. *International Journal of Maritime Economics* 2 (2): 83-106.

Rødseth, K.L. 2013. Capturing the least costly way of reducing pollution: a shadow price approach. *Ecological Economics* 92: 16-24.

Rødseth, K.L., and M. Killi. 2014. Marginale eksterne kostnader for godstransport på sjø og jernbane – en forstudie *TØI rapport 1313/2014*. Transportøkonomisk institutt, Oslo.

Rødseth, K.L., and P.B. Wangsness. 2015a. Application of production analysis in port economics: A critical review of modeling strategies and data management, *TØI-rapport 1390/2015*. Transportøkonomisk institutt, Oslo.

Rødseth, K.L., and P.B. Wangsness. 2015b. Data availability for traditional and environmental productivity and efficiency analyses of Norwegian ports, *TØI report 1461/2015*. Transportøkonomisk instutitt, Oslo.

Rødseth, K.L., P.B. Wangsness, and H. Schøyen. 2018. How do economies of density in container handling operations affect ships' time and emissions in port? Evidence from Norwegian container terminals. *Transportation Research Part D: Transport and Environment* 59: 385-399.

Schøyen, H., and J. Odeck. 2013. The technical efficiency of Norwegian container ports: A comparison to some Nordic and UK container ports using Data Envelopment Analysis (DEA). *Maritime Economics & Logistics* 15 (2): 197-221.

Schøyen, H., and J. Odeck. 2017. Comparing the productivity of Norwegian and some Nordic and UK container ports – An application of Malmquist Productivity Index. *International Journal of Shipping and Transport Logistics* 9: 234-256.

Shephard, R.W. 1970. *Theory of Cost and Production Functions*. Princeton University Press, Princeton.

Simar, L., and P.W. Wilson. 2008. Statistical inference in nonparametric frontier models: recent developments and perspectives, In: Fried, H.O., C.A.K. Lovell, and S.S. Schmidt (Eds.), *The Measurement of Productive Efficiency and Productivity Growth*. Ocford University Press, New York.

Stopford, M. 2009. *Maritime Economics 3ed*. Routledge, London.

Suárez-Alemán, A., L. Trujillo, and K. Cullinane. 2014. Time at ports in short sea shipping: When timing is crucial. *Maritime Economics & Logistics* 16 (4): 399-417.

Statistics Norway. 2015. https://www.ssb.no/statbank/list/havn

The Norwegian Coastal Administration. 2015. https://www.kystverket.no/Maritim-infrastruktur/Havner/Bygging-og-vedlikehold-av-fiskerihavner/

Tongzon, J., 2001. Efficiency measurement of selected Australian and other international ports using data envelopment analysis. *Transportation Research Part A: Policy and Practice* 35 (2): 107-122.

Torgersen, A.M., F.R. Førsund, and S.A.C. Kittelsen. 1996. Slack-adjusted efficiency measures and ranking of efficient units. *Journal of Productivity Analysis* 7(4): 379-398.

Tzannatos, E., 2010. Ship emissions and their externalities for the port of Piraeus – Greece. *Atmospheric Environment* 44 (3): 400-407.

Wang, T., K. Cullinane, and D.W. Song. 2005. *Container Port Production and Economic Efficiency*. Palgrave Macmillan, New York.

APPENDIX

We start with the program in Eq. 10:

$$TP\left(x^{l'}, b^{l'}, y^{l'}\right) = \min_{\mu,\theta,\lambda}\left\{\frac{\mu}{\theta}: \begin{array}{ll} \sum_{l=1}^{L}\lambda^{l} y_{m}^{l} \geq \frac{y_{m}^{l'}}{\mu}, & m=1,..,M \\ \sum_{l=1}^{L}\lambda^{l} b^{l} \leq \frac{b^{l'}}{\theta} & \\ \sum_{l=1}^{L}\lambda^{l} x_{n}^{l} \leq \frac{x_{n}^{l'}}{\theta}, & \mathrm{n}=1,..,N \\ \sum_{l=1}^{L}\lambda^{l} = 1, \quad \lambda \geq 0 \end{array}\right\} \tag{i}$$

Its inverse is:

$$\frac{1}{TP\left(x^{l'},b^{l'},y^{l'}\right)}=\max_{(1/\mu),(1/\theta),\lambda}\left\{\frac{(1/\mu)}{(1/\theta)}:\begin{array}{l}\sum_{l=1}^{L}\lambda^{l}y_{m}^{l}\geq(1/\mu)\,y_{m}^{l'},\quad m=1,..,M\\ \sum_{l=1}^{L}\lambda^{l}b^{l}\leq(1/\theta)\,b^{l'}\\ \sum_{l=1}^{L}\lambda^{l}x_{n}^{l}\leq(1/\theta)\,x_{n}^{l'},\qquad \mathrm{n}=1,..,N\\ \sum_{l=1}^{L}\lambda^{l}=1,\ \ \lambda\geq 0\end{array}\right\} \tag{ii}$$

Which may be rewritten as:

$$\frac{1}{TP\left(x^{l'},b^{l'},y^{l'}\right)}=\max_{(1/\mu),(1/\theta),\lambda}\left\{\frac{(1/\mu)}{(1/\theta)}:\begin{array}{l}\sum_{l=1}^{L}\frac{1}{(1/\theta)}\lambda^{l}y_{m}^{l}\geq\frac{(1/\mu)}{(1/\theta)}y_{m}^{l'},\quad m=1,..,M\\ \sum_{l=1}^{L}\frac{1}{(1/\theta)}\lambda^{l}b^{l}\leq b^{l'}\\ \sum_{l=1}^{L}\frac{1}{(1/\theta)}\lambda^{l}x_{n}^{l}\leq x_{n}^{l'},\qquad \mathrm{n}=1,..,N\\ \sum_{l=1}^{L}\frac{1}{(1/\theta)}\lambda^{l}=\frac{1}{(1/\theta)},\ \ \frac{1}{(1/\theta)}\lambda\geq 0\end{array}\right\} \tag{iii}$$

Consider the summing-up condition for the modified intensity variable, i.e., $\sum_{l=1}^{L}\frac{1}{(1/\theta)}\lambda^{l}=\frac{1}{(1/\theta)}$. This condition ensures that $\sum_{l=1}^{L}\lambda^{l}=1$, but it places no bounds on $\sum_{l=1}^{L}\frac{1}{(1/\theta)}\lambda^{l}$. Intuitively, this means that λ^{l}, *l=(1,..,L)*, is used for constructing the frontier by selecting a point, or convex combination of data points, while the scalar $\frac{1}{(1/\theta)}$ allows contracting or expanding the selected data point(s).

Consequently, since $\sum_{l=1}^{L} \frac{1}{(1/\theta)} \lambda^l$ is unbounded, the summing up condition for the modified intensity variables can safely be omitted from Eq. (iii) without influencing the result of the optimization.

Let $\delta = ((1/\mu)/(1/\theta)) = (\theta/\mu)$ and $\tilde{\lambda} = (\lambda/(1/\theta))$. Then program (iii) collapses into Eq. 11:

$$\frac{1}{TP\left(x^{l'}, b^{l'}, y^{l'}\right)} = \max_{\delta, \tilde{\lambda}} \left\{ \delta : \begin{array}{l} \sum_{l=1}^{L} \tilde{\lambda}^l y_m^l \geq \delta y_m^{l'}, \quad m = 1,..,M \\ \sum_{l=1}^{L} \tilde{\lambda}^l b^l \leq b^{l'} \\ \sum_{l=1}^{L} \tilde{\lambda}^l x_n^l \leq x_n^{l'}, \qquad \text{n} = 1,..,N \\ \tilde{\lambda} \geq 0 \right\} \end{array} \tag{iv}$$