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Decomposing growth in Norwegian seaport container throughput and associated air pollution

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ABSTRACT

While policy makers worldwide view maritime transport as a sustainable alternative to road freight transport, increased cargo volumes by sea inevitably boost activities in ports that are in the proximity of where people live. This paper proposes a production analysis framework for examining intertemporal changes in cargo volumes and in-port air pollution that decomposes the contributions of ship characteristics and port container handling productivity, efficiency, and technical changes to the overall changes. The framework is applied to analyze container handling in Norway from 2010 to 2015. The results indicate that increasing ship sizes lead to more pollution per hour spent berthing, but at the same time it often leads to higher container handling productivities and thus possibly to ships spending less time in port per container loaded/unloaded. While technical changes are found to reduce the duration of container handling by about 2–3 percent per quarter, port container handling productivity and efficiency changes appear to be the main drivers of environmental productivity growth.

1. Introduction

Policy makers view maritime freight transport as a means to achieve a more sustainable transport system and to relieve road congestion. Norway and the EU target a 30 percent shift from road to rail or sea for all freight transports exceeding 300 km. In Norway, the prospect for mode shift lies in container shipping, which has increased in volume by more than 60 percent since 2003; cf. Fig. 1. This merely reflects the global development: Tran and Haasis (2015) report a sixfold increase of the carrying capacity of the world container fleet since 1990.

70 percent of air emissions from ships' diesel engines occur within a range of 400 km from land where they can affect coastal areas (Eyring et al., 2010). The contribution of ship emissions to population load and mortality is largest in areas where settlements are found in close proximity of a harbor (Andersson et al., 2009; Corbett et al., 2007; Salo et al., 2016). In Norway, many of the largest ports are located in city centers.

There are several pathways towards cleaner (i.e. environmental productive) port operations (Dai et al., 2018; UNCTAD, 2018), e.g., investments in environmental projects, air emission charges, and changes in demand patterns of transport markets. Styhre et al. (2017) identify four key measures to reduce ship emissions in port: Speed reductions in fairway channels; on-shore power supply; alternative fuels; and reducing ship turnaround times.

Factors that contribute to ports' environmental productivity development are subject to the decision domains of several agents. On the one hand, global regulations have been put in place to curb air emissions from ships in port areas (e.g., EU's Sulfur Directive)

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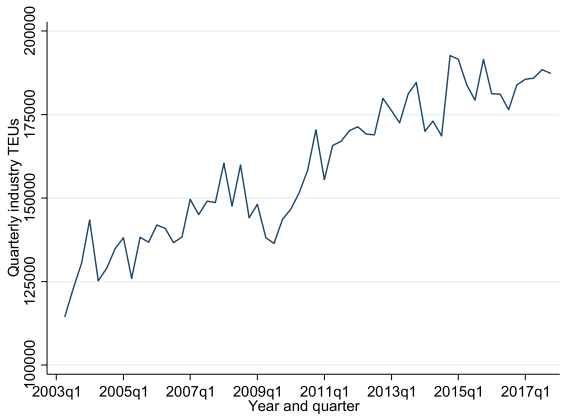

Fig. 1. Quarterly lo-lo container volumes (TEUs) handled by Norwegian ports. (Source: Statistics Norway).

or coastal regions (e.g., Emission Control Areas). The promotion of low-sulfur fuels is expected to bring about substantial reductions in sulfur dioxides emissions and to affect particulate emissions and sulphate, which is a dominating aerosol component (i.e., particulates) from ship emissions (Contini et al., 2011). Moreover, port managers are adopting tools, including market access control and monitoring, to promote sustainable operations (Song and Panayides, 2012; Lam and Notteboom, 2014). On the other hand, economies of scale in shipping mean that the marginal private costs are reduced as the freight volumes grow (Stopford, 2009), which results in a tendency towards larger ships in many shipping segments. This trend leads to higher emissions per ship per hour at berth or at sea. However, Rødseth et al. (2018) find that larger ships and consequently greater volumes per call reduce the handling time per container and therefore increase the environmental efficiency of port operations. The outcomes of these opposing forces on ports' environmental productivity development cannot be determined a priori, which calls for empirical productivity analysis.

There exists an extensive literature that uses Stochastic Frontier Analysis (SFA) or Data Envelopment Analysis (DEA) – with DEA being the most common method (Odeck and Bråthen, 2012) – to analyze port productivity and efficiency. Most of these studies emphasize economic efficiency and only a few studies treat environmental performance (OConnor et al., 2019). In addition, most port productivity studies disregard the time that ships spend in port (Suárez-Alemán et al., 2014; Rødseth et al., 2019), leaving them incapable of analyzing how improvements in port performance contribute to reducing ship turnaround times and consequently to environmental productivity growth. De Langen et al. (2007) consider the scarcity of empirical analyzes of ship turnaround times to be associated with the lack of publicly available data.

This paper presents a novel analysis of the environmental productivity development of container ports in Norway. A Data Envelopment Analysis (DEA) framework for decomposing the contributions of ship characteristics and port container handling productivity, efficiency, and technical changes to the environmental productivity development is proposed. A unique panel dataset containing the largest container ports in Norway, covering port inventories, container volumes, time at berth during container handling, and associated sulfur oxides (SO_x) emission, is used to evaluate their quarterly environmental productivity growth between 2010 and 2015. The paper also contributes to the literature by developing and using a bottom-up methodology to estimate and compare SO_x emissions of several ports, while the literature on in-port emissions predominately comprises case studies of a single port or port city (see for example Berechman and Tseng, 2012; Chang et al., 2012). The variety of methods and definitions used makes it difficult to compare their results (Merk, 2012).

The reasons for focusing on SO_x are as follows. First, reducing sulfur oxides emissions from ships has received much attention for decades, mainly in Europe and North America (Salo et al., 2016). Moreover, SO_x emissions have in recent times been the main environmental concern related to merchant shipping (Zis and Cullinane, 2020). Second, SO_x is the only pollutant that was subject to intensity standards in Norwegian waters in the period under consideration in this paper. It should therefore be considered among the most important detrimental effects of shipping, and environmental legislation makes it very relevant to consider its environmental productivity development.

Environmental productivity growth is inevitably tied to the concept of decoupling. While studies that examine the relative development of freight volumes and emissions to air in road transport are plentiful (e.g., Alises et al., 2014; Kveiborg and Fosgerau, 2007; Sorrell et al., 2009), studies that explicitly address the relationship between the volume of containers handled and ship emissions whilst berthed are lacking. With the prospects of and political will to promote growth in maritime transport, this paper provides important new evidence of the development of ship emissions accompanying the growth in maritime transports.

This paper is outlined as follows. Section 2 presents the proposed methodology. Section 3 presents the dataset and its compilation, while Section 4 presents the empirical results. Section 5 discusses the main findings and identifies topics for future research.

2. Methodology

This section presents the proposed methodology to estimate and decompose environmental productivity change in container handling. The point of departure is a microeconomic production model framework for analyzing container handling based on

technology sets. This section outlines how the associated technology sets and minimal emissions can be estimated using nonparametric methods. Finally, an environmental productivity index is proposed and decomposed into multiple sources of changes over time.

2.1. Modeling container handling operations

Technology sets T^t are used to represent all technically feasible container handling operations of the ports in period t, with $t = 1, ...,T$. The ports (superscript P) are assumed to use M inputs $\boldsymbol{x}_t^P \in \mathbb{R}_+^M$ (e.g. the number of quay cranes and reach stackers) to load/unload containers, with $y_t \in \mathbb{R}_+$ denoting the number of containers. Following Rødseth (2017b), the capacities of the ships (superscript S), denoted $x_t^S \in \mathbb{R}_+$, are included as an additional input to account for the impact of ship capacity utilization on freight transport productivity. This variable is largely ignored by port productivity analyzes albeit ship sizes and capacity utilization likely matter for container handling productivities (Martin et al., 2015). To account for environmental pollution generated while handling the cargo, sulfur oxides emissions from the ships being loaded/unloaded, which are denoted by $b_t \in \mathbb{R}_+$, are included. These emissions are calculated as $b_t = e_t z_t$, where $e_t \in \mathbb{R}_+$ denotes emissions per hour the (average) ship is berthed and $z_t \in \mathbb{R}_+$ denotes the total duration of container handling operations in period t.

The technology set of period t contains all technically feasible input–output combinations. The modeling of technologies that encompass intended and unintended outputs has received much attention in recent years: Plentiful modeling approaches have been proposed, including weak disposability (Färe et al., 1989; 2005), the by-production model (Førsund, 2009; Murty et al., 2012), and the materials balance approach (Coelli et al., 2007; Rødseth, 2017a). Our approach is rooted in the materials balance approach that uses emission factors to characterize emissions. To model the container handling and the environmental pollution in a joint technology set, this paper follows Hampf (2014) by defining the overall technology set T^t as the intersection of the production technology set T_y^t and the emission generating technology set T_b^t. Therefore, the overall technology set of period t reads as

$$T^t = T_y^t \cap T_b^t = \{(\boldsymbol{x}_t^P, x_t^S, z_t, y_t, b_t): (\boldsymbol{x}_t^P, x_t^S, z_t, y_t) \in T_y^t, \ (z_t, b_t) \in T_b^t\} \tag{1}$$

where

$$\begin{aligned} T_y^t &= \{(\boldsymbol{x}_t^P, x_t^S, z_t, y_t): \ (\boldsymbol{x}_t^P, x_t^S, z_t) \ \text{ can } \ \text{produce } \ y_t\} \\ T_b^t &= \{(z_t, b_t): b_t = e_t z_t\} \end{aligned} \tag{2}$$

To estimate T_y^t and, hence, T^t from empirical data, axioms regarding the structure of the technology need to be imposed. Following Rødseth et al. (2018), T_y^t is considered to satisfy the usual axioms of production analysis; no free lunch, inactivity, closedness, free disposability of inputs and outputs, and convexity. See Färe and Primont (1995) for a description of these axioms.

Note that the duration of container handling operations is treated as a freely disposable input, which means i) there is a lower bound to the amount of time that is required to handle a certain number of containers and ii) that handling time and other inputs are substitutes. The latter implies that the handling duration may be reduced by costly investments in port or ship capacity or other inputs, thereby ensuring that improvements in service quality – operationalized by swift container handling – are costly.

Based on the overall technology set, the minimal emissions needed to load/unload a fixed number of containers can be estimated as

$$b^t(\boldsymbol{x}_t^P, x_t^S, y_t) = \min_{z,b}\{b: (\boldsymbol{x}_t^P, x_t^S, z, y_t, b) \in T^t\} = e_t z^t(\boldsymbol{x}_t^P, x_t^S, y_t) \tag{3}$$

In this optimization, the amount of pollution is minimized by minimizing the berthing time required to load/unload y_t containers given $\boldsymbol{x}_t^P$ and x_t^S. Hence, the inputs and ship characteristics are assumed to be exogenous. In equation (3), the time *superscripts* refer to the time period of the technology while the time *subscripts* refer to the time period of the inputs and outputs. Thus, mixed-period emission amounts, which are obtained e.g. by estimating the minimal emissions given the technological possibilities of period $t + 1$ and the input–output combination of period t, are denoted by $b^{t+1}(\boldsymbol{x}_t^P, x_t^S, y_t)$.

The ratio of minimal to actual emissions $(b^t(\boldsymbol{x}_t^P, x_t^S, y_t)/b_t) \in [0, 1]$ denotes the level to which emissions can be reduced by adopting best-practices. Therefore, it is a measure of efficiency with $(b^t(\boldsymbol{x}_t^P, x_t^S, y_t)/b_t) < 1$ indicating inefficient container handling operations.

In production economic studies based on panel data, the above defined technologies are commonly known as "contemporaneous" sets (see Tulkens and Vanden Eeckaut (1995)) since they only contain observations from time period t. While contemporaneous technology sets allow for a straightforward extension of static technology estimations to dynamic analyses (i.e., a static technology set for each t is estimated independently), this approach leads to several limitations when comparing technologies and minimal emissions over time. First, as noted by Shestalova (2003), the effects of business cycles on the production decisions are captured in changes of the technology sets, leading to recessions or seasonal variations being misclassified as technical regress of the production possibilities[1]. Second, using contemporaneous technologies, the mixed-period emission amounts are not always computable, leading to infeasible results in the decomposition of the environmental productivity index presented in Section 2.3. Finally, using technologies from periods t and $t + 1$, it is not a priori clear whether technical change is evaluated relative to the production points in period

[1] We are grateful to an anonymous referee for adding a caveat that business cycles may affect efficiency changes (rather than technical changes) when sequential technologies are being used.

t or $t+1$. To resolve this issue, most of previous analyzes follow Färe et al. (1994) and use the geometric mean of changes in the technology set to quantify technical change.

In this study, sequential and biennial technology sets are used to avoid the limitations of contemporaneous technology sets. Following Tulkens and Vanden Eeckaut (1995) as well as Shestalova (2003), the sequential technology set of period t is given by

$$\widetilde{T}^t = \text{convex}\left\{\bigcup_{s=1}^{t} T^t\right\} \tag{4}$$

i.e., by the convex hull of the union of all contemporaneous technology sets from periods 1 to t. This implies that production points which are feasible in a period s also are feasible in all following periods $t \geqslant s$. Therefore, technical regress is precluded. Moreover, the convex hull ensures that $\widetilde{T}^t$ satisfies the convexity axiom since the union of convex sets is not necessarily convex.

In addition, by combining the biennial technology set proposed by Pastor et al. (2011) with the sequential technology set defined above, this paper uses a novel biennial, sequential technology

$$\widetilde{T}_B^{t,t+1} = \text{convex}\{\widetilde{T}^t \cup \widetilde{T}^{t+1}\} \tag{5}$$

Using a biennial technology set, the mixed-period minimal emission amounts are always computable. Hence, feasible results for the environmental productivity index can be derived for all observations. This is useful for the application on Norwegian container ports, for which the number of observations is limited. Note that by construction $\widetilde{T}_B^{t,t+1} = \widetilde{T}^{t+1}$ and, thus, the biennial, sequential technology of periods t and $t+1$ as well as the sequential technology of period $t+1$ describe the same production possibilities.

2.2. Estimating technology sets and minimal emissions

In this study, nonparametric methods are applied to estimate the above defined technology sets and minimal emissions using empirical data. In contrast to parametric approaches, these methods neither rely on specific functional forms of the boundary of the technology set (the production function) nor on a specific distribution of the inefficiency term. The nonparametric DEA by Charnes et al. (1978) estimates the technology set by a piecewise linear envelopment of the observed input–output combinations subject to the axiomatic restrictions of the sets as described in Section 2.1.

Given a sample of $i = 1, ..., n$ decision making units (DMUs, in this study ports) with input–output combinations $(\boldsymbol{x}_{it}^P, x_{it}^S, z_{it}, b_{it}, y_{it})$, the DEA estimator for the contemporaneous, overall technology set reads as

$$\hat{T}^t = \left\{ \begin{array}{c} (\boldsymbol{x}_t^P, x_t^S, z_t, b_t, y_t)\colon \boldsymbol{x}_t^P \geq \boldsymbol{X}_t^P \boldsymbol{\lambda}_t,\ x_t^S \geq \boldsymbol{x}_t^{S'} \boldsymbol{\lambda}_t,\ y_t \leq \boldsymbol{y}_t' \boldsymbol{\lambda}_t,\ z_t \geq \boldsymbol{z}_t' \boldsymbol{\lambda}_t, \\ b_t = e_t z_t,\ \mathbf{1}' \boldsymbol{\lambda}_t = 1,\ \boldsymbol{\lambda}_t \geq \mathbf{0} \end{array} \right\} \tag{6}$$

Here, $\boldsymbol{X}_t^P$ denotes the $M \times n$ matrix of port inputs for all n ports while $\boldsymbol{x}_t^{S'}$, $\boldsymbol{y}_t'$ and $\boldsymbol{z}_t'$ denote the transpose of the $n \times 1$ vectors of ship capacities, loaded/unloaded containers and container handling times, respectively. The inequality constraints on the inputs and outputs follow from the free disposability assumption: See Thanassoulis et al. (2008) for a further discussion on the construction of nonparametric DEA estimators. Moreover, $\boldsymbol{\lambda}_t$ denotes the $n \times 1$ vector of weight factors which are used to construct convex combinations of observations. Restricting these factors to be non-negative and to sum to unity imposes variable returns to scale (VRS) on the technology sets (see Banker et al. (1984)). Constant returns to scale (CRS) can be imposed by dropping the summing-up constraint in equation (6).

Like the contemporaneous technology set, the DEA estimator for the sequential technology set is given by

$$\hat{\widetilde{T}}^t = \left\{ \begin{array}{c} (\boldsymbol{x}_t^P, x_t^S, z_t, b_t, y_t)\colon \boldsymbol{x}_t^P \geq \widetilde{\mathbf{X}}_t^P \widetilde{\boldsymbol{\lambda}}_t,\ x_t^S \geq \widetilde{\mathbf{x}}_t^{S'} \widetilde{\boldsymbol{\lambda}}_t,\ y_t \leq \widetilde{\mathbf{y}}_t' \widetilde{\boldsymbol{\lambda}}_t,\ z_t \geq \widetilde{\mathbf{z}}_t' \widetilde{\boldsymbol{\lambda}}_t, \\ b_t = e_t z_t,\ \mathbf{1}' \widetilde{\boldsymbol{\lambda}}_t = 1,\ \widetilde{\boldsymbol{\lambda}}_t \geq \mathbf{0} \end{array} \right\} \tag{7}$$

In this formulation, the matrices and vectors exhibiting a tilde contain the corresponding data for all periods from 1 to t. For example, the $M \times (n \cdot t)$ matrix $\widetilde{\boldsymbol{X}}_t^P$ contains the port inputs for all n ports covering the periods 1 to t. In addition, the $1 \times (n \cdot t)$ vector $\widetilde{\boldsymbol{\lambda}}_t$ of weight factors also allows for intertemporal convex combinations to impose convexity on the sequential technology set.

As previously noted, the biennal, sequential technology set of periods t and $t+1$ is equal to the sequential technology set of period $t+1$. Therefore, the corresponding DEA estimator is given by

$$\hat{\widetilde{T}}_B^{t,t+1} = \hat{\widetilde{T}}^{t+1} \tag{8}$$

Based on these estimators of the technology sets, the minimal emissions as defined in (3) can be estimated for a DMU i by solving linear programming problems. Given a contemporaneous specification of the technology set, the associated linear programming problem reads as

$$\begin{aligned} \min_{z,b,\lambda_t} \quad & b \\ & \boldsymbol{x}_{it}^P \geq \boldsymbol{X}_t^P \boldsymbol{\lambda}_t \\ & x_{it}^S \geq \boldsymbol{x}_t^{S'} \boldsymbol{\lambda}_t \\ s.\ t. \quad & y_{it} \leq \boldsymbol{y}_t' \boldsymbol{\lambda}_t \\ & z \geq \boldsymbol{z}_t' \boldsymbol{\lambda}_t \\ & b = e_{it} z \\ & \mathbf{1}' \boldsymbol{\lambda}_t = 1 \\ & \boldsymbol{\lambda}_t \geq \mathbf{0} \end{aligned} \tag{9}$$

Here, the minimal emissions associated with loading/unloading y_{it} containers are estimated by identifying the best-practice observations (or a convex combination thereof) via the $\boldsymbol{\lambda}_t$-variables and the optimal container handling time z.

Denoted by $\hat{b}^t(\boldsymbol{x}_{it}^P, x_{it}^S, y_{it})$ are the minimal emissions estimated by solving (9). The minimal emissions resulting from a sequential technology set can be obtained by replacing the restrictions in (9) by the restrictions of (7). The corresponding minimal emissions are denoted by $\hat{\hat{b}}^t(\boldsymbol{x}_{it}^P, x_{it}^S, y_{it})$ while the minimal emissions resulting from the biennial technology set are denoted by $\hat{\hat{b}}_B^{t,t+1}(\boldsymbol{x}_{it}^P, x_{it}^S, y_{it})$.

The estimation of minimal emissions can be simplified by noting that in the optimum $z = \boldsymbol{z}_t' \boldsymbol{\lambda}_t$ must hold. Moreover, the emission constraint $b = e_{it} z$ in (9) is redundant since b and z are endogenously determined. Therefore, the programming problem reduces to

$$\begin{aligned} \min_{\lambda_t} \quad & \boldsymbol{z}_t' \boldsymbol{\lambda}_t \\ & \boldsymbol{x}_{it}^P \geq \boldsymbol{X}_t^P \boldsymbol{\lambda}_t \\ s.\ t. \quad & x_{it}^S \geq \boldsymbol{x}_t^{S'} \boldsymbol{\lambda}_t \\ & y_{it} \leq \boldsymbol{y}_t' \boldsymbol{\lambda}_t \\ & \mathbf{1}' \boldsymbol{\lambda}_t = 1 \\ & \boldsymbol{\lambda}_t \geq \mathbf{0} \end{aligned} \tag{10}$$

and the minimal emissions can be computed as

$$\hat{b}^t(\boldsymbol{x}_{it}^P, x_{it}^S, y_{it}) = e_{it} \boldsymbol{z}_t' \hat{\boldsymbol{\lambda}}_t(\boldsymbol{x}_{it}^P, x_{it}^S, y_{it}) = e_{it} \hat{z}^t(\boldsymbol{x}_{it}^P, x_{it}^S, y_{it}) \tag{11}$$

2.3. Measuring and decomposing environmental productivity

In the following, the actual as well as the optimal values of output and environmental pollution are used to construct and decompose environmental productivity indices. The analysis differentiates between the environmental productivity development of individual ports and at the sectoral level by aggregating the individual ports' outputs and emissions.

To measure the degree of decoupling in container handling operations at the port level, the environmental productivity index for port i is defined as

$$EPC_i^{t,t+1} = \frac{y_{it+1}/y_{it}}{b_{it+1}/b_{it}} \tag{12}$$

i.e., the ratio of output growth to growth in emissions, which defines environmental productivity change. The index is larger than 1 under (relative) decoupling, 1 under coupling, and smaller than 1 if the growth in emissions exceeds the growth in the good output. Note that the index can equally be written $EPC_i^{t,t+1} = (y_{it+1}/b_{it+1})/(y_{it}/b_{it})$, where the numerator and denominator define environmental productivities in periods $t + 1$ and t, respectively.

The industry environmental productivity index is defined

$$EPC^{t,t+1} = \frac{\sum_{i=1}^n y_{it+1} / \sum_{i=1}^n y_{it}}{\sum_{i=1}^n b_{it+1} / \sum_{i=1}^n b_{it}} \tag{13}$$

which is a weighted average of the port environmental productivity indices, where changes in the ports' shares of the industry container output and emissions are defined as weights; i.e.

$$EPC^{t,t+1} = \frac{1}{n} \sum_{i=1}^n \left(\frac{\frac{y_{it+1} / \sum_{i=1}^n y_{it+1}}{y_{it} / \sum_{i=1}^n y_{it}}}{\frac{b_{it+1} / \sum_{i=1}^n b_{it+1}}{b_{it} / \sum_{i=1}^n b_{it}}} \right)^{-1} \frac{y_{it+1}/y_{it}}{b_{it+1}/b_{it}} \tag{14}$$

The weight is larger (smaller) than 1 if the growth in port i's share of the industry emissions exceeds (fall short of) the growth in port i's share of the industry container volume. If the shares change in proportion, the weights are 1 and the industry environmental productivity index corresponds to the arithmetic mean of the port environmental productivity indices.

To understand the driving factors behind the environmental productivity changes, the port and industry indices can be

decomposed into the following components

$$\text{(Industry) } EPC^{t,t+1} = \underbrace{\left(\frac{\sum_{i=1}^{n}\frac{z_{it+1}}{\sum_{i=1}^{n} z_{it+1}} e_{it+1}}{\sum_{i=1}^{n}\frac{z_{it}}{\sum_{i=1}^{n} z_{it}} e_{it}}\right)^{-1}}_{\text{Emission factor change}} \times \underbrace{\frac{\sum_{i=1}^{n} y_{it+1} / \sum_{i=1}^{n} y_{it}}{\sum_{i=1}^{n} z_{it+1} / \sum_{i=1}^{n} z_{it}}}_{\text{Container handling productivity change}}$$

$$\text{(Port) } EPC_i^{t,t+1} = \underbrace{\left(\frac{e_{it+1}}{e_{it}}\right)^{-1}}_{\text{Emission factor change}} \times \underbrace{\frac{y_{it+1} / y_{it}}{z_{it+1} / z_{it}}}_{\text{Container handling productivity change}} \tag{15}$$

where the former component evaluates changes in emissions due to changes in ship characteristics (i.e., in the average emission factor for ship auxiliary engines) while the latter denotes changes in port productivity, measured in containers handled per hour.

Using the minimal emissions based on the frontier analysis of technology sets from Section 2.2., the port productivity component can be decomposed into the following components

$$\frac{y_{it+1} / y_{it}}{z_{it+1} / z_{it}} = \underbrace{\frac{y_{it+1} / y_{it}}{\tilde{z}_B^{t,t+1}(\boldsymbol{x}_{it+1}^P, x_{it+1}^S, y_{it+1}) / \tilde{z}_B^{t,t+1}(\boldsymbol{x}_{it}^P, x_{it}^S, y_{it})}}_{\text{Input-output mix change}} \times \underbrace{\frac{\tilde{z}_B^{t,t+1}(\boldsymbol{x}_{it+1}^P, x_{it+1}^S, y_{it+1}) / \tilde{z}^{t+1}(\boldsymbol{x}_{it+1}^P, x_{it+1}^S, y_{it+1})}{\tilde{z}_B^{t,t+1}(\boldsymbol{x}_{it}^P, x_{it}^S, y_{it}) / \tilde{z}^{t}(\boldsymbol{x}_{it}^P, x_{it}^S, y_{it})}}_{\text{Technical change}} \times \underbrace{\frac{\tilde{z}^{t+1}(\boldsymbol{x}_{it+1}^P, x_{it+1}^S, y_{it+1}) / z_{it+1}}{\tilde{z}^{t}(\boldsymbol{x}_{it}^P, x_{it}^S, y_{it}) / z_{it}}}_{\text{Efficiency change}} \tag{16}$$

The *input–output mix change* component evaluates port productivity changes at the frontier (i.e., for minimal emissions given the input–output mixes in periods t and $t + 1$, where minimal emissions are evaluated using the biennial, sequential frontier). Values of this component larger (smaller) than 1 imply that the input–output mix of period $t + 1$ allows for a higher (lower) port productivity than the input–output mix in period t. The *technical change* component compares the minimal emissions estimated based on the biennial and the sequential technologies. Hence, it measures changes in the frontier over time and thereby provides a measure of technical change. Note that since the biennial, sequential frontier is equal to the sequential frontier of period $t + 1$, the denominator of the component is equal to 1 and technical change is measured relatively to the input–output combination of period t. As discussed above, technical regress is precluded by construction and, thus, this component can only exhibit values larger or equal to one. Finally, the *efficiency change* component compares the efficiency in period $t + 1$ to the efficiency in period t. If this measure exhibits a value larger (smaller) than 1, then the efficiency has increased (decreased).

Estimates of the decomposition can be obtained by replacing the theoretical minimal emissions by their nonparametric estimators presented above.

To visualize the approach to a frontier-based decomposition of the environmental productivity index, Fig. 2 depicts an example of a nonparametric technology set and frontier estimation as well as the corresponding minimal amounts of z (time berthed during container handling in the application). The figure shows the sequential and biennial technologies for two periods, t and $t + 1$. The technologies are bounded by the piecewise-linear frontier functions. To simplify the graphical example, the remaining inputs are ignored and the focus is on the two-dimensional case.

DMU A exhibits the container handling time and output (z_{At}, y_{At}) in period t and (z_{At+1}, y_{At+1}) in period $t + 1$. The efficiency in period t $(t + 1)$ is measured as the ratio of minimal to actual emissions $\hat{\tilde{z}}^{t}(t)/z_{At}$ $(\hat{\tilde{z}}^{t+1}(t + 1)/z_{At+1})$. The ratio of these results indicates whether DMU A has moved towards the frontier in period $t + 1$. The movement of the frontier, i.e., the technical change, is measured as the ratio of minimal emissions in period t to the minimal emissions in period $t + 1$ given the output-level of period t and is given by $\hat{\tilde{z}}^{t}(t)/\hat{\tilde{z}}_B^{t,t+1}(t)$. Finally, due to changes in the output level, which increases from y_{At} to y_{At+1}, the minimal emissions increase. The ratio of y_{At+1}/y_{At} to $\hat{\tilde{z}}_B^{t,t+1}(t + 1)/\hat{\tilde{z}}_B^{t,t+1}(t)$ reveals if the port productivity at the frontier has improved or declined as a result of the change in output.

3. Data

Access to raw data from Statistics Norway's port statistics from 2010 to 2015 has been granted subject to a confidentiality clause. This dataset contains information about each port of call (covering ship characteristics, activities in port, cargo types, volume loaded and unloaded etc.) in the largest ports in Norway. The process of data management and cleaning is thoroughly described in Rødseth and Wangsness (2015). It involves combining two datasets (cargo and container handling time data) and implementing selection criteria that ensure consistency with Statistics Norway's publicly available statistics. Data on handling time is set equal to the duration of container handling operations when time spent at different activities is reported. When time allocated to container handling is not specified, the total duration of the call is assumed to be the container handling time for calls that report loading/unloading of cargo. In odd cases where information about the time at berth is missing or if durations or container handling productivities are implausible (e.g., calls lasting < 15 min), the container handling time is imputed using regression analysis.

This study focus on the loading and unloading of containers in the largest container ports in Norway; Borg, Drammen,

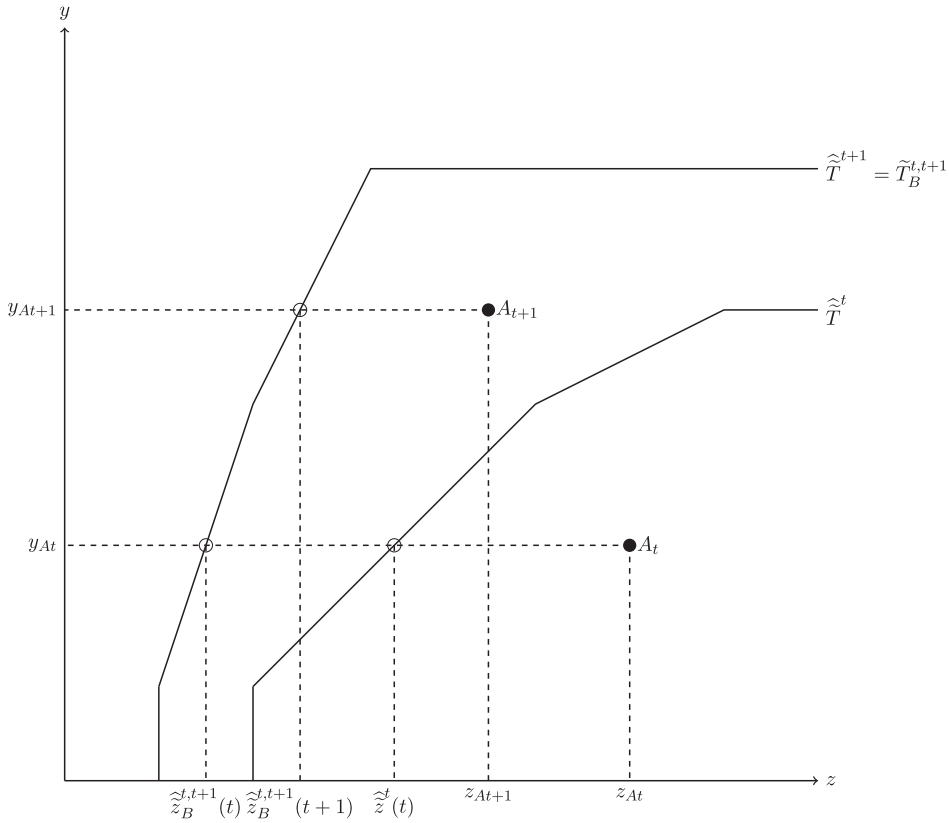

Fig. 2. Example of decoupling decomposition.

Kristiansand, Larvik, Moss, Oslo, Risavika and Ålesund. To evaluate productivity at the port level, the information at the level of the port of call is aggregated to per port per quarter. Hence, the dataset on which this study is based reports the quarterly sum of containers handled by each of the ports, the total time they have spent on handling containers per quarter, and the corresponding sums of ship gross tonnages (approximating quarterly total ship capacity) and emission to air from operating the ships' auxiliary engines whilst containers are being loaded/unloaded. Following eight ports over six years provides 186 quarterly observations. Data on cargo volumes are unavailable for the port of Kristiansand in the fourth quarter of 2015. There are also some challenges with the data from the port of Risavika from the 4th quarter of 2014, which we return to later.

In addition to the aggregated port statistics, quarterly terminal inventory data for each port are added. This concerns the variables i) port area (sq.km), ii) berth length (m), iii) quay cranes (no), iv) yard cranes (no), v) straddle carriers (no), and vi) container handling trucks (no). The data were provided by Halvor Schøyen, who compiled it whilst undertaking the research documented in Schøyen and Odeck (2013, 2017), and updated it during the implementation of this study. As DEA is vulnerable to the curse of dimensionality (i.e., it becomes difficult to discriminate between efficient and inefficient ports when the number of input and output variables increases), this study follows Cullinane et al. (2002) and also considers an alternative specification where a new input (i.e., container handling equipment) is constructed by summing each port's yard cranes, straddle carriers, and container handling trucks. The results obtained from the parsimonious model specification are reported in Appendix E.

Emissions to air from ships that operate auxiliary engines whilst being loaded/unloaded are estimated per call using the method by EPA (2009). Emissions per hour per ship are determined by the maximum continuous rating power (kW) of the ships' auxiliary engines, auxiliary engine load factors, and fuel type-specific emission factors (g/kWh). Because the dataset covers the period from 2010q1 to 2015q4, all ships are assumed to use marine gas oil (0.1% sulfur) to comply with EU's sulfur directive that was implemented in 2010. This implies that the estimated emissions amount to about 10 percent of estimated emissions using marine diesel oil (1% sulfur) that complies with the ECA regulation in force between 2010 and 2014. This suggests that emissions standards play a key role in promoting emission factor improvements.

While parameters from EPA (2009) are used to describe auxiliary engine load and emission factors, the maximum continuous rating power for each ship in the dataset must also be established. For this purpose, the Norwegian Costal Administration provided a register on ships' maximum continuous rating power subject to a confidentiality clause. Maximum continuous rating power for ships

Table 1
Summary statistics.

Variables (per port per quarter level)	Obs	Mean	Std. Dev.	Min	Max
Quay length (m)	186	406.0	222.5	140	875
Port area (m^2)	186	63,772.9	37,499.8	10,000	140,000
Quay cranes (no)	186	2.0	1.1	0	4
Yard cranes (no)	186	0.6	1.7	0	8
Straddle carriers (no)	186	0.5	1.6	0	5
Reach stackers (no)	186	5.1	3.2	2	16
Containers (TEUs)	186	16,746.9	13,804.5	1,009	57,751
Aggregate ship capacity (GT)	186	535,241.1	224,904.2	60,300	995,501
Container handling time (hrs)	186	907.0	568.6	80	2,685
SO_x emissions (kg)	186	113.8	76.6	8	389
For calls which solely load/unload containers					
Containers (TEUs)	186	15,779.9	13,948.9	964	57,719
Aggregate ship capacity (GT)	186	444,601.3	202,685.0	29,970	960,422
Container handling time (hrs)	186	830.6	548.5	74	2625
SO_x emissions (kg)	186	105.1	76.8	8	383

Fig. 3. Intertemporal growth in the industry container volume (8 ports).

that are not listed in the Norwegian Coastal Administration's register were imputed using regression analysis: See Rødseth and Wangsness (2015) for details.

The emission factors are constructed for each port and quarter by dividing the total emissions by the corresponding hours of container handling. Formally, this leads to quarterly weighted sums of the emission factors of all ships that have berthed in each port, where each ship's time in port relative to the total berthing time per port constitute the weights; cf. (15).

While most calls involve the loading/unloading of containers only, about 6% of the total throughput of containers were handled together with other cargo types. As the time spent on handling cargo is reported for the call, not per cargo type, the time spent loading/unloading containers must be imputed in these cases. Regression analysis is used for this purpose, which has the potential drawback of introducing noise in the quarterly time data. Alternatively, the analysis could have emphasized calls that solely load/unload containers. This has the drawback of reducing the number of calls that go into the dataset, and it would lead to underestimating port capacity utilization and thus to biased efficiency estimates. This is further complicated by that differences among container-only and mixed calls vary both across ports and time. Therefore, the decision was made to favor estimates based on the sample comprising all calls. As a sensitivity test, the environmental productivity index and its decomposition based on the subsample containing calls that solely load/unload containers are reported in Appendices A and B.

From the 4th quarter of 2014, the Port of Risavika only reports calls where containers are loaded/unloaded in conjunction with other cargo. This means that the environmental productivity index cannot be computed for the subsample containing calls that solely load/unload containers and that the duration of handling operations must be imputed for each call in Risavika in this period. Because of these limitations, Risavika is not included in the analysis from the 4th quarter of 2014.

Summary statistics for the full sample spans the first eleven rows of Table 1. The last five rows contain summary statistics for the subsample of calls that solely load/onload containers. For further comparison, Fig. 3 presents the sample industry container volumes (in TEUs) for all calls as well as ships that only carry containers over the period under consideration.

4. Results

The empirical analysis starts by evaluating whether Norwegian container ports exhibit a positive environmental productivity growth (i.e., relative decoupling of the container volume and local air pollution caused by the emission of SO_x), and to identify the role of port handling productivity and ship characteristics in facilitating environmental productivity growth. Figure 4 presents the *cumulative* industry environmental productivity index and its decompositions according to equations (13) and (15) using the full sample, for which each period is compared to the first quarter of 2010 (base period). The corresponding figures for the subsample containing calls that solely load/unload containers are reported in Appendix B. Appendices A and B show that limiting the analysis to the subsample has little or no impact on the overall results.

Environmental productivity changes (i.e., the bold line) at the industry level did deteriorate between 2010 and 2011 and from the first quarter of 2014. The industry environmental productivity change is volatile. The productivity decline from 2014 is affected by the exclusion of the port of Risavika from the sample in this period. Appendix A shows that this port exhibits a particularly strong productivity growth in the period under consideration.

Fig. 4a shows that container handling productivity development (measured in TEUs handled per hour) is the driving force behind the environmental productivity improvements, while the industry emission factor deteriorates over the timespan of the dataset. The latter is a weighted sum of the emission factors of all ships calling on the ports under consideration, for which each ship's time in port relative to the total time in port is used as the weighing factor; cf. (15). Hence, the introduction of larger ships and/or more frequent calls by larger ships will, ceteris paribus, cause the emission factor changes to be < 1 as emissions in general increase by ship (engine) size.

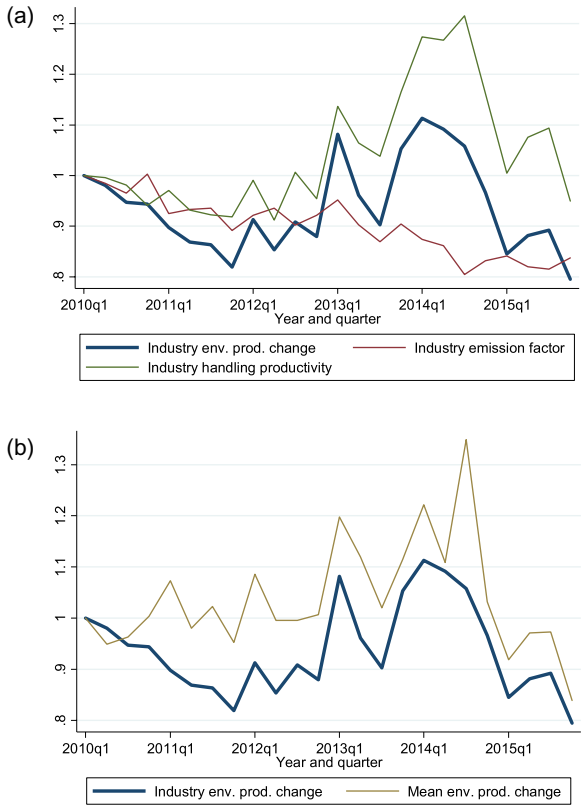

Fig. 4. (a) Cumulative changes in emission factors, handling productivity, and environmental productivity from 2010 to 2015 for all 8 ports. (b) Comparing cumulative industry environmental productivity change to mean cumulative port environmental productivity change.

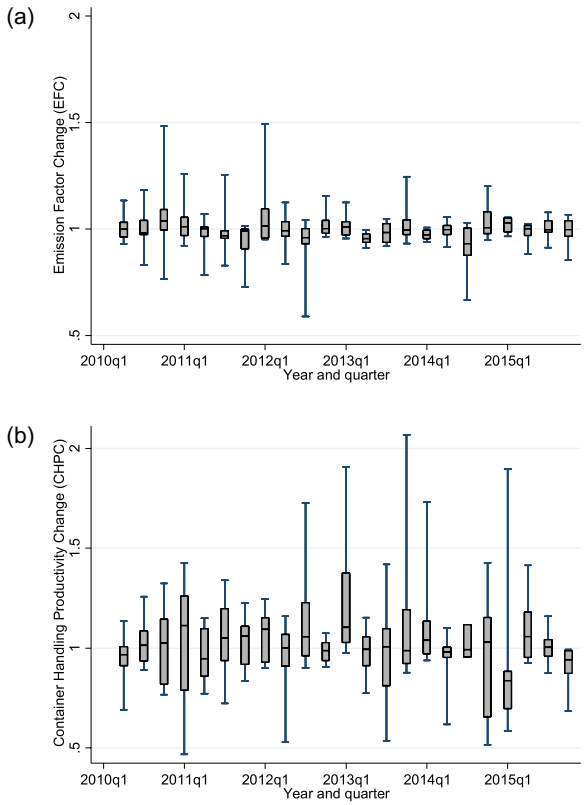

Fig. 5. (a) Quarterly emission factor change from 2010 to 2015. Median, Min, and Max. (b) Quarterly container handling productivity change: Median, Min, and Max.

Equation (14) shows that the industry environmental productivity index represents a weighted average of the individual ports' environmental productivity indices, for which changes in their relative shares of containers and emissions define the weights. To describe the impacts of changes in these shares, Fig. 4b compares the cumulative industry index to the arithmetic mean of the cumulative port indices (which would correspond to the industry environmental productivity index if the shares had remained unchanged). The comparison shows that the mean port exhibits a more positive productivity development compared to the overall port industry. The difference between the two measures is due to changes in the sectoral composition. Appendix A reports intertemporal developments of the cumulative port decoupling indices. They show that Risavika and Moss experience productivity growth in the period under consideration, while Borg, Larvik, and Oslo experience periods of productivity decline.

Having considered the overall results for the port industry, the emphasis is now on the individual ports. Figs. 5 present the intertemporal developments of the emission factor change and container handling productivity change indicators defined by equation (15). The whiskers indicate the continuum between the minimal and maximal change in each quarter, while the boxes present the continuum between the 25th and 75th quartiles. The bands within the boxes indicate the median changes. The ranges of panels 5a and 5b are identical, which allow comparing the indicators in terms of variation and magnitude. Note that the maximal container handling productivity change in the third quarter of 2014 is approximately 4 and consequently that the whiskers are not reported to maintain comparable scales.

Figs. 5 reveal that the median intertemporal emission factor change fluctuates around 1, with the gap between the highest and lowest quarterly emission factor changes in general being modest. While the median container handling productivity change exhibits

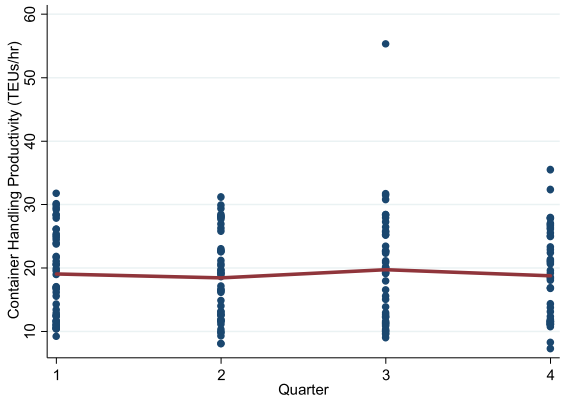

Fig. 6. Seasonal variations in container handling productivities. The line demonstrates seasonal mean values.

productivity growth in a majority of the periods considered, quarterly container handling productivities are volatile. One explanation for this could be seasonal variations in the demand for container transport. To investigate, Fig. 6 exhibits the variation in container handling productivity (i.e., TEUs/hr) per quarter, with mean values indicated by the line. While the ranges and means are comparable across quarters, one datapoint is found to be substantially different from the other observations in terms of quarterly productivities. Fig. 6 provides no decisive support to the proposition that seasonal variations drive container handling productivity changes.

In addition to changes in the demand for freight transport, changes in the characteristics of ships that call on Norwegian ports are likely to be important. While emission factors by construction depend on ship (engine) sizes, Rødseth et al. (2018) also find that loading/unloading of large ships is in general more productive than handling of small ships because the (average) container volume is greater and thus allows for the exploitation of economies of scale in container handling. Figs. 7 visualize the relationships between quarterly average ship sizes per port and the corresponding i) container handling productivities and ii) aggregate emission factors. Quadratic predictions are included to illustrate the direction of the relationships.

Figs. 7 reveal that there is a close relationship between ship sizes and emission factors, in particular for ships below 10 000 GT. Hence, changes in ship sizes should be considered the driving factor behind the emission factor development in Figure 4. Moreover, the quadratic prediction indicates that container handling productivity increases linearly in ship size[2], although the variation is much larger than for the emission factors. This can reflect economies of scale in container handling. An alternative explanation is that the positive correlation is an outcome of a matching process, whereby the most productive ports attract ships with the highest value of time (i.e., large ships). To study this further, the relationship between container handling productivities and ship sizes is examined using the variation within each port, which effectively eliminates the problem of port selection for the statistical analysis. Appendix C provides scatterplots for each port in the dataset. Except for Larvik and Oslo, all ports exhibit a positive relationship between average ship sizes and container handling productivities. Moreover, a linear prediction using the Fixed Effects estimator suggests that the average effect of an increase in ship size (GT) on container handling productivity is 0.002. The parameter estimate is found to be statistically significant.

Finally, container handling productivity changes are decomposed into i) input–output mix changes (i.e., productivity changes measured at the frontier), ii) technical changes, and iii) efficiency changes in line with equation (16). Technical changes describe positive shifts in the technology frontier, while efficiency changes allow pinpointing if the ports are catching up with the technology frontier over time. Table 2 presents the average results per port and year, while Figs. 8a-c visualize the quarterly variation of the results for the full model specification. Appendix E presents the quarterly variation of the results for the parsimonious model specification, for which yard cranes, straddle carriers, and container handling trucks are combined into one input. While both set of results are comparable, the parsimonious specification suggests slightly more moderate technical changes compared to the full specification. Note that the analysis does not address intertemporal changes in the year 2010 since the limited number of observations in the sequential technology set of the initial period does not allow for a valid discrimination between efficient and inefficient ports.

The results (full model) suggest that the container handling productivity improves by 2–3 percent quarterly because of technical changes. Fig. 8b shows that the variation in technical change is modest, and that the major contributors to environmental productivity changes are mix and efficiency changes. This is particularly the case for Risavika, which exhibits the strongest environ-

[2] When removing the observation that exceeds 15,000 GT in Fig. 7a (i.e., Risavika in the 3th quarter of 2014), the relationship between container handling productivity and ship size has a vertex at about 9 000 GT. Alternative scatter plots and their corresponding Fixed Effects regression table are given in Appendix D. As for the DEA results, they are largely unaffected by omitting Risavika in the 3th quarter of 2014 from the sample.

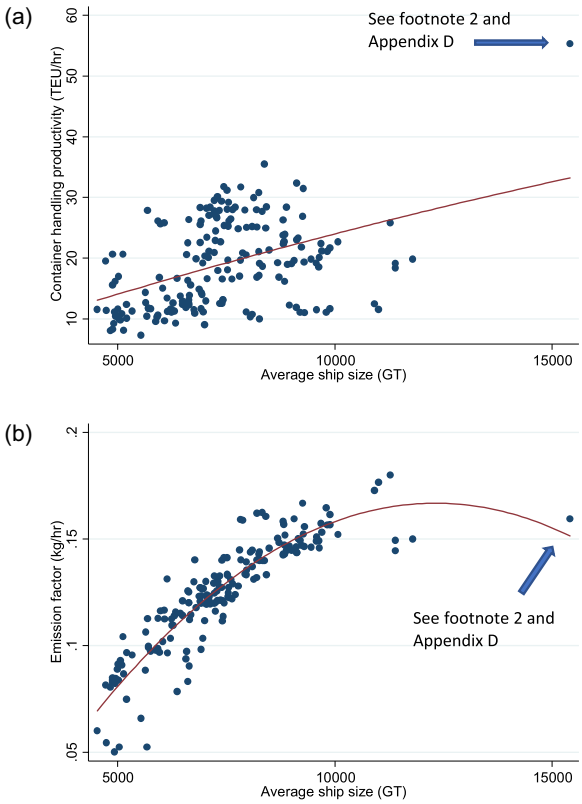

Fig. 7. (a) Variation in quarterly container handling productivities and average ship sizes. (b) Variation in quarterly emission factors and average ship sizes.

Table 2
Decomposing productivity changes per port and year.

	Input-output mix change					Technical change					Efficiency change				
Port/Year	2011	2012	2013	2014	2015	2011	2012	2013	2014	2015	2011	2012	2013	2014	2015
Borg	0.97	0.99	0.99	0.97	1.03	1.04	1.08	1.02	1.06	1.00	1.04	0.97	1.24	1.00	0.93
Drammen	1.08	1.04	0.98	0.92	0.95	1.02	1.00	1.01	1.00	1.16	1.00	0.97	1.03	1.01	0.91
Kristiansand	1.02	0.97	1.00	1.00	1.01	1.02	1.08	1.04	1.00	1.00	0.96	1.09	0.96	1.03	1.04
Larvik	0.86	1.20	1.13	1.03	0.99	1.15	1.00	1.01	1.04	1.00	1.00	0.89	1.23	0.83	1.22
Moss	1.00	0.99	1.00	1.05	1.01	1.00	1.03	1.01	1.01	1.00	0.95	1.04	1.05	1.00	0.93
Oslo	1.00	1.00	1.00	1.00	0.91	1.00	1.00	1.00	1.02	1.00	0.97	0.99	1.04	1.02	0.98
Risavika	1.13	1.05	0.98	1.94		1.01	1.01	1.06	1.00		0.94	1.00	0.98	1.39	
Ålesund	1.06	0.99	1.10	0.92	1.13	1.00	1.01	1.01	1.04	1.00	1.00	1.00	0.91	1.17	0.95
Mean	**1.01**	**1.03**	**1.02**	**1.10**	**1.00**	**1.03**	**1.03**	**1.02**	**1.02**	**1.02**	**0.98**	**0.99**	**1.05**	**1.06**	**0.99**

mental productivity growth of the ports in the sample (cf. Appendix A). Mix and efficiency changes are, on the other hand, far more volatile than technical changes and with more inter-port variation. Considering the mean annual changes in Table 2, the explanation for the first period of decline in industry container handling productivity found in Figs. 4 appears to be deterioration in average port efficiency in 2011 and 2012, but with the average port catching up with the best practice port over time.

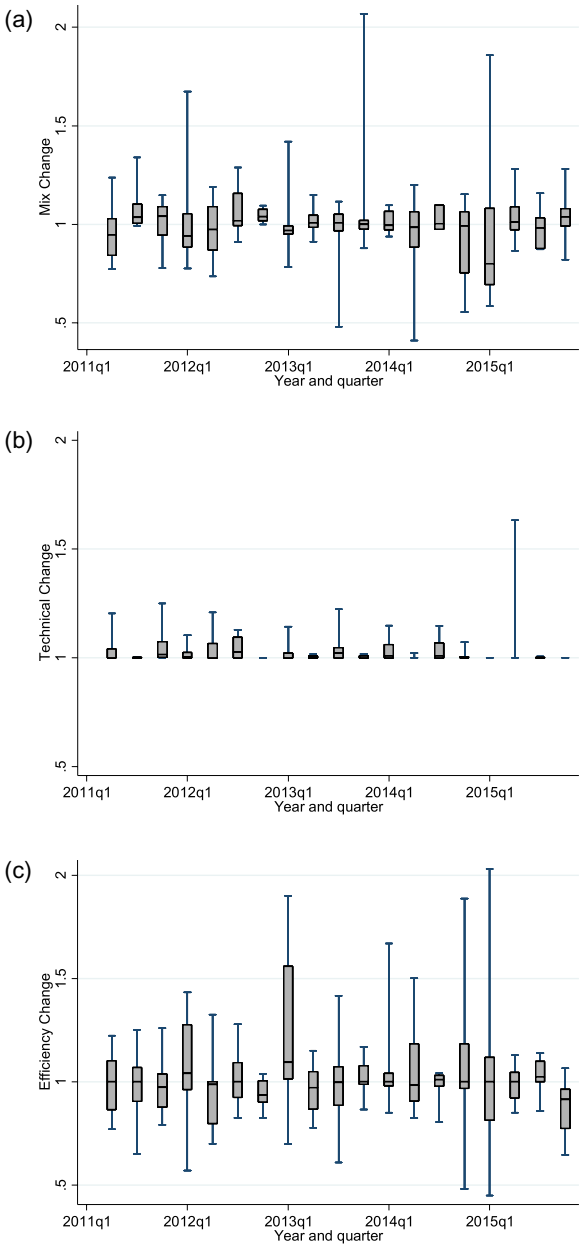

Fig. 8. (a) Quarterly input–output mix change from 2011 to 2015. (b) Quarterly technical change from 2011 to 2015. (c) Quarterly efficiency change from 2011 to 2015.

5. Conclusions and implications

Policy makers worldwide view maritime transports as a sustainable alternative to road freight transport. However, strengthening the position of maritime transport inevitably leads to increased activities in ports, which in the case of Norway often are in city centres. While port externalities are plentiful, this paper emphasizes local air pollution that is harmful to both health and the environment. The paper examines the extent to which Norwegian ports show relative decoupling of container volumes and sulfur dioxides and analyzes the reasons for intertemporal changes in environmental productivity. Industry environmental productivity (measured in TEUs/SO_x emissions) is found to deteriorate between 2010 and 2011, increase periodically between 2013 and 2014, and to deteriorate in 2015. While the average ship emissions per hour of berthing are found to be increasing over time because of more frequent calls by large ships, improvements in container handling productivity (measured in TEUs/hr) counteract this development and thus promote environmental port productivity.

This paper introduces a novel approach to analyzing the environmental productivity development of container ports. The usefulness of the approach is illustrated by means of an empirical analysis that provides decision makers and stakeholders in Norway with new evidence concerning the environmental productivity development of its container ports. By establishing a decomposition approach, the contributions of different sources (i.e., ship characteristic and port efficiency, technical, and input–output mix changes) to the overall environmental productivity development can be identified. This offers stakeholders valuable information about which ports perform below par and hence can improve sustainability by improving managerial practices. Moreover, technical changes that can be considered the engine of long-term sustainable development are identifiable. The empirical results indicate that Norwegian container ports exhibit moderate technical progress while mix and efficiency changes are the primary determinants of environmental productivity change.

Benchmarking of environmental performance is already high on the agenda of port managers. EcoPorts is the main environmental initiative of the European port sector, integrated in the European Sea Ports Organization in 2011. Air quality is since 2013 ranked as the top environmental priority by European ports (ESPO, 2019). EcoPorts offers a self-diagnosis method that allows port managers to self-assess their environmental performances relative to the sector and international standards. The model framework developed in this paper can help improving the environmental performance management of members and non-members of EcoPorts alike, including smaller ports. Kuznetsov et al. (2015) discuss sustainability management of small ports, like those considered in this study. Further development of our methodological framework to accommodate multiple outputs can be a relevant task in this regard, especially to facilitate environmental productivity measurement for multi-purpose ports (e.g., as in Rødseth et al, 2019). We leave this task for further research.

Section 1 discusses the wide range of factors that may influence the environmental productivity development. Some of these factors are subject to the decision domain of policy makers (e.g., environmental standards for ships) and port managers (e.g., port pricing), while others are beyond their control (e.g., market factors). While a comprehensive mapping of the effects of such factors on the environmental productivity development is beyond the scope of this paper, the aspects of seasonal variations, sulfur emission standards, and the development of the characteristics of container ships calling in Norway have been examined. The role of emission standards and ship characteristics has proved important to the Norwegian ports' environmental productivity development. In line with Rødseth et al. (2018) we find that container handling productivity often increases in ship size, intuitively because of economies of scale in container handling.

The question remains whether port productivity gains from servicing larger ships can overcome the corresponding increases in ship emissions per hour. Moreover, if ships' time gains reaped from more productive container handling in ports are not being translated into shorter turnaround time (e.g. reduced ship waiting time, manoeuvring time and idle time) and reduced speed at sea (see for instance Johnson and Styhre, 2015), the environmental productivity gains presented in this paper will be largely overestimated. On the other hand, if time savings in port are converted into slow steaming, the environmental benefits may be substantial (Cariou, 2011). Another important research question is how the Norwegian container ports' recent introduction of environmental discounts on port tariffs subject to ESI scores will influence their environmental productivity development. We leave these topics for future research.

CRediT authorship contribution statement

Kenneth Løvold Rødseth: Conceptualization, Methodology, Validation, Formal analysis, Investigation, Writing - original draft, Writing - review & editing, Visualization, Funding acquisition. **Halvor Schøyen:** Investigation, Writing - original draft, Writing - review & editing, Funding acquisition. **Paal Brevik Wangsness:** Formal analysis, Investigation, Writing - original draft, Writing - review & editing.

Acknowledgement

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Appendix A

Fig. A1

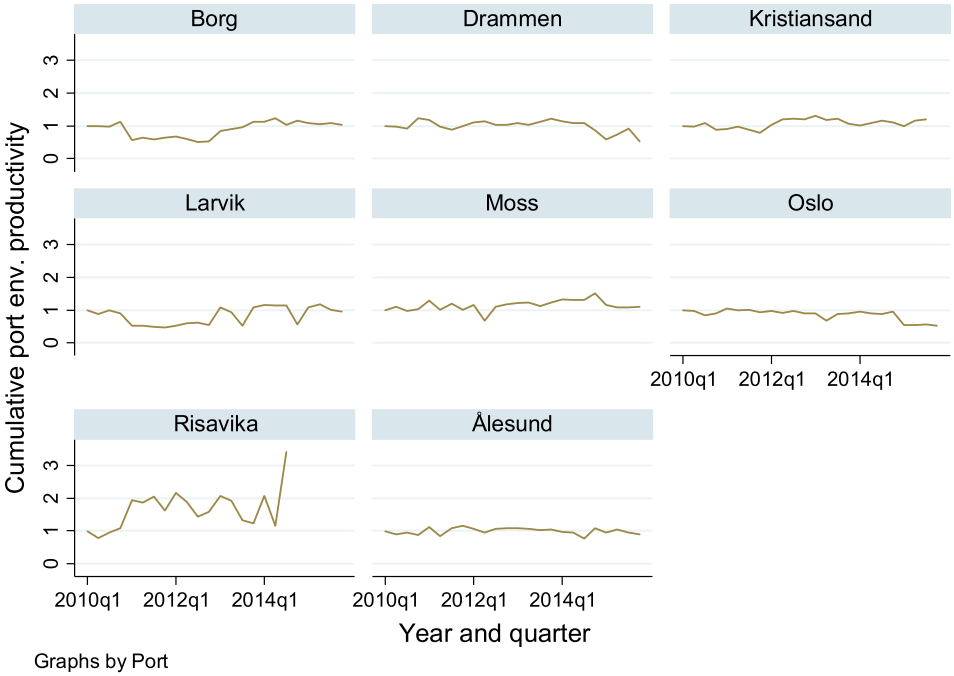

Fig. A1. Cumulative port decoupling indices, all calls.

Fig. A2

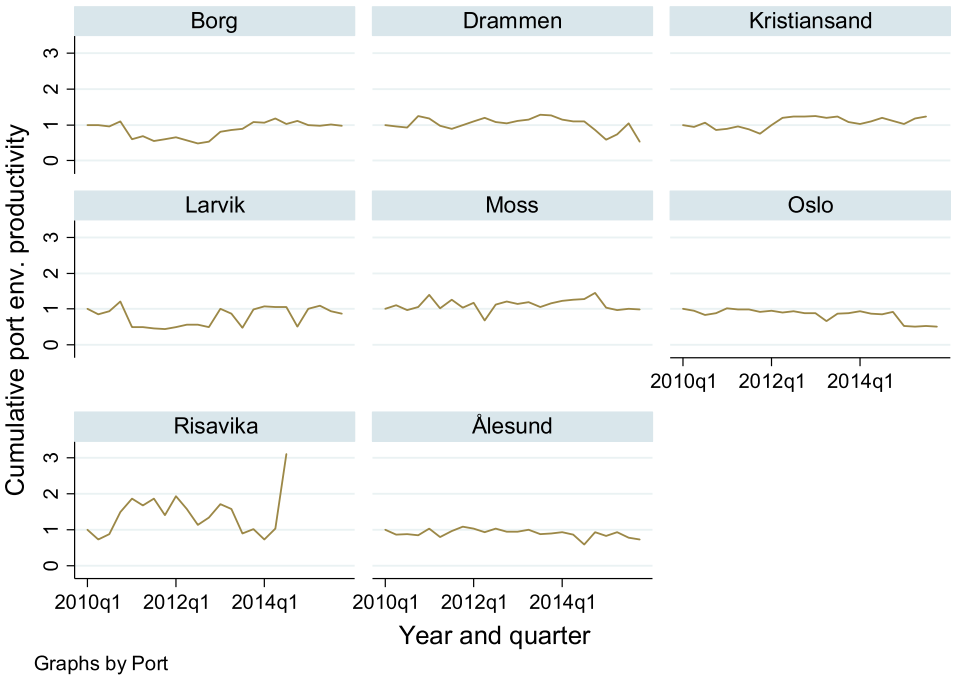

Fig. A2. Cumulative port decoupling indices, container-only calls.

Appendix B

Fig. A3a

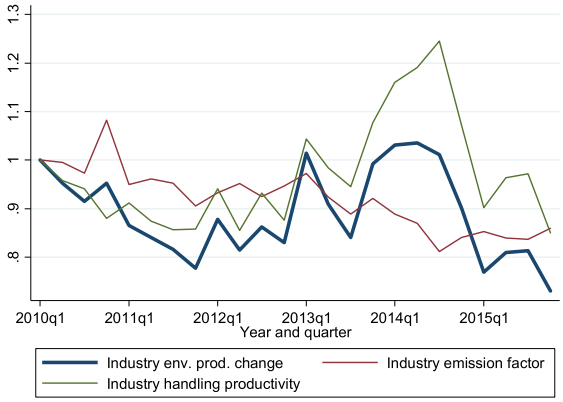

Fig. A3a. Cumulative growth in emission factors, handling productivity, and environmental productivity from 2010 to 2015 for all 8 ports. Container-only calls.

Fig. A3b

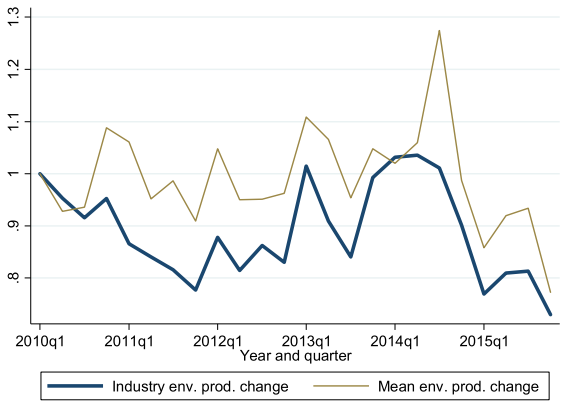

Fig. A3b. Comparing cumulative industry environmental productivity change to mean cumulative port environmental productivity change. Container-only calls.

Appendix C

Fig. A4

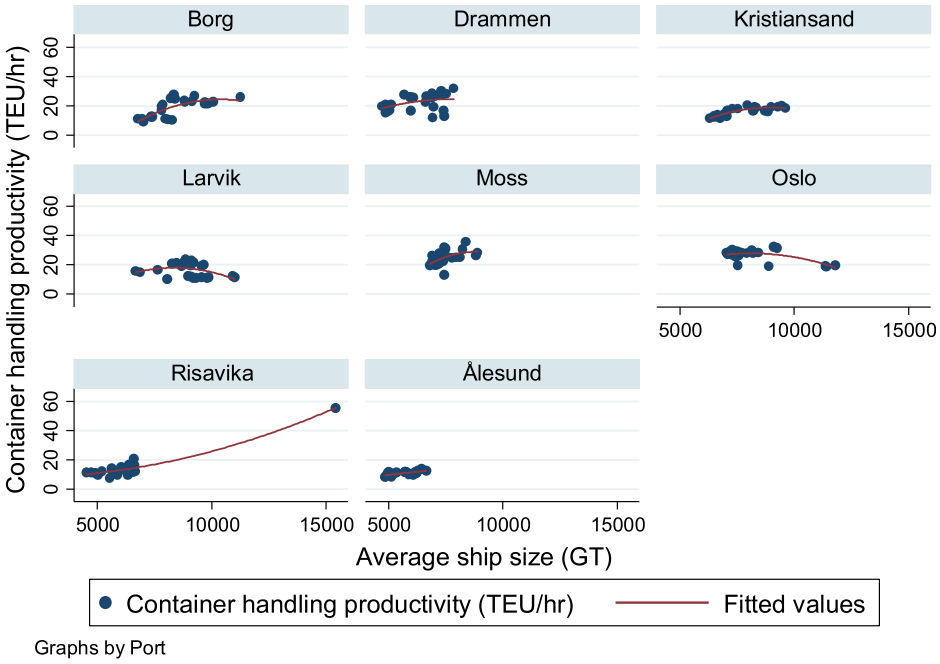

Fig. A4. Within variation in quarterly container handling productivities and average ship sizes.

Appendix D

Fig. A5a

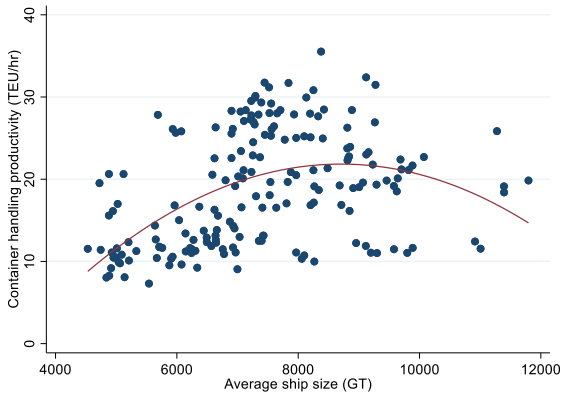

Fig. A5a. Variation in quarterly container handling productivities and average ship sizes. Without the observation that exceeds 15,000 GT in Fig. 7a.

Fig. A5b

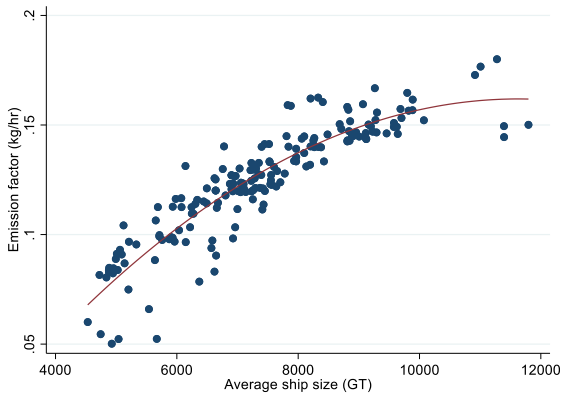

Fig. A5b. Variation in quarterly emission factors and average ship sizes. Without the observation that exceeds 15,000 GT in Fig. 7a.

Table A1.

Table A1
Fixed effects models of ship size effects on container handling productivity. Models with and without the outlier in Fig. 7a.

	(all observations) Container handling productivity (TEU/hr)	(wo outlier) Container handling productivity (TEU/hr)	(all observations) Container handling productivity (TEU/hr)	(wo outlier) Container handling productivity (TEU/hr)
1000 GT	2.177***	1.017***	0.124	9.204***
	(0.296)	(0.332)	(1.660)	(1.878)
(1000 GT)ˆ2			0.115	−0.504***
			(0.091)	(0.114)
Constant	2.803	11.283***	11.427	−20.525***
	(2.226)	(2.478)	(7.211)	(7.569)
Observations	186	185	186	185
Adjusted R^2	0.200	0.007	0.203	0.102

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$,*** $p < 0.01$

Appendix E

Description: *Results from reduced model specification.*

Fig. A6a

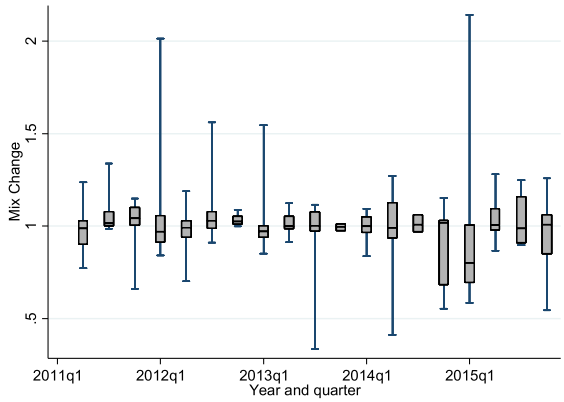

Fig. A6a. Quarterly input–output mix change from 2011 to 2015.

Fig. A6b

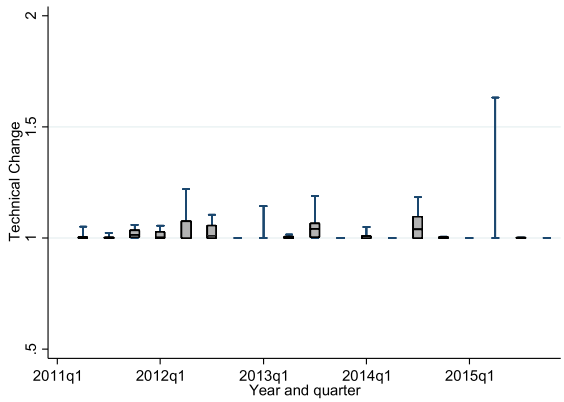

Fig. A6b. Quarterly technical change from 2011 to 2015.

Fig. A6c

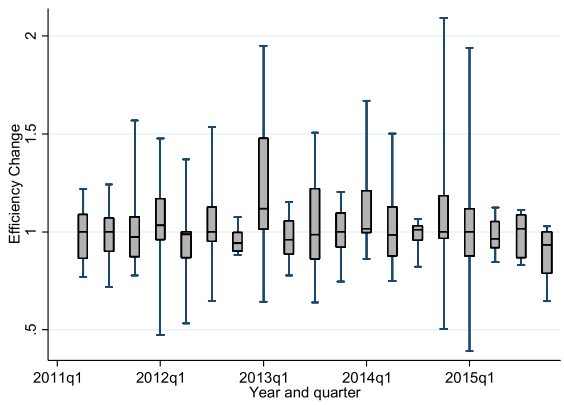

Fig. A6c. Quarterly efficiency change from 2011 to 2015.

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