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Mitigating simultaneity bias in seaport efficiency measurement

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ABSTRACT

Seaport efficiency measurement is one of the most popular topics in maritime economics. Studies within this research area have not paid attention to the well-known simultaneity bias in productivity and efficiency measurement that can lead to inconsistent estimates of best practices. This paper investigates simultaneity in seaport efficiency measurement and proposes a novel strategy to mitigate the bias by exploiting the relationship between port efficiency and choice, another key topic within the maritime literature. A non-parametric framework for joint estimation of production and control functions subject to shape constraints is further developed. Contrary to comparable methods for controlling for simultaneity, the new method does not require multiple steps and rigorous assumptions about the error term to retrieve the port production function. An empirical investigation is provided for the eight largest container ports in Norway to showcase presence and mitigation of simultaneity bias in efficiency analysis of seaports.

1. Introduction

Seaport efficiency is vital for competitive maritime transports and is therefore receiving ample attention in the literature on maritime economics. The popularity of the subject can be illustrated by means of the recent survey by O'Connor et al. (2019), where 128 of 243 articles on port performance selected for review concern productivity and efficiency measurement. The literature on productivity and efficiency analysis of seaports encompasses both analyses of handling of a single type of cargo and joint handling of multiple cargo types at a seaport.[1] A common denominator of the two strands of literature is that their key objective is to estimate a *best-practice frontier*, typically by means of a port production or cost function.

In econometrics, Marschak and Andrews (1944) note that presence of *technical inefficiency* in the error term can distort the estimation of a production (or cost) function when the unobserved efficiency term correlates with inputs. In the current context, this can imply that (unobservable) port efficiency affects ports' investment strategies and use of variable inputs, which poses a traditional endogeneity problem in statistical analysis. This concern – frequently referred to as *simultaneity bias* – has received ample attention in production function estimation, but has so far gone unnoticed in the literature on seaport efficiency. There exist studies that address endogeneity related to seaport efficiency measurement (e.g., Sakyi and Immurana, 2021; Ayesu et al., 2022), but their attention is primarily directed towards the role of seaport efficiency in trade and economic growth, not simultaneity bias.

To respond to the identified research gap, the current paper proposes a remedy for the simultaneity bias in seaport efficiency measurement. Whilst building on conventional approaches for correcting simultaneity bias, we show that the relationship between *port*

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[1] The former is reviewed by Gonzalez and Trujillo (2009) and Pallis et al (2011), while the latter is surveyed by Tovar et al. (2007), among others.

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efficiency and port choice can be exploited to establish novel controls for unobserved inefficiency.

Our paper also relates to the more general methodological literature on how to deal with input simultaneity in productivity estimation. In conventional econometrics using non-frontier productivity estimation, so-called control function approaches have become the standard way to handle simultaneity biases related to factor inputs in production function estimation (e.g. Olley and Pakes 1996; Levinsohn and Petrin 2003; Wooldridge 2009; Ackerberg et al. 2015). So far, simultaneity biases related to factor inputs have received limited attention within *frontier* production and cost function estimation.

A second contribution of this paper is consequently the proposal of a new method for joint estimation of non-parametric production and control functions subject to shape constraints. We present a frontier estimation procedure that integrates the control function idea into the Stochastic Nonparametric Envelopment of Data (StoNED) approach (Kuosmanen, 2006; Kuosmanen and Kortelainen, 2012). Compared to conventional, parametric approaches frequently used to mitigate simultaneity bias the new non-parametric approach avoids multiple steps and rigorous assumptions about the error term to retrieve the port production function. Sign constraints are also used to ensure a *strict monotonic* control function – a crucial assumption for the control function method used for mitigating simultaneity bias. In contrast, strict monotonicity is vulnerable to violation in comparable studies using parametric efficiency analysis, where monotonicity of the control function is not ensured.

The methodological framework is applied for analyzing port efficiency subject to the consideration that the port capital stock may be endogenous. We exploit that port choice is related to port inputs and technical efficiency. Under strict monotonicity, it allows us to define a non-parametric function of managerial efficiency that can be estimated from observable data.

The proposed approach is employed to address simultaneity bias in the estimation of a production function for the eight largest container ports in Norway. The results show that the production function tends to be underestimated when the correlation among inputs and inefficiency is ignored (i.e., for the standard approach to estimating port production functions). The theoretical requirement that the control function is strictly monotonic has implications for the fitted production function, suggesting that the results of previous comparable control function studies are potentially biased.

This paper is organized as follows: We provide an overview of the topic at hand in Section 2. This includes literature reviews on simultaneity bias in production function estimation and port efficiency and choice. Section 3 presents the novel method to mitigate simultaneity bias, while Section 4 presents the case study and dataset. Section 5 presents the empirical results, while Section 6 offers summary and conclusions.

2. Literature review

This section sets the stage for the treatment of simultaneity bias in seaport efficiency measurement. Because the scope of the paper is multi-faceted, we find it necessary to provide brief and selective reviews of the main strands of literature considered herein – simultaneity biases in productivity and efficiency measurement, seaport efficiency and port choice.

2.1. *Productivity and efficiency measurement subject to simultaneity bias*

2.1.1. *Simultaneity bias in production function estimation*

Estimation of production functions has a long tradition in economics (see e.g. Cobb and Douglas (1928), Solow (1957), Kmenta (1967), Berndt and Christensen (1973)). Econometricians have been aware of simultaneity in production and cost estimation for more than half a century (e.g., Marschak and Andrews (1944) on random simultaneous equations and Mundlak (1961) on managerial behavior for early contributions). Early attempts to address simultaneity in factor inputs in case of production and cost estimation include fixed effect and first order condition approaches (confer Griliches and Mairesse 1995 for an overview). The fixed effects approach requires endogeneity problems to be time-invariant, which is a strict assumption. The first order condition approach instruments observed inputs by input prices. This approach breaks down in the case of input price endogeneity, for instance related to quality improvements or differences in adaptions to a downward sloping input supply curve.

Following Olley and Pakes (1996) and Levinsohn and Petrin (2003), the recent literature on production function estimation has adopted the so-called control function approach. In this case, a control function is estimated in addition to the production or cost function. It controls for endogeneity with the aid of a proxy for unobserved productivity shocks (e.g. investments in case of Olley and Pakes (1996) and intermediates in case of Levinsohn and Petrin (2003)).

Specifically, a functional relationship between the proxy variable, the control variables and the unobservable productivity is defined, where the productivity shock follows a first-order Markov process. Next, this relationship is inverted such that the unobservable productivity shock becomes an independent variable. In the first estimation step, the production (cost) and control functions are estimated jointly by linear regression, with the control function being approximated by a third-degree polynomial or some other parametric specification. In the second step, the production (cost) function is retrieved by general method of moments, exploiting the moment conditions and the obtained parameters from the first step.

Compared to Olley's and Pakes' (1996) estimation procedure, the procedure of Levinsohn and Petrin (2003) is slightly more sophisticated and replaces investments with intermediates as a proxy for productivity impulses, as intermediates opposed to investments are non-negative for active units. However, both approaches are vulnerable to critique. First, collinearity between free and proxy variables may leave coefficients unidentifiable (Bond and Söderbom, 2005). Second, the first-generation control function approaches focus solely on simultaneity related to capital input, while other factor inputs may also suffer from similar endogeneity issues. Third, the two-step procedure applied by Olley and Pakes and Levisohn and Petrin involve a loss in estimation efficiency.

The need for addressing these concerns has paved the way for a second generation of control function approaches, most notably

Wooldridge (2009) and Ackerberg et al. (2015). Exploiting the Markovian nature of productivity, Wooldridge (2009) derives a one-step estimator based on stacked moments. Ackerberg et al. (2015) propose to utilize Blundell and Bond's (2000) dynamic panel estimator, conditioning the inverted proxy function on the choice of labor. However, the more sophisticated features of the second-generation control function methods come at the expense of inferior small sample properties and challenges with convergence. Other influential examples include De Loecker (2007), Doraszelski and Jaumandreu (2013) and Gandhi et al. (2020). Van Beveren (2012) provides a comparative review on some of the key non-frontier control function approaches.

In conventional panel data econometrics, causality has become a focus in recent years. In the context of productivity estimation, much attention has been devoted to simultaneity in factor inputs, particularly capital inputs. The essence of the simultaneity issue is that the factor inputs are partly determined by unobserved productivity shocks, making factor inputs endogenous in estimation of the production function (or cost function).

2.1.2. *Simultaneity bias and frontier methods*

Since the late 1970 s, the frontier approaches that distinguish between the technology frontier (i.e. best practice) and technical efficiency (i.e. deviation from best practice) have proved useful in applied research. Beyond the theoretical appealing distinction between best practice and efficiency, frontier productivity approaches are devoted to estimation of non-parametric production technologies (e.g., *Data Envelopment Analysis*, abbreviated *DEA,* confer Charnes et al. (1978)), distinguishing technical efficiency and random noise (e.g., *Stochastic Frontier Analysis*, abbreviated *SFA*, confer Aigner et al., 1977; Meeusen and van den Broeck, 1977) or both (e.g., *StoNED*; confer Kuosmanen, 2006; Kuosmanen and Kortelainen, 2012).

There exist some notable contributions on handling of simultaneity bias within the frontier literature (e.g, Santín and Sicilia 2017 on DEA and Mutter et al. 2013 on SFA). An early demonstration of simultaneity bias in the context of non-parametric methods was provided by Orme and Smith (1996), who argue that simultaneity in factor inputs is likely to cause severe challenges for productivity measurement of public services. Applying Monte Carlo simulation combined with DEA, the authors demonstrate that efficiency scores may be affected by endogeneity bias, particularly for small sample sizes. Moreover, inefficient observation units applying little of an endogenous factor input may face tougher efficiency targets than equally inefficient observations units applying high levels of an endogenous factor input.

Wilson (2003) depicts a dependency between technical and artificial input efficiency related to a positive relationship between scale and professional management. Kumbhakar (2013) investigates the primal formulation in specification and estimation of a multiple-outputs – multiple-inputs production technology, applying an instrumental variable both for single equation and system approaches. He shows that outputs must be separable from inputs to avoid inconsistent estimation of a distance function.

Santín and Sicilia (2017) propose to handle variable endogeneity in DEA model by a simple statistical heuristic procedure for endogeneity detection and an instrumental input approach. In another DEA study on simultaneity biases, Mayston (2015) studies endogeneity caused by public funding. To accommodate the multiplicator effect caused by the mutual dependencies, the author proposes to estimate a frontier reflecting the wider opportunities available to the public service provider to improve its own output quality. Vishkaeii et al. (2021) propose to relax the convexity axiom in DEA, showing that their model outperforms the standard model under severe input endogeneity. Some other studies depict the conventional DEA model's vulnerability to variable endogeneity (e.g., Bifulco, 2001; 2003, Ruggiero, 2002; 2004, Cordero et al., 2016.).

Investigating the stochastic frontier model with a Bayesian framework, Griffiths and Hajargasht (2016) propose to combine an instrumental variable approach with introduction of a generalized error covariance structure to handle simultaneity biases. A comparative study on how variable endogeneity may be handle in DEA and SFA within a Bayesian framework – with investigations on the consequences for estimation results – is provided by Tsionas et al. (2021).

In the stochastic frontier literature, early contributions on variable simultaneity in production estimation were made by Kutlu (2010) – applying the Battese-Coelli estimator – and Tran and Tsionas (2013) – applying generalized methods of moments. Mutter et al. (2013) point out that SFA models handling input factor endogeneity are unavailable for the general case. Since their publication, some relevant contributions have emerged in this field. To control for the impacts of endogeneity on the frontier or efficiency scores, Karakaplan and Kutlu (2017a) propose a practical maximum-likelihood-based approach suited for cross sectional analysis, which is extended to a panel data setting by Karakaplan and Kutlu (2017b). Shee and Stefanou (2015) integrate Levinsohn and Petrin's (2003) control function approach in SFA, while Gronberg et al. (2015) deal with endogeneity with the help of pseudo-instrumental variables. Kutlu and Tran (2019) present an SFA framework for panel data assessments, which allows for both heterogeneity and endogeneity in factor inputs.

Tran and Tsionas (2015) make use of a copula to allow dependence between the inputs and the composed error term and develop a corresponding maximum likelihood estimator. Amsler et al. (2016) address simultaneity bias in two ways. First, they propose to apply the reduced form equations for the endogenous variables as control functions. Second, they suggest utilizing maximum likelihood estimation of a combination of the equation system of interested and unrestricted reduced form equations for the endogenous variables. Applying somewhat similar approaches, Amsler et al. (2016) and Amsler et al. (2017) study the case where contextual variables are correlated with the efficiency term or the error term. In this case, the endogeneity will affect the efficiency scores, but not the frontier.

In a series of recent papers, Paul and Shankar (2018; 2020; 2022) model efficiency as a deterministic function of covariates in combination with parametric frontier estimation. In Section 3, we extend this modeling approach to non-parametric efficiency analysis.

2.2. *Seaport efficiency measurement*

Port efficiency analysis dates to Roll and Hayouth (1993). The literature on port productivity and efficiency analysis broadly consists of two strands – *terminal* and *port* studies. We herein define the former analyses to concern handling of one type of cargo – typically containers – while the latter focuses on the joint handling of multiple cargo types. In general, choice of method and data differ among the two groups of studies. The placement of the subsequent empirical analysis is within terminal studies, with emphasis on container handling.

Jara-Díaz et al. (2006) contend that port operations consist of numerous smaller operations, each forming a chain of successive links, where the strength of the entire chain is determined by its weakest link. On the contrary, Bichou (2011) argues that modern container terminal systems are designed and operated in terms the quay, the yard, and the gate (cf. Marconsult 1994 for a resembling argument). While land, labor and equipment are considered key factors in container handling, labor is omitted in almost all published empirical studies (Spengler et al., 2024). The standard model specification in terminal studies concerns throughput of cargo as the sole output and capital and equipment as inputs (see Rødseth et al. (2024) for a comprehensive mapping of variables used for seaport efficiency measurement). A review paper by Zhang et al. (2024) regards Cullinane et al. (2006) as the reference study for this strand of the seaport efficiency literature. Critical reviews of this standard model specification are provided by Suárez-Alemán et al. (2014) and Talley (2016), who focus on different aspects of service quality. The influential study by Wang et al. (2005) justifies the conventional model specification, arguing that that cargo output is correlated with service quality. In a recent study, Spengler et al. (2024) investigate how implementing a multi-output technology spanning different container types (i.e., dry and reefer containers) impacts efficiency scores, relative to a technology with throughput as the sole output. While this study indicates that there could be benefits from output disaggregation, the current paper adopts a single-output technology to ensure that the empirical model specification is aligned with most empirical studies found in the literature. This allows generalizing our findings on simultaneity bias to the vast majority of existing container studies.

A complimentary classification of the seaport efficiency literature is made in the recent review by Zhang et al. (2024): Technical, allocative and economic efficiencies. Technical efficiency studies aim to evaluate maximum output for given inputs, while allocative efficiency studies involve choosing the right combination of inputs and outputs subject to prices. Economic efficiency studies adopt a broader definition of efficiency, including eco-efficiency. Zhang et al.'s (2024) review finds that a majority of studies on seaport efficiency measurement regard technical efficiency measurement, as is also the case for this study. Albeit we select our application and dataset to be representative for a majority of seaport efficiency studies, the methods and results presented herein are equally relevant for other applications in seaport efficiency measurement (e.g., allocative or environmental efficiency analyses) where simultaneity bias is present.

Zhang et al.'s (2024) review finds that *frontier methods* are used in a vast majority of seaport efficiency studies. The most common methods for analyzing seaport efficiency in terminal studies is DEA, followed by SFA (Odeck and Bråthen, 2012). The recent publication by Rødseth et al. (2023) introduces StoNED in seaport efficiency measurement. These three methodologies aim to estimate best practices from data, enabling measurement of port efficiency by comparing current productivities to best practice benchmarks. This paper utilizes the StoNED method that combines the best features of DEA and SFA.

Multi-output port studies tend to focus on the estimation of *neo-classical* or mean-valued cost or distance functions (see Kuosmanen and Fosgerau (2009) for a description and comparison of frontier and neo-classical production models). They pay attention to estimated marginal productivities of the cost function and their relationship to economies of scale and scope (e.g., Jara-Díaz et al., 2002; 2005). Parametric methods are typically used, offering simple calculation of derivatives and elasticities of the fitted function. Cost functions are fitted using input prices in combination with cargo volumes.

A common feature of terminal and port studies is their use of production theory in empirical analysis of ports, fitting production functions in the case of a single output or cost or distance functions in the case of multiple outputs. Any of the mentioned functions are vulnerable to endogeneity bias if inputs are correlated with technical efficiency, as previously discussed. Hence, evidence of simultaneity bias for technical efficiency measurement for a single-output technology also carries important implications for port studies focusing on multi-output production.

2.3. *Port choice*

A key challenge related to application of the control function methodology in maritime economics is the identification of a valid control variable for ports. To circumvent this shortcoming, we next look to the interrelated literature on port choice for suitable controls. While the literatures on port efficiency and port choice are closely related (Rødseth et al., 2023), they are usually seen as separate research areas within maritime economics (Rezaei et al., 2018).

Moya and Valero (2017) provide an in-depth review of the literature on port choice; i.e., the study of determinants of shippers' and carriers' choices of which ports to service. They classify this literature into two main strands; the perspective that port choice depends on factors under control of port authorities (abbreviated FC) and the perspective that port choice is solely influenced by factors beyond control of port authorities (abbreviated FBC). We refer to Moya and Valero (2017) for a complete account of variables used in port choice assessments. In this brief review, we focus on the most common and empirically sound covariates in port choice analysis, sufficient for a parsimonious (yet adequate) specification of a control function for port production function estimation.

A crucial factor for port choice is geographical location. Different aspects and measures of port location are considered in a majority of the studies reviewed by Moya and Valero (2017), considering both FC and FBC studies. Various measures have been used for this purpose, including *hinterland* distance (e.g., Andersson et al., 2009) and transport costs (e.g., Veldman and Bükmann, 2003; Veldman et al., 2011) and *foreland* (i.e., oceanic) distance (e.g., Malchow and Kanafani, 2001, 2004) and transport costs (e.g., Ng et al., 2013; Veldman et al., 2011). Malchow and Kanafani (2001, 2004) consider both hinterland and foreland distances, and show that hinterland distance matters more for carriers than foreland distance. Several studies find that parameter estimates of hinterland transport costs are higher than for hinterland distance (Yeo et al., 2008; Anderson et al., 2009; Ng et al., 2013).

Moya and Valero (2017) note that there appears to be a consensus among FC studies that port performance significantly affects port choice. Port performance is a multi-faceted concept that is frequently classified into efficiency and effectiveness (Brooks and Pallis, 2008). Studies that consider *port efficiency* a key determinant of port choice include Tiwari et al. (2003), Tai and Hwang (2005), Ng (2006), Ugboma et al. (2006), De Langen (2007), Wiegmans et al. (2008), Tongzon et al. (2009), Chou (2010), Park and Min (2011), Tang et al. (2011), and Steven and Corsi (2012).

While other port attributes (e.g., port effectiveness and pricing policies) have been considered in the port choice literature, they do not seem to share the same consensus as geographic location and port efficiency. Hence, we focus on these key determinants in the following. A benefit of this delimitation is that it enables a parsimonious specification of the control function. This is important for avoiding the curse of dimensionality in non-parametric estimators, which we turn to next.

3. Theoretical underpinnings

In the following, we present our theoretical model. To test the model's validity, we have performed a Monte Carlo experiment, which is presented in subsection 3.3.

3.1. Theoretical model

Following the econometric literature on simultaneity bias (cf., Section 2.1.1) and the empirical literature on terminal studies (cf., Section 2.2) we consider port production to encompass multiple inputs, $\boldsymbol{x} \in \mathscr{R}_+^N$ (e.g., areas, cranes and handling machines) that are employed for the handling of container throughput, $y \in \mathscr{R}_+$. In this case, the production possibility frontier of the container port can be characterized by a production function $f(\boldsymbol{x})$.

The current production may fall short of the technical maximal production, described by the production function, because of *technical inefficiency* in cargo handling. Drawing on the literature on productivity and efficiency analysis, Eq. (1) formally defines a port production model framework that captures these dynamics.

$$y = f(\boldsymbol{x})e^{v-u} \tag{1}$$

Following the literature on *stochastic* frontier analysis, we assume a composite error term; $\varepsilon = v - u$. Here, v captures random noise, while u is a one-sided error that embodies technical inefficiency. Note that assuming $v = 0$ makes the model *deterministic*, implying that any deviation from best practice is considered technical inefficiency. This stringent assumption is fundamental to the DEA model. Herein, we adopt a methodology with similar desirable features as DEA, but which does not assume away random noise.

Further assumptions about the production function are needed for empirical estimation. In the parametric stream of literature, the standard approach is to assume $\ln f(\mathbf{x})$ is linear in parameters. Taking logs of both sides of equation (1), the log-transformed model can be estimated by linear regression. However, Marschak and Andrews (1944) were the first to note that if the input demands $\boldsymbol{x}$ depend on the level of inefficiency u that is present in the composite error term, then the error term correlates with the explanatory variables of the regression model, and hence the commonly used Ordinary Least Squares (OLS) estimator is biased. Addressing this simultaneity bias is a central theme in the econometric estimation of production function.

In this paper, we do not impose any specific assumptions about the functional form of f, but only require it to satisfy a set of axioms from economic theory:

1. $f(\boldsymbol{x})$ is monotonically increasing in inputs, $\boldsymbol{x}$.
2. $f(\boldsymbol{x})$ is globally concave
3. $f(\boldsymbol{x})$ exhibits variable returns to scale (VRS)

In the present setting of a shape-constrained, non-parametric production function subject to random noise, the simultaneity bias remains unaddressed. In the next sub-section, we show how the control function approach (Olley and Pakes, 1996) can be adapted to this setting.

3.2. Convex regression

To estimate model (1) in a non-parametric fashion, we apply Convex Non-parametric Least Squares (CNLS, Kuosmanen, 2008). We will throughout consider a panel comprising I ports (indexed by $i = 1,.., I$) that are observed over multiple time periods (indexed $t = 1,..,T$). The CNLS estimator of the port production function is in this case defined by Eq. (2).

$$
\begin{aligned}
& min\sum_{t=1}^{T}\sum_{i=1}^{N}\varepsilon_{it}^{2} \\
& \text{s.t.} \\
& lny_{it} = lnf_{it} + \varepsilon_{it}, \forall it \\
& f_{it} = \alpha_{it} + \boldsymbol{\beta}_{it}^{'}\boldsymbol{x}_{it}, \forall it \\
& f_{it} \leq \alpha_{hs} + \boldsymbol{\beta}_{hs}^{'}\boldsymbol{x}_{it}, \forall it, hs \\
& \boldsymbol{\beta}_{it} \geq \mathbf{0}, \forall it
\end{aligned}
\tag{2}
$$

The CNLS predictions $\widehat{f}_{it}$ provide estimates of $E(y_{it}|\mathbf{x}_{it}) = f(\mathbf{x})^{E(-u)}$. The $\boldsymbol{\beta}$-coefficients are estimates of marginal products of inputs (i.e., $\partial f(\mathbf{x}_{it})/\partial\mathbf{x}_{it}$). The first set of inequality constraints ensures that the production function is concave, while the second set of inequality constraints ensures monotonicity (i.e., non-negative marginal products).

Eq. (2) offers a consistent estimator of the average practice port production function ($f(\mathbf{x})^{E(-u)}$) in absence of simultaneity bias (Seijo and Sen, 2011). To circumvent this endogeneity problem, we propose an extension of the model framework that estimates the port production function jointly with a non-parametric control function estimator of the inefficiency term as function of other covariates; cf. Section 2.1.1 for a review of the use of the control function method to mitigate simultaneity bias. This is enabled by utilizing the close relationship between port efficiency and choice, as elaborated in Section 2.3.

To fix ideas, let $c \in \Re_{+}$ denote a port choice indicator (e.g., the number of calls at a port) and let $\mathbf{z} \in \Re_{+}^{M}$ denote a vector of attributes that describe a port's geographical location. In line with the FC port choice literature (cf., Section 2.3), we assume that that shippers and carriers are aware of ports' efficiencies (e.g., through interaction and experience). Hence, we define port choice as a function of port location and technical inefficiency:

$$
c = g(\boldsymbol{z}, u) \tag{3}
$$

Following Olley and Pakes (1996), we assume that the port choice function in Eq. (3) is strict monotonic decreasing in the inefficiency term u, which enables inverting the function. Hence, the inefficiency term can be expressed as a function of port location and choice:

$$
u = g^{-1}(\boldsymbol{z}, c) \tag{4}
$$

Eq. (5) extends the CNLS estimator in Eq. (2) by replacing the inefficiency term by a non-parametric estimator of the control function – defined by Eq. (4) – which makes the CNLS port framework robust to simultaneity bias.

In Eq. (5), ω is an infinitesimal negative number that ensures that port inefficiency is strict monotonic decreasing in port choice (or inversely, that port choice is strict monotonic decreasing in port inefficiency). The control function is assumed to exhibit convexity and constant returns to scale (CRS). The former is guaranteed by the second set of inequality constraints in Eq. (5). The latter is a convenient assumption in our setting, as it makes sure that the production and control functions do not "trade-off" scale properties among each other. The port production function, on the other hand, is assumed to exhibit VRS, which is ensured by including constant terms, α_{it}, in the model.

Eqs. (2) and (5) constitute quadratic optimization problems that can be solved using commercial Non-Linear Programming (NLP) solvers such as Minos or Conopt. The solutions to these programs provide the average practice production- and control functions. Since the control function in Eq. (5) can be considered to estimate *mean* technical inefficiencies, we follow Schmidt and Sickles (1984) and adjust the optimization results to obtain unbiased estimates of *technical inefficiencies* and the *frontier* production function using Eq. (6):

$$
\begin{aligned}
& min\sum_{t=1}^{T}\sum_{i=1}^{N}v_{it}^{2} \\
& \text{s.t.} \\
& lny_{it} = lnf_{it} - g_{it} + v_{it}, \forall it \\
& f_{it} = \alpha_{it} + \boldsymbol{\beta}_{it}^{'}\boldsymbol{x}_{it}, \forall it \\
& g_{it} = \delta_{it}c_{it} + \boldsymbol{\lambda}_{it}^{'}\boldsymbol{z}_{it}, \forall it \\
& f_{it} \leq \alpha_{hs} + \boldsymbol{\beta}_{hs}^{'}\boldsymbol{x}_{it}, \forall it, hs \\
& g_{it} \geq \delta_{hs}c_{it} + \boldsymbol{\lambda}_{hs}^{'}\boldsymbol{z}_{it}, \forall it, hs \\
& \boldsymbol{\beta}_{it} \geq \mathbf{0}, \forall it \\
& \delta_{it} \leq \omega, \forall it \\
& \boldsymbol{\lambda}_{it} \geq \mathbf{0}, \forall it
\end{aligned}
\tag{5}
$$

$$
E[lny_{it}|\boldsymbol{x}_{it}, c_{it}, \boldsymbol{z}_{it}] = \underbrace{(lnf_{it} - g^{MIN})}_{\text{Frontier function}} - \underbrace{(g_{it} - g^{MIN})}_{\text{Techical inefficiency}}, \forall it \tag{6}
$$

where $g^{MIN} = \min_{i=1,.I,t=t,.,T}\{g_{it}\}$.

3.3. Monte Carlo experiment

Before proceeding with the empirical implementation, we demonstrate the usefulness of the proposed method by implementing a Monte Carlo experiment. We adopt the Data Generation Process from other comparable studies to ensure that key assumptions have previously been carefully considered and validated. Following Cordero et al. (2015), we assume that the true production function is represented by the Cobb-Douglas function $y^{*} = x_1^{0.3}x_2^{0.35}x_3^{0.35}$, where the inputs are drawn from the uniform distribution over the interval [5,50]. Observed outputs may not reflect the true frontier but are perturbed by random variations and inefficiency. Following Rødseth et al. (2023), the random error term v^{Eff} is drawn from the normal distribution with mean 0 and standard deviation 0.5. Inspired by Cordero et al. (2015), the inefficiency term u is correlated with input x_3 (in accordance with Rødseth et al., 2023) using the formula by Wang and Schmidt (2002), specifically:

$$u = \rho\frac{5}{x_3} + w^{Eff}\sqrt{1-\rho^2} \tag{7}$$

where ρ is the (positive) correlation coefficient and w^{Eff} is the absolute value of the natural logarithm of a random number drawn from the uniform distribution over the interval [0.5, 1]. We use 100 draws for each of the following correlation coefficients: 0 (no simultaneity bias); 0.45 (mild simultaneity bias); 0.9 (severe simultaneity bias). Observed outputs are consequently calculated by $y = x_1^{0.3}x_2^{0.35}x_3^{0.35}e^{v^{Eff}-u}$, assuming a sample size of 100 observations per draw.

Let the true port choice function (cf. Eq. (3)) be $c = 2 + 0.5z_1 - 20\widehat{u} + v^{Choice}$, where z_1 is drawn from the uniform distribution over the interval [25,75] and the error term is drawn from the normal distribution with mean 0 and standard deviation 0.5. To test the influence of the quality of the control variable on the performance of the CNLS control function estimator, we assume that port inefficiency as experienced by shippers and carriers $(\widehat{u})$ can be described using Wang's and Schmidt's (2002) approach:

$$\widehat{u} = \rho u + w^{Choice}\sqrt{1-\rho^2} \tag{8}$$

We use 100 draws for each of the following correlation coefficients: 0.45 (weak control function); 0.9 (strong control function). The disturbance term w^{Choice} is drawn from the normal distribution with mean 0 and standard deviation 0.05.

To showcase the overall performance of the non-parametric CNLS in the presence of endogeneity, we apply a correctly specified OLS estimator (i.e., $y = x_1^{\beta_1}x_2^{\beta_2}x_3^{\beta_3}e^{\beta_0}$) alongside the conventional and robust CNLS estimator presented by Eqs. (2) and (5). The results of the Monte Carlo exercise are presented by Table 1, which shows how the Mean Squared Error (MSE; calculated by normalizing deviations between the estimated and true frontier by the true best practices) of the estimated frontier develops as the correlation of the input x_3 and the efficiency term gradually increases from 0 to 0.9. Because we use Eq. (6) to disentangle the frontier function for the control function model, we report results both for (unadjusted) OLS and CNLS as well as modified OLS (MOLS) and modified CNLS to ensure just comparisons. The latter approach is generally known as the StoNED method (Kuosmanen and Kortelainen, 2012). The adjustment involves shifting the frontier estimates upwards using the method of moments to estimate the expected value of the efficiency term (see Kuosmanen and Kortelainen, 2012, p. 18 for details).

Overall, the results demonstrate that the CNLS and StoNED estimators perform similar to the correctly specified parametric OLS and MOLS estimators. The adoption of the control function approach further boosts the performance of the non-parametric estimator under simultaneity bias. The performance of the control function model is not severely affected by the degree of simultaneity bias when the control function accurately represents port efficiency. The superior performance of the control function approach also in absence of endogeneity suggests that exploiting the relationship between port choice and efficiency can be valuable even in the absence of simultaneity bias.

4. Dataset and empirical implementation

In the following, we account for the preparation of the dataset applied in our study. Next, we present our initial screening.

4.1. Preparing the dataset

We implement the theoretical models in Section 3 empirically using data from the eight largest container ports in Norway with quarterly observations from 2010 to 2016, amounting to 224 observations in total.[2] The dataset used herein was compiled by Rødseth et al. (2020). We refer to this study for a complete account of the data collection and processing.

The ports' locations are in southern Norway, as illustrated in Fig. 1. Five of the ports under consideration (i.e., the ports of Borg,

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[2] One referee raised a question about the current sample size and how it may affect the performance of the control function approach. Note that the sample size used for the empirical analysis is comparable to several previous seaport efficiency studies (e.g., Odeck and Schøyen 2020, Rødseth et al. 2020; 2023; and 2024, and Schøyen and Odeck 2017) and panel data is frequently used for measuring seaport efficiency (see Zhang et al, 2024). While a small sample size can reduce the performance of statistical techniques for mitigating endogeneity, performance is dependent on the quality of the instrument or control variable (e.g., Crown et al., 2011). The Monte Carlo experiment documented in Section 3.3 demonstrates that the control function approach has a superior performance to other frontier estimation approaches even in absence of endogeneity. This Monte Carlo study uses 100 observations per sample, which is substantially smaller than the sample size used for the empirical analysis.

Table 1
Results of the Monte Carlo experiment (MSEs).

Estimator	Control function	Simultaneity bias		
		No	Weak	Strong
OLS		0.069	0.107	0.099
MOLS		0.053	0.060	0.064
CNLS		0.075	0.110	0.100
StoNED		0.063	0.055	0.067
CF-CNLS	Weak	0.043	0.042	0.059
CF-CNLS	Strong	0.040	0.037	0.048

Fig. 1. Map of South Norway, where red dots indicate ports in our sample. Source: Rødseth el al. (2020). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Drammen, Larvik, Moss and Oslo) are located on the east coast and belong to the Oslo fjord region, which is the most populated area in Norway. The other three ports (i.e., the ports of Kristiansand, Risavika and Ålesund) are in Western Norway.

In our study, we consider a standard specification of the production function within the container terminal efficiency literature (e.g. Roy et al. 2020) with one output and four inputs. As the sole output, we apply container throughput, which is obtained by processing source data from Statistic Norway's quarterly port statistic. As factor inputs, we apply data on quay length, port area, handling machines and quay cranes, which are collected in cooperation with the container ports under consideration. It is worth mentioning that it has ensured more reliable data compared to publicly available data sources that are commonly used for seaport efficiency measurement; see Odeck and Schøyen (2020) for further details.

As evident from the mappings of variables used in terminal efficiency studies by Rødseth et al. (2024; Table 1) and Sprengler et al. (2024; Table 1), the current paper's choice of inputs and output is common in the literature on port efficiency measurement. It is also aligned with the model specification used by Cullinane et al. (2006), which is cited as the main representative study in port technical efficiency research by Zhang et al.'s (2024) recent review of the port efficiency literature. Handling machines and quay cranes may also function as proxies for labor inputs, which are unavailable for our study. Omitting variables that are consumed in tandem with other inputs (outputs) is a well-known strategy to reduce the dimensionality of the input (output) vector to mitigate the curse of dimensionality inherent in non-parametric efficiency analysis.

As discussed in Section 2.2, terminal efficiency studies commonly exclude labor as a factor input due to unavailable data. Nevertheless, Marconsult (1994) finds evidence of a relatively fixed relationship between the number of quay cranes and number of workers, implying that quay cranes may serve as a decent proxy for labor. This has become the conventional approach in this part of the literature (Rødseth et al. 2024). We refer to Cullinane and Wang (2006) for an overview of the physical attributes applied in port production functions.

Applying container throughput as a sole output is a common approach in terminal efficiency literature (cf. Section 2.2 for an overview and discussion). While authors of port studies often prefer a model specification with several outputs, authors of terminal studies put more emphasis on input heterogeneity (Rødseth et al. 2024). We refer to Cullinane et al. (2002) and Odeck and Schøyen (2020) for further justification of the choice of inputs and output used in this study, as well as the operational definition of cargo handling machines.

Next, we turn to the empirical specification of the control function. First, we consider the number of calls (with the purpose of loading/unloading containers) at a port per quarter a good proxy of the popularity of a port, i.e., of port choice. Second, we consider Harris' (1954) market access measures to provide approximate geographical location of a port (see Rødseth et al., 2023 for a definition and implementation). These measures enable operationalizing a port's foreland and hinterland economic potential subject to geographical location by evaluating potential market connections (e.g., measured by amounts of people or production) weighted by a measure of friction over space (e.g. by travel time or distance). Based on Section 2.3, we consider hinterland market access to be the most important indicator and delimit the scope of our current assessment to this variable. This choice is also justified by the observation that the ports under consideration are fairly homogenous with regards to foreland market potential (especially to foreign ports, where sea distances are relatively comparable across ports), and the higher weight on hinterland market access is also in line with the results of Malchow and Kanafani (2001, 2004). To approximate geographical location of a port, this study consequently uses onshore access to markets: Hinterland employment by workplace and residence at zip code level is utilized to measure market potential, while friction is measured by travel time.

In summary, to avoid circumstantial factors to interfere with our efficiency measurement, we include controls for port choice (measured by number of calls) and geographical location (measured by hinterland market access). Note that these controls are justified by and explored in other papers (e.g., Cheon, 2009, Yuen et al., 2013; Rødseth et al. 2023).

Summary statistics of the data are provided by Table 2.

4.2. *Initial screening*

The presence of simultaneity bias can be tested using the heuristic by Santin and Sicilia (2017). This method is developed for DEA but still provides a relevant screening for endogeneity for this study since DEA is a special case of CNLS (see Kuosmanen and Johnson, 2010). We refer to Section 2 in Santin and Sicilia (2017) for details regarding the heuristic, which we implement using 2 000 bootstrap replications. The general idea behind the endogeneity test is to compute Pearson correlations between DEA efficiency scores and inputs for each bootstrap sample, which in turn enable forming input-specific metrics that evaluate whether inputs are systematically correlated with DEA efficiency scores. The results suggest that investments in mobile port capital are strongly correlated with (DEA-based) port efficiency: We find a positive association between efficiency and quay cranes and the number of handling machines, respectively, for all bootstrap replications. Port area is positively correlated with efficiency in 53 percent of the replications. Thus, taking action to mitigate simultaneity bias in port efficiency measurement seems in order.

A referee stressed the importance of the homogeneity assumption for non-parametric efficiency analysis. By homogeneity, we here mean that units under considerations undertake similar activities, produce comparable outputs, use common technologies, have availability to a similar range of resources and operate in similar environments.

According to Dyson et al. (2001), it is protocol to seek external comparators or cluster units into homogenous sets. The dataset presented in Section 4 fits very well to this protocol: It focuses solely on container operations and on ports of comparable sizes. All ports are situated in southern Norway and are involved in feeder transport to central Europe. The ports are all state-owned enterprises, operate under the same regulatory standards and have access to similar resources.

The concerns of Dyson et al. (2001) are of special importance to DEA, which is a deterministic estimator based on envelopment of data (and therefore "extreme observations"). CNLS, on the other hand, fits a non-parametric frontier by minimizing the sum of squared residuals (that can either be positive or negative), which substantially mitigates this problem.

There are some methods developed for DEA that allow evaluating influential datapoints or "outliers" (e.g., super-efficiency), which are not readily applicable to CNLS. There are also several methods for outlier testing in conventional statistics (e.g., Difference-in-fits and Cook's D) that also are not readily available for CNLS. To evaluate the presence of influential datapoints we herein develop a simple *leave-one-out* approach inspired by the Difference-in-fits statistic: We evaluate the influence of observation *(i,t)* by estimating the mean ratio of best practices of *all other* observations subject to reference frontiers estimated with and without observation *(i,t)*. This test shows that the industry mean ratio (i.e., evaluated for all DMUs) is 1.000 while the minimum mean (observation-specific) ratio is 0.997 and the maximum mean ratio is 1.010. This suggests that there are no single observations in the dataset that substantially influence the estimated benchmarks of other observations. Based on this result and on the preceding discussion, we conclude that the current sample meets the homogeneity assumption in frontier analysis.

5. Results

Having described the dataset, empirical model specifications and robustness tests, we now turn to the empirical results. Fig. 2

Table 2
Summary statistics.

Function	Variables (per port per quarter)	Obs	Mean	Std. Dev.	Min	Max
Production	Quay length (m)	224	417.8	228.2	140.0	875.0
	Port area (1000 m^2)	224	64.9	37.7	10.0	140.0
	Quay cranes (no)	224	2.0	1.1	0.0	4.0
	Cargo handling machines (no)	224	6.2	6.0	2.0	24.0
	Containers (TEUs)	224	16,610.1	13,612.0	1,009.0	57,751.0
Controls	Harris hinterland measure	224	52.0	77.3	6.2	253.7
	Calls (no)	224	71.5	36.5	3	143

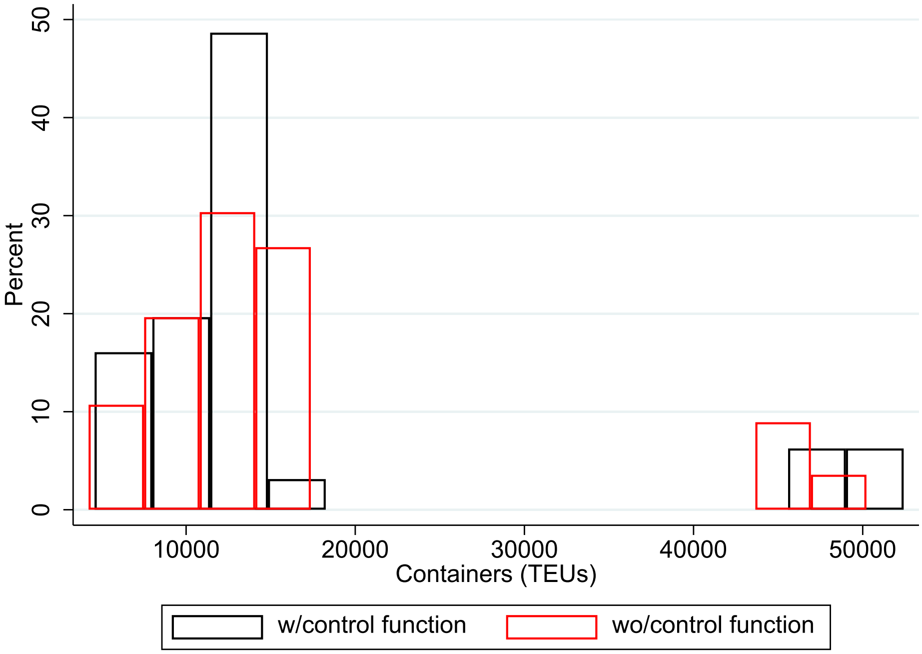


Fig. 2. Histograms for expected container output estimated with and without the control function

presents histograms of the expected value of the dependent variable (i.e., container output) estimated with (cf. Eq. (5)) and without (cf. Eq. (2)) the control function, i.e., with and without consideration of simultaneity bias. By expected value, we here mean the predicted container output *prior to* adjusting for technical efficiency; cf. Eq. (6). Fig. 2 showcases that the distributions of expected container outputs estimated with and without the control function differ. It weakly indicates that the expected container output tends to be underestimated when simultaneity bias is ignored. This estimation bias appears to be increasing in port size, measured in terms of the number of containers handled.

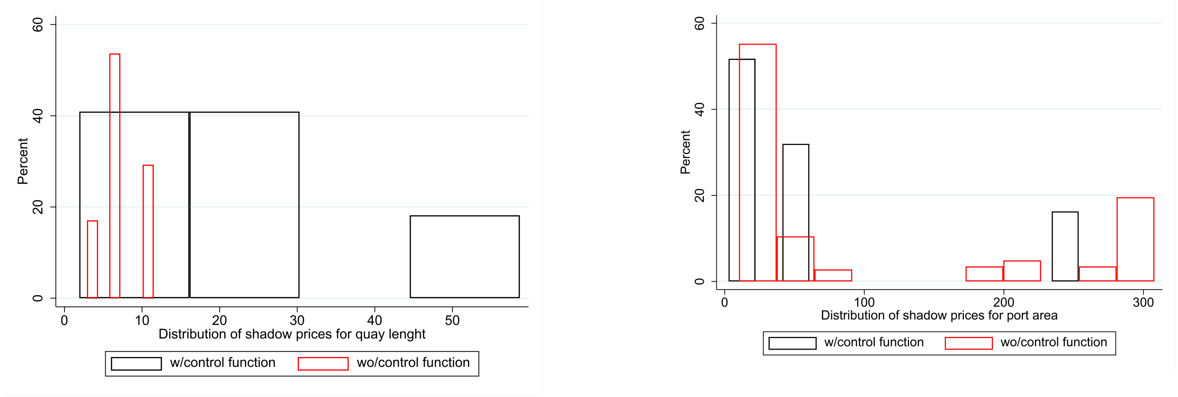
To provide an in-depth comparison, Table 3 presents means and maximums of expected container output estimates with and without the consideration of simultaneity bias (i.e., with and without the use of a control function). It shows that means are higher for 4 (out of 8) ports and maximums are higher for 7 ports when controlling for simultaneity bias. On the one hand, expected container outputs with consideration of simultaneity bias are higher than the corresponding estimates without consideration of simultaneity bias for only 111 of the 224 observations in the dataset. On the other, the sum of deviations for these 111 observations surpasses the sum of deviations for the remaining observations.

Fig. 3 provides further comparisons of the production functions estimated with and without the control function. It presents distributions of shadow prices (i.e., marginal products) of inputs, estimated with and without control for simultaneity. It is well-known that presence of endogeneity leads to biased parameter estimates, where the sign of the bias relates to the correlation between an independent variable (i.e., an input) and the omitted variable (i.e., the efficiency term). Fig. 3 shows that the production model estimated jointly with the control function puts more weight on quay length compared to the production model estimated without the control function. On average, shadow prices are lower for the three remaining inputs when simultaneity is ignored, compared to the empirical model that controls for simultaneity. This suggests that economically important indices that rely on weighting of inputs, e.g., elasticities of substitution and allocative efficiency scores, also are vulnerable to simultaneity bias.

Having compared expected container outputs estimated with and without controls for simultaneity, we next provide an

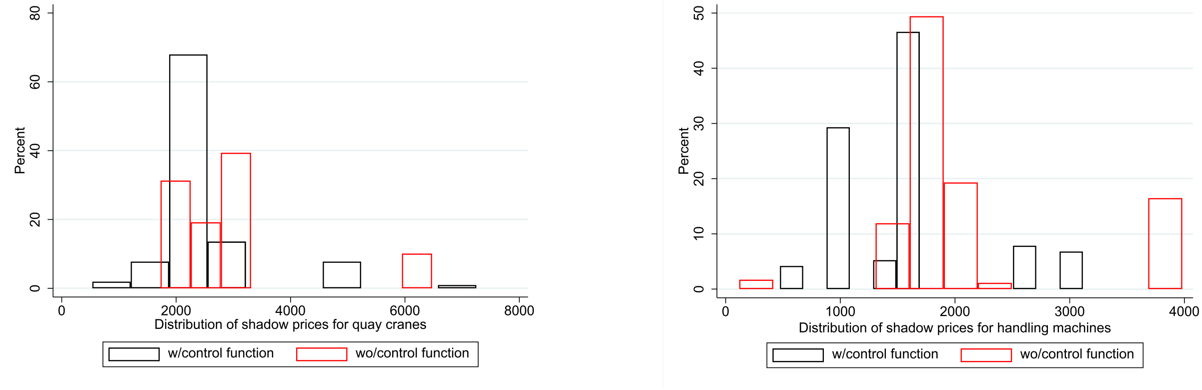
Table 3
Summary statistics of the fitted production function with and without the control function per port (Mean and Max).

Port	Without control		With Control	
	Mean	*Max*	*Mean*	*Max*
Borg	14 607.8	14 607.8	13 749.4	14 035.7
Drammen	6 231.4	8 235.1	6 169.2	8 376.4
Kristiansand	11 743.2	11 743.2	11 757.8	13 033.4
Larvik	14 315.1	14 429.6	13 965.8	14 626.3
Moss	13 077.3	13 077.3	13 321.2	14 031.6
Oslo	47 238.9	50 222.0	48 910.6	52 422.8
Risavika	8 067.3	9 204.9	7 886.0	11 086.7
Ålesund	12 223.9	14 444.5	12 994.8	15 775.2



a) Shadow prices for quay length

b) Shadow prices for port area



c) Shadow prices for quay crane

d) Shadow prices for handling machines

Fig. 3. Comparison of shadow prices for the production function estimated with and without the control function

investigation into the empirical consequences of relaxing strict monotonicity of the control function in the port choice output. Strict monotonicity is paramount for control function estimation, being a prerequisite for inverting – and consequently estimating – the control function. While our novel non-parametric model ensures strict monotonicity through sign constraints, the literature on control

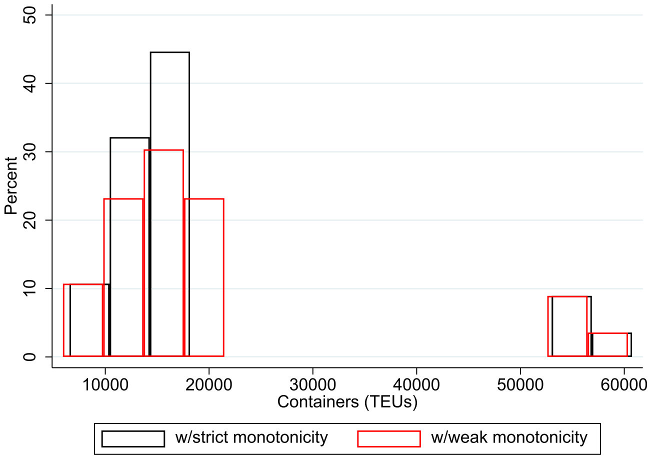


Fig. 4. Comparison of production functions estimated with strict and weak monotonicity.

function estimation typically uses parametric specification of the production and control functions that do not ensure compliance with strict monotonicity. Note that the subsequent analysis focuses on the distinction between the frontier production function and technical inefficiency, as defined by Eq. (6).

Fig. 4 compares the distributions of (frontier) production function estimates subject to strict and weak monotonicity. The latter is estimated assuming that the shadow price of the port choice output (i.e., no. of calls) is non-positive (i.e., can be 0). Fig. 5 compares the distributions of production function estimates subject to strict monotonicity and without imposing monotonicity. The latter is estimated without requiring that the shadow price of the port choice output is non-positive. In general, the pairwise correlation between the production function estimates subject to strict, weak and no monotonicity is very high (i.e., 0.99 for all cases considered). Consequently, ignoring the strict monotonicity property has limited consequences for the current dataset and estimation method. However, Fig. 4 showcases that production function estimates can be affected by the strict monotonicity requirement and should consequently be considered a warning that control function studies that ignore this basic assumption can be vulnerable to estimation bias.

Finally, we note that the adjusted control function estimates in Eq. (6) can be considered estimates of technical inefficiency. Hence, $\exp\left(-\left(g_{it}-g^{MIN}\right)\right)$ readily provides technical efficiency scores, which are presented by Fig. 6. It suggests that the efficiency score distribution of the Norwegian container port sector is right skewed, with a minimum efficiency score of 0.68 and an average efficiency score of 0.82.

6. Summary and conclusions

Policy makers in Norway and abroad aim for a green, competitive and resource efficient transport sector. Modal shift in freight transport from road to sea is inherent in meeting this objective. Ports are a key component of the maritime supply chain, hence making continuous improvement of port efficiency a key instrument for enabling green transformation of the transport sector. While unbiased information about port performances provides vital decision support for port managers, industry actors and policy makers alike, this study raises a question about the validity of seaport efficiency measurements that are occasionally used as a tool to identify improvement potential in policy design and managerial practices. For these analyses to be as useful as possible and not misleading, it is important that the affiliated results do not suffer from simultaneity bias.

Seaport efficiency measurement is one of the major topics in maritime economics. While drawing on methods from the literature on productivity and efficiency measurement, seaport efficiency studies have previously not adopted associated state-of-the-art practices to handle simultaneity bias. The presence of endogeneity bias can distort any key metric used for decision-making that is derived from port productivity and efficiency analysis – including best practices, marginal productivities, input substitution and efficiency scores – thereby making the outputs of the production analysis less relevant for decision makers. This paper therefore fills the identified research gap while also bridging the gap between the distinct research literatures on port efficiency and choice.

Our empirical application to Norwegian container ports illustrates that simultaneity bias can influence productivity and efficiency measurement, also in the case of non-parametric frontier analysis. For the Norwegian case study, the production function tends to be underestimated when the simultaneity bias is unaccounted for. This has repercussions for the evaluation of best practices, e.g., for studying productivity and technical changes, and for technical efficiency measurement. We also find evidence of asymmetric effects of endogeneity on estimated marginal products of factor inputs, suggesting that the shadow pricing approach (see e.g., Rødseth (2023) for an example of this technique to estimate unobservable prices using production theory) can be especially vulnerable to simultaneity bias. This further implies that allocative efficiency scores that depend on shadow prices of inputs (outputs) are biased subject to simultaneity bias.

The empirical port production function framework adopted by this study – using port capital items as inputs to measure technical efficiency – is comparable to the majority of studies in seaport efficiency measurement (cf., Zhang et al, 2024). Hence, we anticipate that many former studies are vulnerable to the critique put forth in this paper, implying that previous results can be biased. We consequently encourage additional investigation into endogeneity of port production functions and appropriate controls for port efficiency analysis, including also replication of former studies.

As part of our inquiry, we have extended the StoNED method by simultaneously estimating production and control functions. This adds to the literature on control function estimation in general, where non-parametric estimation of the control function is rare. Our approach has two advantages when compared to the conventional, parametric approach to control function estimation. First, it does not require multiple steps and rigorous assumptions about the error term to retrieve the port production function. Second, our approach ensures compliance with strict monotonicity of the control function. Sensitivity tests showcase that imposing sign constraints to ensure strict monotonicty has implications for the fitted production function. Since compliance with strict monotonicity (as well as other regularity conditions for the control function) is in general not imposed – and thus not guaranteed – by conventional empirical control function methods, we conclude that most other studies using the control function methodology are vulnerable to estimation bias. In principle, the control function approach is flawed in the absence of strict monotonicity as the control function cannot be inverted and thus not identified in this case. We leave this topic for further research.

The current paper focuses on single-output production (i.e., container throughout) as this is the traditional model specification used both in container terminal studies and in studies on simultaneity bias correction in production function estimation. As outlined in Section 2.2, there is also a strand of the seaport efficiency literature that models cargo handling as a multi-output production. Our results are generalizable to multi-output production as correlation between the error term and inputs causes estimation bias regardless of the dimensionality of the output vector. Kuosmanen and Johnson (2017) provide a CNLS model specification for multiple outputs

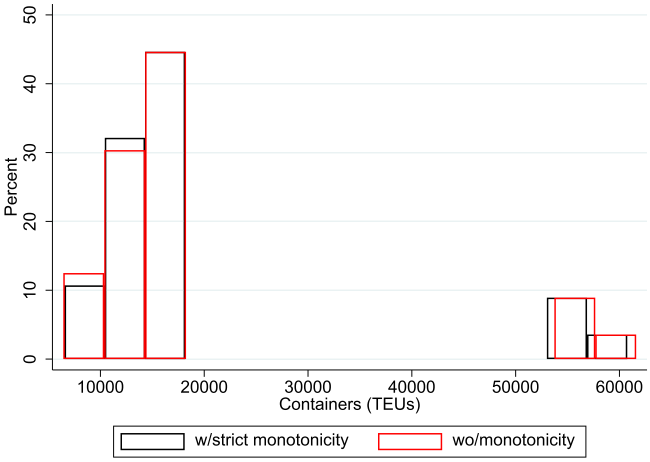


Fig. 5. Comparison of production functions estimated with strict monotonicity and without imposing monotonicity.

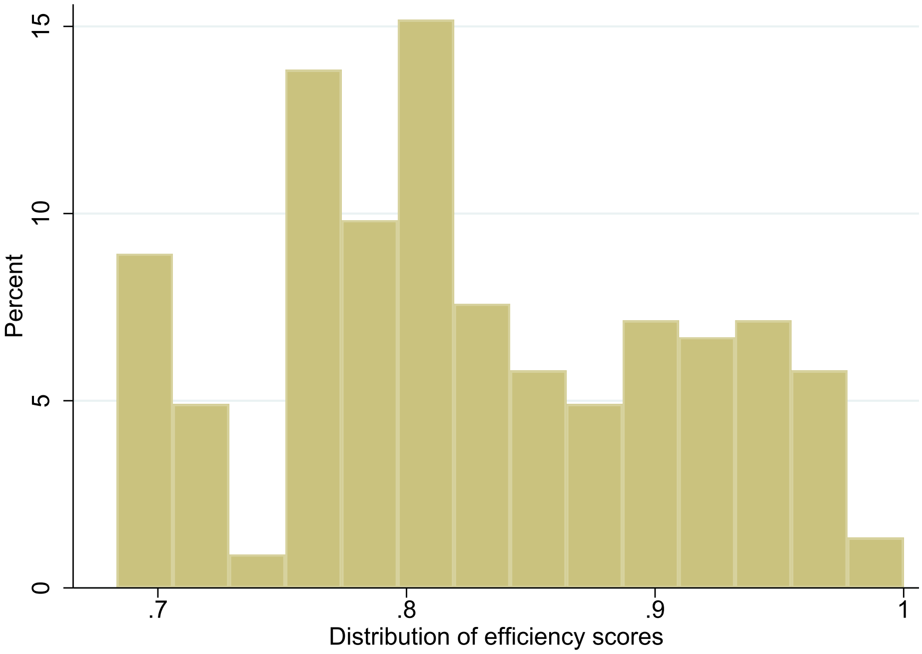


Fig. 6. Histogram of efficiency scores fitted based on the control function estimates.

using the directional distance function, which could be combined with the control function approach proposed in this paper to circumvent simultaneity bias in multi-output production settings, both in the seaport sector and beyond. We consider an extension of the control function approach to the multi-output setting a promising avenue for future research.

CRediT authorship contribution statement

Kenneth Løvold Rødseth: Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Timo Kuosmanen:** Writing – editing, Methodology, Conceptualization. **Rasmus Bøgh Holmen:** Writing – original draft, Investigation, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

The authors do not have permission to share data.

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