CO_2 emission performance evaluation of Chinese port enterprises: A modified meta-frontier non-radial directional distance function approach

Yan Li[a], Jiawei Li[a], Yu Gong[b], Fangqing Wei[c], Qingbo Huang[a, *]

[a] *School of Maritime Economics and Management, Dalian Maritime University, Dalian, Liaoning 116026, P. R. China*

[b] *Southampton Business School, University of Southampton, Southampton SO17 1BJ, UK*

[c] *School of Management, University of Science and Technology of China, Hefei, Anhui 230026, P.R. China*

Abstract

The rapid development of China's port industry has led to serious CO_2 emission problems. In this study, using the panel data of 16 port enterprises in China during 2013–2018, we first classified port enterprises into two groups based on the criterion of size and complexity. Then, we use a modified non-radial directional distance function in the meta-frontier framework to evaluate the port CEP and its dynamic changes as well as driving forces. The results show that the CEP of the whole is poor over the sample period on the basis of meta-frontier. Both groups performed well in CEP with respect to their specific group frontiers. Driving forces of the growth of CEP differ among port groups and individual port. Additionally, the effect of environmental regulation on CEP is positive, while the effect of openness on the growth of CEP is negative.

Keywords: CO_2 emission performance; non-radial directional distance function; meta-frontier; data envelopment analysis; port enterprises

1. Introduction

Ports are supporting points of an integrated transportation network and an important window for international trade and transportation, 80% of the world's trade and transportation rely on port transhipment (United Nations Conference on Trade and Development, 2018); in other words, ports are important participants in regional economic development. In the past four decades, the trade volume of China has increased 224 times, that is, increased from 20.60 billion US dollars in 1978 to 4,623 billion US dollars in 2018 (China Statistical Yearbook, 2019). The rapid development of international trade has greatly promoted the port industry in China, e.g., the cargo throughput of Chinese ports increased from 280 million tons in 1978 to 14.35 billion tons in 2018 (China Port Statistical Yearbook, 2019). However, the growth of the port industry is at the expense of severe environmental pollution, such as solid waste pollution, air pollution (Psaraftis and Kontovas, 2010; Dessens *et al*., 2014; Sueyoshi *et al.*, 2017). For example, the emissions of SO_2, NO_X, and hydrocarbons, generated from China's port ships were 85.30 (10^4 tons), 134.60 (10^4 tons), and 7.90 (10^4 tons) respectively in 2017 (Ministry of Ecology and Environment of the People's Republic of China, 2018). Among these pollutants, CO_2 emissions generated by ports play a decisive role in global warming. The development of low-carbon port industry can help alleviate increasing global warming and achieve the goal of reducing CO_2 emissions intensity by 7% in 2020 compared to that in 2015 (Ministry of Transport of the People's Republic of China, 2018). Therefore, it is of great significance to evaluate and analyse the CO_2 emission performance (CEP) of ports in China, thus providing valuable information to decision makers to improve CEP and even coordinate the sustainable development of the port industry and economic growth.

Many scholars have analysed the CEP of port by using various qualitative and quantitative approaches (e.g., Mamatok and Chun, 2017; Wan *et al*., 2018; Tovar and Wall, 2019b). Among these approaches, data envelopment analysis (DEA) arouse the significant attention of scholars and practitioners because this method can be used to the efficiency evaluation of decision making units with multiple inputs and outputs

(Charnes *et al*., 1978). DEA neither need to pre-assume a specific form of production between input and output, nor subjectively set input and output weights (Sun *et al*., 2017). Given its advantages, DEA was firstly applied in port efficiency assessment by Roll and Hayuth (1993), and later used to the sustainable development of ports from the perspective of environmental performance considering environmental pollution (e.g., Chang, 2013; Lee *et al*., 2014; Li *et al*., 2020; Tovar and Wall, 2019b). Although DEA and its extended methods have been used for environmental performance evaluation of ports from different perspectives, prior studies always assume that all ports share a common technology, and ignore the technology heterogeneity among ports caused by specialization, size and complexity as pointed out by Tovar and Wall (2019a). In addition, few studies analyse the dynamic changes in environmental performance of ports and explore the underlying driving forces of environmental performance changes.

In this study, using the panel data of 16 port enterprises in China during the period of 2013–2018, we first classified 16 ports into two groups based on the criterion of size and complexity. Then, we use a modified non-radial directional distance function (DDF), an approach that simultaneously considers expanding desirable outputs and contracting undesirable outputs (Chung *et al*., 1997), in the meta-frontier framework to evaluate and analyse the CEP and its dynamic changes as well as driving forces (e.g., catch-up effect, innovation effect, and leadership effect). Last, via a regression approach of feasible generalized least squares (FGLS), we explore the effects of specialization in some certain outputs (e.g., coal, oil, ore, and containers), port size, environmental regulation, and openness on CEP and CEP changes to provide additional information for decision makers.

Overall, this paper tries to enrich the extant studies in several ways. First, the current study combines both static and dynamic perspectives to comprehensively assess port CEP. Second, the incorporation of meta-frontier avoids bias in the assessment results caused by unobserved heterogeneity. Third, the models used in this study is independent of the lengths of directional vectors, and it considers multiple abatement capacities of different ports, which is in line with environmental economics theory.

The rest of this paper is arranged as follows. In Section 2, we review important literature relevant to our research. Section 3 presents the modified methods to evaluate both the static and dynamic CEP in the meta-frontier framework. An empirical example of 16 Chinese port enterprises is analysed in Section 4. We give the discussion and conclusion in Section 5.

2. Literature review

The current work is broadly associated with existing studies on port performance/efficiency evaluation by using DEA method. Given its advantage, DEA approach has aroused the interest of scholars and has been extensively applied for port efficiency measurement. Roll and Hayuth (1993) originally used DEA approach in port efficiency assessment. Their pioneered work opened the door for the scholarly study of port efficiency evaluation based on DEA method. By dividing 26 Spanish ports into three groups according to their complexity, Martinez-Budria *et al*. (1999) applied DEA to evaluate their efficiency during the period of 1993 to 1997. They found that every group exhibited different efficiency trend, and the ports with high complexity moved closer to the frontier over time. Turner *et al*. (2004) measured the seaport efficiency in North America from 1984 to 1997 via DEA method, and they examined the effects of industry structure and conduct on seaport efficiency. The results showed that the longstanding relationship between seaports and the rail industry significantly and positively influenced seaport efficiency. Cullinane *et al*. (2005) employed DEA and Free Disposal Hull methods to evaluate the efficiency of the world’s most important container ports and terminals. They confirmed that different models lead to different results and appropriate input/output variables played a key role in meaningful applications of both models. Barros (2006) used DEA approach to evaluate the efficiency of Italian seaports from 2002 to 2003, and they further explored the impacts of size, containerisation, and labour on the efficiency of seaports. Rios and Maçada (2006) also applied a BCC-DEA model to calculate port efficiency of Mercosur.

In addition to the commonly CCR-DEA and BCC-DEA models, various extended DEA approaches are developed to address the practical problems occurred in the port efficiency evaluation. Considering heterogeneity among ports, Wu *et al*. (2009) employed a modified cross-efficiency DEA method to efficiency evaluation of 28 Asian container ports. Wu *et al*. (2010) combined cross-efficiency DEA with cluster analysis technique to measure the efficiency and benchmarking of 77 world container ports in 2007. To explore the internal structure of the port, Wanke (2013) divided the operation process of the port into physical infrastructure stage and shipment consolidation stage. They applied a network-DEA centralize model to the efficiency evaluation of 27 Brazilian ports in 2011. In addition, to overcome the biased results obtained from traditional DEA models, bootstrapped parametric techniques were incorporated into DEA. Niavis and Tsekeris (2012) employed a bootstrapped DEA approach to measure and identified major determinants of the efficiency of container seaports in South-Eastern Europe. Nguyen *et al*. (2016) applied a bootstrapped DEA method to the efficiency evaluation of 43 largest Vietnamese ports and found that the efficiency scores generated by bootstrapped DEA are consistent, unbiased, and not sensitive to the sample size. Wanke and Barros (2016) also used a bootstrapped DEA model to measure the efficiency of 27 major Brazilian ports from 2007 to 2011. To deal with vague and imprecise of some input and output variables, Fuzzy-DEA models were proposed for the port efficiency evaluation. Wanke *et al*. (2018) used a two-stage Fuzzy-DEA approach to evaluate efficiency of six major Nigerian ports from 2007 to 2013. Moreover, to improve the validity of the efficiency estimates and provide vertical and horizontal efficiency evaluation for ports, several scholars applied DEA based Malmquist productivity index approach to evaluate the changes of efficiency and productivity of ports. Chang and Tovar (2017) estimated the Malmquist productivity index of 14 terminals from 2004 to 2014 in a meta-frontier framework. They further used a dynamic panel estimation (Arellano-Bond model) to explain the differences in the productivity changes of ports. Both DEA-Malmquist model in a meta-frontier framework and a dynamic panel estimation were also applied for 26 Spanish ports by Tovar and Wall (2019a). Iyer and Nanyam (2020) also applied the same method and measured the efficiency and productivity of container terminals in India.

In recent years, the environmental pollution problems caused by ports have become serious, and some scholars have switched attention to the environmental performance assessment of ports by considering undesirable environmental outputs since the progress of environmental performance is important for environmental improvement. Because the SBM-DEA model can provide a comprehensive efficiency of combining economic performance and environmental performance and capture input/output slacks, such method had been applied for port environmental efficiency evaluation. Chin and Low (2010) measured the environmental efficiency of 13 major East Asian ports by using an SBM-DEA approach. Chang (2013) also used SBM-DEA method to analyse the environmental efficiency of 23 Korean ports and the corresponding CO_2 emissions reduction. Later, Lee *et al.* (2014) applied a modified SBM-DEA approach to assess the environmental performance of 11 world's top container ports in 2011, and they found that New York has the highest environmental performance and Tianjin has the lowest environmental performance. Considering the inseparable characteristics of inputs and outputs, Na *et al*. (2017) used an inseparable input-output SBM model to evaluate the environmental efficiency of eight Chinese ports during 2005 to 2014. The inseparable input-output SBM method can estimate environmental efficiency more accurately than traditional SBM models. Quintano *et al*. (2020) combined SBM-DEA method and the response based procedure for detecting unit segments to analyse the eco-efficiency of firms in port sector. Recently, the DDF approach has been applied in assessing the environmental efficiency of ports since this approach is more in line with sustainable development requirements. Sun *et al.* (2017) introduced a non-radial DDF preference method to estimate the environmental performance of 17 Chinese-listed port enterprises in 2013. They further investigated the effects of port assets, berth quantity, and geographical location on the environmental efficiency of port enterprises. Additionally, Tovar and Wall (2019b) used an output-oriented DDF to measure environmental efficiency for a cross section of 28 Spanish Port Authorities in 2016. Some other modified DEA models were also proposed to meet the decision needs. Li *et al*. (2020) measured environmental performance of 21 coastal ports in China and provided closest targets for inefficient ports by using a closest targets DEA model. Wang *et al*. (2020) assessed the environmental performance of 11 Chinese ports by constructing three DEA models with respect to three circumstances, namely environmental control, non-environmental control and particulate matter (PM) emission through inter-ports cooperation.

Through the review of the above literature, we can find that prior studies on the environmental performance estimation of ports using DEA assumed that all ports share a common technology, which ignores the technology heterogeneity among ports. In addition, few studies analysed the dynamic changes in environmental performance of ports and explored the underlying driving forces of environmental performance changes. Accordingly, considering the heterogeneity among ports, the current study uses a modified meta-frontier non-radial DDF approach to estimate CO_2 emission performance of 16 Chinese port enterprises during 2013 to 2018 from the static and dynamic perspectives. Additionally, we investigate the determinants of static and dynamic CO_2 emission performance via a regression method.

3. Methodology

3.1 Kuosmanen production technology

Suppose that there are n homogenous decision making units (DMUs) to be evaluated, and any $\mathrm{DMU}_j (j = 1,2,\cdots,n)$ uses m inputs to obtain s desirable/good outputs accompanied by h undesirable/bad outputs (e.g., CO_2 emissions), which represented by $x_{ij} = (x_{1j}, x_{2j}, \cdots, x_{mj})$, $y_{rj} = (y_{1j}, y_{2j}, \cdots, y_{sj})$, and $b_{pj} = (b_{1j}, b_{2j}, \cdots, b_{hj})$, respectively.

Considering that the pollution treatment capacity varies for each DMU (e.g., port in this paper) in practical activities, a single abatement factor that is always used in a traditional production process is not appropriate to characterize the weak disposability between desirable/good outputs and undesirable/bad outputs (Kuosmanen and Podinovski, 2009). Accordingly, consistent with Kuosmanen (2005) and Zhou *et al*. (2018), the production possibility set (PPS) based on variable returns to scale (VRS) considering multiple abatement factors instead of a single abatement factor is defined as follows (Kuosmanen, 2005; Zhou *et al*., 2018):

$$T=\left\{(x_i,y_r,b_p)\left|\begin{array}{l}\sum_{j=1}^{n}\gamma_j x_{ij}\le x_i, i=1,2,\cdots,m\\ \sum_{j=1}^{n}\epsilon_j\gamma_j y_{rj}\ge y_r, r=1,2,\cdots,s\\ \sum_{j=1}^{n}\epsilon_j\gamma_j b_{pj}=b_p, p=1,2,\cdots,h\\ \sum_{j=1}^{n}\gamma_j=1,\gamma_j\ge 0, 0\le\epsilon_j\le 1, j=1,2,\cdots,n\end{array}\right.\right\} \tag{1}$$

where $\gamma_j(j=1,2,\cdots,n)$ are intensity variables and $\epsilon_j(j=1,2,\cdots,n)$ are individual abatement factors that correspond to each $\mathrm{DMU}_j(j=1,2,\cdots,n)$.

By defining $\lambda_j=\gamma_j\epsilon_j$ and $\eta_j=(1-\epsilon_j)\gamma_j$, formulation (1) can be transformed into the following formulation (2):

$$\hat{T}=\left\{(x_i,y_r,b_t)\left|\begin{array}{l}\sum_{j=1}^{n}(\lambda_j+\eta_j)x_{ij}\le x_i, i=1,2,\cdots,m\\ \sum_{j=1}^{n}\lambda_j y_{rj}\ge y_r, r=1,2,\cdots,s\\ \sum_{j=1}^{n}\lambda_j b_{pj}=b_p, p=1,2,\cdots,h\\ \sum_{j=1}^{n}\left(\lambda_j+\eta_j\right)=1,\lambda_j,\eta_j\ge 0, j=1,2,\cdots,n\end{array}\right.\right\} \tag{2}$$

3.2 A modified directional distance function

The directional distance function (DDF) proposed by Chambers *et al*. (1996; 1998) and later developed by Chung *et al*. (1997) is a useful technique for environmental performance estimation. The conventional radial DDF may overestimate the efficiency when non-zero slacks are existed, recently, the non-radial DDF models were introduced and have been extensively applied in the field of environmental performance evaluation since they take input/output slacks into account and allow desirable outputs or inputs (or undesirable outputs) to increase or decrease with various proportions (Zhou *et al*., 2012). The non-radial DDF is defined as follows (Zhou *et al*., 2012).

$$\overrightarrow{ND}(x,y,b;g)=\sup\{\boldsymbol{w}^T\boldsymbol{\beta}:((x,y,b)+g\times diag(\boldsymbol{\beta}))\in\hat{T}\} \tag{3}$$

In formula (3), $w=(w_i^x,w_r^y,w_p^b)$ is the normalized weight vector that is associated with the number of inputs and outputs; $g=(-g_i^x,g_r^y,-g_p^b)\neq\mathbf{0}$ is the directional vector along which the evaluated DMU improves towards the best-practice frontier; $\beta = (\beta_i^x, \beta_r^y, \beta_p^b)^T \geq 0$ is the vector of scaling factors that represent the potential improvement for each input, desirable output and undesirable output.

We can calculate the value of $\overrightarrow{ND}(x, y, b; g)$ for the evaluated DMU, denoted as DMU_o by solving the following linear programming (Yao *et al*., 2016; Zhou *et al*., 2018):

$$
\begin{aligned}
\overrightarrow{ND}(x, y, b; g) = \max \quad & \sum_{i=1}^{m} w_i^x \beta_i^x + \sum_{r=1}^{s} w_r^y \beta_r^y + \sum_{p=1}^{h} w_p^b \beta_p^b \\
\text{s.t.} \quad & \sum_{j=1}^{n} (\lambda_j + \eta_j) x_{ij} \leq x_{io} - \beta_i^x g_i^x, i = 1,2,\cdots,m \\
& \sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{ro} + \beta_r^y g_r^y, r = 1,2,\cdots,s \\
& \sum_{j=1}^{n} \lambda_j b_{pj} = b_{po} - \beta_p^b g_p^b, p = 1,2,\cdots,h \\
& \sum_{j=1}^{n} \left(\lambda_j + \eta_j\right) = 1 \\
& \beta_i^x, \beta_r^y, \beta_p^b \geq 0, \lambda_j, \eta_j \geq 0, j = 1,2,\cdots,n
\end{aligned}
\tag{4}
$$

In model (4), $\overrightarrow{ND}(x, y, b; g) = 0$ means that DMU_o is located on the efficient frontier, i.e., it achieves environmental efficiency at 100%. The optimal values of β_i^x, β_r^y, and β_p^b obtained from model (4) measure inefficiency, but they are not compatible with inefficiency measures generated by traditional radial and non-radial DEA models since they may be larger than unity (Cheng & Zervopoulos, 2014; Yang *et al*., 2018); as a result, the final performance evaluation results may have a bias. Accordingly, referring to Cheng & Zervopoulos (2014) and Yang *et al*. (2018), the current study uses a modified non-radial DDF approach to calculate the environmental efficiency (CEP in this paper) of DMUs, as described in the following.

$$
\begin{aligned}
\min \theta = \quad & \frac{1 - \frac{1}{m} \sum_{i=1}^{m} \beta_i^x g_i^x / x_{io}}{1 + \frac{1}{s+h} \left(\sum_{r=1}^{s} \beta_r^y g_r^y / y_{ro} + \sum_{p=1}^{h} \beta_p^b g_p^b / b_{po}\right)} \\
\text{s.t.} \quad & \sum_{j=1}^{n} (\lambda_j + \eta_j) x_{ij} \leq x_{io} - \beta_i^x g_i^x, i = 1,2,\cdots,m \\
& \sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{ro} + \beta_r^y g_r^y, r = 1,2,\cdots,s
\end{aligned}
\tag{5}
$$

$$\sum_{j=1}^{n} \lambda_j b_{pj} = b_{po} - \beta_p^b g_p^b, p = 1,2,\cdots,h$$
$$\sum_{j=1}^{n} (\lambda_j + \eta_j) = 1$$
$$\beta_i^x, \beta_r^y, \beta_p^b \geq 0, \lambda_j, \eta_j \geq 0, j = 1,\cdots,n$$

The optimal solution of model (5) is denoted as $(\theta^*, \beta_i^{x*}, \beta_r^{y*}, \beta_p^{b*}, \lambda_j^*, \eta_j^*)$. θ^* measures the CEP of DMU_o. Clearly, the value of θ^* is between 0 and 1, and the greater the value of θ^* is, the better the CEP. By letting $\omega = \frac{1}{1+\frac{1}{s+h}(\sum_{i=1}^{m} \beta_r^y g_r^y / y_{ro} + \sum_{i=1}^{m} \beta_p^b g_p^b / b_{po})}$, model (5) can be converted into the following linear programming model:

$$\begin{aligned}
\min \rho = \quad & \omega - \frac{1}{m}\sum_{i=1}^{m} \beta_i^{x\prime} g_i^x / x_{io} \\
\text{s.t.} \quad & \omega + \frac{1}{s+h}\left(\sum_{r=1}^{s} \beta_r^{y\prime} g_r^y / y_{ro} + \sum_{p=1}^{h} \beta_p^{b\prime} g_p^b / b_{po}\right) = 1 \\
& \sum_{j=1}^{n} (\lambda_j^{'} + \eta_j^{'}) x_{ij} \leq \omega x_{io} - \beta_i^{x\prime} g_i^x, i = 1,2,\cdots,m \\
& \sum_{j=1}^{n} \lambda_j^{'} y_{rj} \geq \omega y_{ro} + \beta_r^{y\prime} g_r^y, r = 1,2,\cdots,s \\
& \sum_{j=1}^{n} \lambda_j^{'} b_{pj} = \omega b_{po} - \beta_p^{b\prime} g_p^b, p = 1,2,\cdots,h \\
& \sum_{j=1}^{n} (\lambda_j^{'} + \eta_j^{'}) = \omega \\
& \beta_i^{x\prime}, \beta_r^{y\prime}, \beta_p^{b\prime} \geq 0, \omega > 0, \lambda_j^{'}, \eta_j^{'} \geq 0, j = 1,\cdots,n
\end{aligned} \tag{6}$$

where ω is a non-negative constant, and $\beta_i^{x\prime} = \omega\beta_i^x$, $\beta_r^{y\prime} = \omega\beta_r^y$, $\beta_t^{b\prime} = \omega\beta_t^b$, $\lambda_j^{'} = \omega\lambda_j$, and $\eta_j^{'} = \omega\eta_j$. An optimal solution of model (6) is defined as $(\rho^*, \beta_i^{x\prime*}, \beta_r^{y\prime*}, \beta_p^{b\prime*}, \lambda_j^{\prime*}, \eta_j^{\prime*}, \omega^*)$; then, the optimal solution of model (5) is

$$\theta^* = \rho^*,\ \beta_i^{x*} = \frac{\beta_i^{x\prime*}}{\omega^*},\ \beta_r^{y*} = \frac{\beta_r^{y\prime*}}{\omega^*},\ \beta_p^{b*} = \frac{\beta_p^{b\prime*}}{\omega^*},\ \lambda_j^* = \frac{\lambda_j^{\prime*}}{\omega^*},\ \eta_j^* = \frac{\eta_j^{\prime*}}{\omega^*} \tag{7}$$

3.3 CO_2 emission performance evaluation on the basis of the group frontier and meta-frontier

Considering the heterogeneity production technologies among DMUs due to differences in geographical location, policy, resource endowment, and economic development (Du *et al*., 2014; Wang *et al*., 2016; Song *et al*., 2019), we further incorporate the concept of meta-frontier to estimate CEP. For this, following Battese *et* *al*. (2004) and O'Donnell *et al*. (2008), group-frontier and meta-frontier technologies are defined. To be specific, all assessed DMUs are divided into K groups and the DMUs in the same group $k(k = 1,2,\cdots,K)$ share the same production technology. Then, the group-frontier technology of group k is defined as $T^k = \{(x^k, y^k, b^k)|x^k \text{ can produce } (y^k, b^k)\}, k = 1,2,\cdots,K$. The meta-frontier technology envelopes all group-frontier technologies, which is defined as $T^m = \{T^1 \cup T^2 \cup \cdots \cup T^K\} = \{(x, y, b)|x \text{ can produce } (y, b)\}$. Therefore, we can calculate the CEP with respect to group-frontier (labelled as group-CEP), denoted as θ^{g*}, and CEP with respect to meta-frontier (labelled as meta-CEP), denoted as θ^{m*}, by solving model (5) through the use of inputs and outputs from group k and all groups, respectively. Furthermore, $TGR = \theta^{m*}/\theta^{g*}$ ($\in (0,1]$) measures how close the group frontiers and the meta-frontier. The higher TGR is, the group-CEP is closer to the meta-CEP, i.e., the production technology of the given DMU is closer to the common potential technology.

3.4 Meat-frontier non-radial Malmquist CO_2 emission performance evaluation

The models mentioned above provide static CEP indices of a DMU in a certain period, and such indices fail to reflect dynamic changes in CEP over time. To capture the dynamic changes in CEP resulting from production technology changes and consider group heterogeneity, the meta-frontier non-radial Malmquist CO_2 emission performance index was introduced by Zhang and Choi (2013). This index calculates the changes of CEP during two adjacent periods, i.e., t and t+1. The measurement of dynamic changes in CEP helps decision makers to evaluate DMUs from perspective of vertical and horizontal (Zhang and Choi, 2013; Yao *et al*., 2016; Zhou *et al*., 2018).

In line with the existing literature (e.g., Zhang and Choi, 2013; Wang *et al*., 2016; Yao *et al*., 2016), three production technology sets are defined in this study. The first set, named the contemporaneous production technology frontier, is defined as $T^C_{k,t} = \{(x_{k,t}, y_{k,t}, b_{k,t})|x_{k,t} \text{ can produce } (y_{k,t}, b_{k,t})\}, k = 1,2,\cdots,K, t = 1,2,\cdots,T$, which indicates the optimal production status for a certain group k at a specific period t. The second set, named the inter-temporal production technology frontier, is represented by $T^I_k = T^C_{k,1} \cup T^C_{k,2} \cup \cdots \cup T^C_{k,T}$, which represents the optimal production practice for a certain group k

across all periods. The third set, named the global production technology frontier, is denoted as $T^G = T_1^I \cup T_2^I \cup \cdots \cup T_K^I$, which indicates that the best production practice envelops all DMUs during the whole observation period. Dividing production technology into the contemporaneous production technology frontier, inter-temporal production technology frontier, and global production technology frontier is helpful for understanding the heterogeneity characteristic among DMUs and different time periods (Wang *et al*., 2016).

$\theta^C(t)$, $\theta^I(t)$, and $\theta^G(t)$ are defined as the CEP of a DMU based on production technologies $T_{k,t}^C$, T_k^I, and T^G at period *t*, respectively. The following model (8) can be used to obtain $\theta^C(t)$, $\theta^I(t)$, and $\theta^G(t)$:

$$
\begin{aligned}
\min \theta^T(t) = \quad & \frac{1 - \frac{1}{m}\sum_{i=1}^{m} \beta_i^{x,T} g_i^{x,T} / x_{io}^{k,t}}{1 + \frac{1}{s+h}\left(\sum_{r=1}^{s} \beta_r^{y,T} g_r^{y,T} / y_{ro}^{k,t} + \sum_{p=1}^{h} \beta_p^{b,T} g_p^{b,T} / b_{po}^{k,t}\right)} \\
\text{s.t.} \quad & \sum_{con} (\lambda_j^{k,t} + \eta_j^{k,t}) x_{ij}^{k,t} \le x_{io}^{k,t} - \beta_i^{x,T} g_i^{x,T}, i = 1,2,\cdots,m \\
& \sum_{con} \lambda_j^{k,t} y_{rj}^{k,t} \ge y_{ro}^{k,t} + \beta_r^{y,T} g_r^{y,T}, r = 1,2,\cdots,s \\
& \sum_{con} \lambda_j^{k,t} b_{pj}^{k,t} = b_{po}^{k,t} - \beta_p^{b,T} g_p^{b,T}, p = 1,2,\cdots,h \\
& \sum_{con} \left(\lambda_j^{k,t} + \eta_j^{k,t}\right) = 1 \\
& \beta_i^{x,T}, \beta_r^{y,T}, \beta_p^{b,T} \ge 0, \lambda_j^{k,t}, \eta_j^{k,t} \ge 0, j = 1,\cdots,n
\end{aligned}
\tag{8}
$$

In model (8), the superscript T respectively represents the types of non-radial DDF in terms of cotemporaneous, inter-temporal, and global, and *con* under $\sum$ denotes the corresponding environmental production frontiers (Zhang and Choi, 2013). To be specific, $T \equiv C$ and $con \equiv T_{k,t}^C$ for contemporaneous non-radial DDF; $T \equiv I$ and $con \equiv T_{k,t}^I$ for inter-temporal non-radial DDF; and $T \equiv G$ and $con \equiv T_{k,t}^G$ for global non-radial DDF. By replacing *t* with *t*+1 in model (8), the CEP of a DMU based on production technologies $T_{k,t}^C$, T_k^I, and T^G at period *t*+1 can be generated, denoted as $\theta^C(t+1)$, $\theta^I(t+1)$, and $\theta^G(t+1)$, respectively. Then, according to Zhang and Choi (2013), Wang *et al*. (2016), Yao et al. (2016), and Zhou *et al*. (2018), the meta-frontier non-radial Malmquist index for CEP (labelled as MNMCEP) with respect to the global production technology frontier is defined in the following Eq. (9):

$$MNMCEP(t, t+1) = \frac{\theta^G(t+1)}{\theta^G(t)} \quad (9)$$

In Eq. (9), MNMCEP measures the dynamic changes in CEP of a specific DMU on the basis of global frontier from time t to t+1. Following Oh and Lee (2010), Zhang and Choi (2013), Yao *et al*. (2016), and Wang *et al*. (2016), MNMCEP can be further decomposed into three components to reveal its underlying driving forces, shown as follows:

$$\begin{aligned} MNMCEP = &\ \frac{\theta^G(t+1)}{\theta^G(t)} \\ = &\ \frac{\theta^C(t+1)}{\theta^C(t)} \times \frac{\theta^I(t+1)/\theta^C(t+1)}{\theta^I(t)/\theta^C(t)} \times \frac{\theta^G(t+1)/\theta^I(t+1)}{\theta^G(t)/\theta^I(t)} \\ = &\ \frac{TE(t+1)}{TE(t)} \times \frac{BPR(t+1)}{BPR(t)} \times \frac{TGR(t+1)}{TGR(t)} \\ = &\ EC \times BPC \times TGC \end{aligned} \quad (10)$$

where TE, BPR, and TGR represent the technical efficiency, the gap between contemporaneous production technology and inter-temporal production technology, and the gap between inter-temporal production technology and global production technology, respectively. Moreover, the efficiency change (EC) measures the change in technical efficiency of CO_2 emission for a specific DMU in group k between two adjacent periods, that is, t and t+1. EC >1 (<1) means that the DMU moves towards (away from) the contemporaneous production technology frontier. It measures the "catch-up effect" of the evaluated DMU (Zhang and Choi, 2013; Yao *et al*., 2016). BPC measures the best-practice gap change between the contemporaneous production technology frontier and the inter-temporal production technology frontier from period *t* to *t*+1. BPC >1 (<1) reflects a shift in the contemporaneous frontier towards (away from) the inter-temporal frontier. This factor measures frontier shifts in a contemporaneous technology, it reflects the "innovation effect". TGC measures the technology gap change between the inter-temporal frontier and global frontier during period *t* to *t*+1. TGC >1 (<1) represents that the gap between the inter-temporal frontier of a specific group and global frontier is narrowing (expanding). It measures the "leadership effect" (Yao *et al*., 2016).

4. Empirical application for Chinese port enterprises

4.1 Dataset and variables

In this study, we evaluate and analyse the CEP of 16 port enterprises from 2013 to 2018: Chongqing Port, Dalian Port, Jinzhou Port, Lianyungang Port, Nanjing Port, Ningbo-Zhoushan Port, Northern Gulf Port, Qingdao Port, Rizhao Port, Shanghai Port, Shenzhen Port, Tangshan Port, Tianjin Port, Xiamen Port, Yingkou Port, and Zhuhai Port. Among them, Chongqing Port and Nanjing Port are inland port enterprises, and the rest are coastal port enterprises. According to the China Port Statistical Yearbook 2019, the number of Chinses ports whose container throughputs over million TEUs is 31 in 2018, including 5 inland ports and 26 coastal ports, while the number of listed port enterprises is 20. Considering the completeness and availability of data, a final sample contains 16 listed port enterprises. Their cargo throughputs were larger than 100 million tons and their container throughputs were more than million TEUs. The total container throughputs of 16 port enterprises accounts for more than 73% of the total throughputs of the whole country. Moreover, they are all listed port enterprises, more information can be obtained from their annual reports. Therefore, it is representative to estimate their CEP in China.

To effectively evaluate the CEP for the port enterprises in our sample, appropriate input and output (desirable output and undesirable output) variables should be selected. Table 1 lists the input and output variables used in environmental efficiency evaluation of ports. Referring to the variables listed in Table 1 and taking availability and completeness of data into account, this study selected the following variables: labor and fixed assets are two inputs; cargo throughput, container throughput, and net profit are three desirable outputs; and CO_2 emission is one undesirable output. The definition and interpretation of each variable are shown below:

(1) Labor: Labor is a typical input variable for production function and it represents the number of staff. It is influenced by the business expansion and contraction, which reflects the operating performance. This variable was often used as an input for port performance evaluation (e.g., Guironnet *et al.*, 2009; Chang, 2013;

Tovar and Wall, 2019a).

(2) Fixed assets: Fixed assets represent the investments of loading and unloading machinery, transportation equipment, port ships, and other equipment which can more directly associated the emission at the same period. It is a comprehensive reflection of port infrastructure and capital status (Chang and Tovar, 2014; Sun et al., 2017).

(3) Cargo throughput: Cargo throughput is an important indicator to measure the size of port production capacity. It reflects the quantity of cargo that the port loads and unloads for ships under certain conditions and within a certain period (Chang, 2013; Li *et al*., 2020).

(4) Container throughput: Container throughput reflects the sum of the number of imported and exported containers at a port. It is an important manifestation of competitiveness and comprehensive strength of a port (Lee *et al*., 2014; Castellano *et al*., 2020). Both cargo throughput and container throughput reflect the operational performance from a non-financial perspective (Cui *et al*., 2017).

(5) Net profit: Net profit is a main indicator to measure the operating performance of the port from the perspective of financial. It reflects the economic effects of port operations and captures port profitability (Sun *et al*., 2017).

(6) CO_2 emission: CO_2 emission represents carbon dioxide emissions from land side of the port. In this paper, we don't take the carbon dioxide emissions from sea side into consideration because the data are limited and cannot be found in public sources.

Due to the CO_2 emissions are not directly provided by official data, following Gao and Zhang (2019), Lin *et al*. (2019), and Wang *et al*. (2020), we utilize the following equation to measure the CO_2 emissions:

$$CO_2 = CT * EC_i * CC_i * COF_i * \frac{44}{12} \tag{11}$$

where CO_2 represents the CO_2 emissions (unit: ten thousand tons); CT denotes the cargo throughput of a port (unit: ten thousand tons); EC_i indicates the unit consumption of energy i (unit: tons of standard coal/ten thousand tons of throughput);

CC_i is the carbon content of energy i which is from the People's Republic of China National Greenhouse Gas Inventory (2005); and COF_i represents the carbon oxidation factor of energy *i* which is from the Intergovernmental Panel on Climate Change (2006).

A statistical description of the input and output variables is reported in Table 2.

Table 1 Input/output variables used in environmental performance evaluation of ports

Author	Input	Desirable output	Undesirable output
Chin and Low (2010)	Frequency of shipping services Bilateral trade flows	Annual container capacity flows	NO_x, SO_2, CO_2, PM
Chang (2013)	Labor Length of quay Area of terminal Energy consumption	Vessel Cargo throughput	CO_2
Lee *et al*. (2014)	Labor	Container throughput GRDP	NO_x, SO_2, CO_2
Cui (2017)	Labor Cash investment Number of productive berths	Container throughput Cargo throughput Main business income	CO_2
Sun *et al*. (2017)	Labor Fixed assets Operational costs	Cargo throughput Net profit	NO_x
Na *et al*. (2017)	Berth length Port area Number of quay cranes Number of yard cranes	Container throughput	CO_2
Tovar and Wall (2019b)	Labor Capital Intermediate consumption expenditure	Ships Cargo traffic Passenger traffic	CO_2
Li *et al*. (2020)	Length of productive quay Number of productive berths	Cargo throughput	NO_x, SO_x
Castellano *et al*. (2020)	Investments Terminal area Employees GPE	Solid bulk Liquid bulk Containers	EQI (PM_{10}, NH_3, NO_2, C_6H_6, SO_2)

Table 2 Statistical description of the inputs and outputs

	Variable	Unit	Mean	St. Dev.	Minimum	Maximum
Input	Labor	Person	5361	4581.06	531.00	19842.00
	Fixed assets	10^8 yuan	99.74	88.25	1.59	356.38
Output	Container throughput	10^4 TEU	992.26	1032.40	72.80	4201.00
	Cargo throughput	10^8 ton	3.59	2.23	0.85	10.84
	Net profit	10^8 yuan	13.05	22.51	0.03	128.46
Undesirable output	CO_2 emissions	10^4 ton	22.90	14.09	5.58	62.16

Data source: China Port Statistical Yearbook (2014-2019), China Statistical Yearbook (2014-2019), Annual Report of port enterprises (2013-2018).

Because of difference degrees of specialisation, complexity and size among ports, heterogeneity may exist in the production technology across them. In line with the approach introduced by Tovar and Wall (2017; 2019a), we classify the 16 ports into different groups based on complexity and size to eliminate the basis resulted from heterogeneity. For a specific port, denoted as d, the following formula is used to measure the importance of the port in a certain output (Tovar and Wall, 2017; 2019a).

$$y_{rd}^{importance} = \frac{y_{rd}}{\sum_d y_{rd}}, \forall d, r \quad (12)$$

where y_{rd} is the d-th output of port d. In this study, all ports are classified based on the criterion of whether the port has average value of $y_{rd}^{importance}$ during the investigated time span was greater than the average value of the whole ports for more than two outputs or not. The results are presented in Table 3. The value of $y_{rd}^{importance}$ greater than the average of the overall system output *r* is marked in bold, and the last column lists the groups, i.e., port in group 1 has average value of $y_{rd}^{importance}$ during period of 2013 to 2018 was greater than the whole average for more than two outputs. We can see that 6 and 10 ports are respectively divided into groups 1 and 2.

Table 3 Group classification

Port	Ore	Coal	Oil	Others	Containers	Passenger	Group
Chongqing	0.0125	0.0247	0.0114	**0.1586**	0.0069	0.0402	2
Dalian	0.0184	0.0168	**0.0896**	**0.1364**	0.0620	**0.1105**	1
Jinzhou	0.0043	0.0142	0.0175	0.0000	0.0064	0.0219	2
Lianyungang	**0.0821**	0.0288	0.0020	0.0026	0.0315	0.0239	2
Nanjing	0.0303	0.0600	**0.0728**	0.0000	0.0187	0.0328	2
Ningbo-Zhoushan	**0.1931**	**0.1227**	**0.2430**	**0.0775**	**0.1358**	**0.1431**	1
Northern Gulf	0.0366	**0.0698**	0.0414	0.0051	0.0108	0.0269	2
Qingdao	**0.1183**	0.0271	**0.1526**	0.0034	**0.1105**	**0.0753**	1
Rizhao	**0.1086**	0.0411	**0.0761**	0.0019	0.0182	0.0451	2
Shanghai	**0.0809**	**0.1127**	0.0503	0.0617	**0.2361**	**0.1471**	1
Shenzhen	0.0010	0.0045	0.0228	**0.1395**	**0.1543**	**0.0680**	1
Tangshan	**0.1756**	**0.2353**	0.0303	0.0000	0.0110	0.0339	2
Tianjin	**0.0914**	**0.1329**	**0.0981**	0.0145	**0.0912**	**0.0805**	1
Xiamen	0.0072	0.0283	0.0091	**0.2226**	0.0592	0.0542	2
Yingkou	0.0305	0.0301	0.0618	0.0009	0.0375	**0.0791**	2
Zhuhai	0.0091	0.0510	0.0212	**0.1754**	0.0099	0.0175	2

4.2 Results and analysis of the static CEP of ports

By solving models mentioned in section 3.3, we can obtain meta-CEP, group-CEP, and TGRs of 16 ports over the period of 2013 to 2018. The results are provided in Table 4. We can see from Table 4 that with respect to meta-frontier, Ningbo-Zhoushan, Shanghai, and Shenzhen ports from group 1 and Tangshan Port from group 2 achieved efficiency in CEP during the investigated time span. While, Dalian Port from group 1 and 9 ports from group 2 had very low meta-CEP, especially for Chongqing, Jinzhou, Lianyungang, Northern Gulf, and Zhuhai ports had the average meta-CEP below 0.1. In addition, with respect to group frontier, 7 ports are efficient in terms of group-CEP: Ningbo-Zhoushan, Shanghai, and Shenzhen ports from group 1; and Nanjing, Tangshan, Xiamen, and Yingkou ports from group 2. The difference between CEP in terms of meta-frontier and group frontier is distinct, especially for ports in group 2, shown as in Figure 1. Except Tangshan Port, the rest of ports from group 2 performed very poorly in CEP with respect to meta-frontier, even worse, 7 out of 10 ports have average meta-CEP less than 0.2, whereas 7 out of 10 ports had average CEP greater than 0.7 on the basis of group frontier and Nanjing, Tangshan, Xiamen, and Yingkou ports achieved efficiency in terms of group-CEP, i.e., some gap exists between the meta-technology and group technologies for these ports, and their inefficiency would be exaggerated when the meta-frontier is used as the basis of evaluation. The results in Table 4 confirm the necessary and importance of measuring CEP of each port with respect to group frontier as well as meta-frontier to improve the validity of the efficiency estimates.

Table 4 also reports the results of meta-CEP, group-CEP, and TGRs of the whole and two port groups from 2013 to 2018. It can be learned from Table 4 that group 1 performed better in terms of meta-CEP with an average score of 0.7980 than that of group 2 with an average score of 0.2104, which indicates that group 1 are more advanced in technology. Both groups performed well in CEP with respect to their specific group frontiers, that is, the average group-CEP are 0.8037 and 0.7968 for groups 1 and 2, respectively. Combined Tables 4 and Figure 2, we can see that all ports in group 1 had TGRs nearly or equal to one during the investigated period, which reflect the frontier of group 1 is quite close to the meta-frontier, in other words, large and complex ports in group 1 have advantages in terms of technology. Additionally, Kruskal-Wallis test was used to further examine the differences of TGRs among different port groups. The test result is 11.41 at a significant level of 1%, which reflects two port groups are heterogeneous in the production technology. Therefore, measuring CEP on the basis of group frontier and meta-frontier could also provide helpful information for the Chinese government to set carbon emission reduction targets for individual port based on their meta-CEP and group-CEP.

Table 4 Meta-CEP, group-CEP, and TGRs of 16 ports, 2013–2018

Port	2013			2014			2015			2016			2017			2018			Average		
	θ^{m*}	θ^{g*}	TGR	θ^{m*}	θ^{g*}	TGR	θ^{m*}	θ^{g*}	TGR	θ^{m*}	θ^{g*}	TGR	θ^{m*}	θ^{g*}	TGR	θ^{m*}	θ^{g*}	TGR	θ^{m*}	θ^{g*}	TGR
Group 1																					
Dalian	0.3241	0.3241	1.0000	0.3158	0.3158	1.0000	0.3028	0.3028	1.0000	0.4004	0.4004	1.0000	0.2661	0.2666	0.9981	0.3065	0.3212	0.9545	0.3193	0.3218	0.9921
Ningbo-Zhoushan	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Qingdao	0.6102	0.6102	1.0000	0.6659	0.6659	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.8484	1.0000	0.8484	0.8541	0.8794	0.9747
Shanghai	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Shenzhen	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Tianjin	0.5864	0.5864	1.0000	0.6360	0.6360	1.0000	0.6702	0.6702	1.0000	0.8419	0.8419	1.0000	0.4973	0.4999	0.9949	0.4556	0.4917	0.9265	0.6146	0.6210	0.9869
Group 2																					
Chongqing	0.0303	0.2799	0.1083	0.0291	0.2912	0.0999	0.0261	0.3350	0.0779	0.0329	0.4254	0.0774	0.0789	1.0000	0.0789	0.0768	1.0000	0.0768	0.0457	0.5553	0.0865
Jinzhou	0.0640	0.4422	0.1447	0.0636	0.5945	0.1069	0.0460	0.4269	0.1078	0.0496	0.3338	0.1484	0.0846	0.6073	0.1393	0.1412	1.0000	0.1412	0.0748	0.5675	0.1314
Lianyungang	0.0545	0.4218	0.1291	0.0395	0.3273	0.1208	0.0218	1.0000	0.0218	0.0033	0.0296	0.1114	0.0069	0.0512	0.1339	0.0383	0.1532	0.2498	0.0274	0.3305	0.1278
Nanjing	0.0670	1.0000	0.0670	0.0784	1.0000	0.0784	0.0729	1.0000	0.0729	1.0000	1.0000	1.0000	0.1316	1.0000	0.1316	0.2443	1.0000	0.2443	0.2657	1.0000	0.2657
Northern Gulf	0.0813	1.0000	0.0813	0.0574	1.0000	0.0574	0.0202	0.4060	0.0496	0.0501	1.0000	0.0501	0.0613	1.0000	0.0613	0.0966	1.0000	0.0966	0.0612	0.9010	0.0661
Rizhao	0.0977	1.0000	0.0977	0.1256	1.0000	0.1256	0.1266	1.0000	0.1266	0.1493	0.5541	0.2694	0.1740	1.0000	0.1740	0.3116	0.6745	0.4620	0.1641	0.8714	0.2092
Tangshan	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Xiamen	0.1648	1.0000	0.1648	0.1157	1.0000	0.1157	0.0736	1.0000	0.0736	0.0851	1.0000	0.0851	0.0912	1.0000	0.0912	0.1692	1.0000	0.1692	0.1166	1.0000	0.1166
Yingkou	0.2066	1.0000	0.2066	0.2119	1.0000	0.2119	0.2185	1.0000	0.2185	0.3147	1.0000	0.3147	0.2659	1.0000	0.2659	0.3143	1.0000	0.3143	0.2553	1.0000	0.2553
Zhuhai	0.0841	1.0000	0.0841	0.0414	0.3134	0.1320	0.0471	0.4082	0.1154	0.0719	0.7341	0.0980	0.1118	1.0000	0.1118	0.2045	1.0000	0.2045	0.0935	0.7426	0.1243
Average of group 1	0.7535	0.7535	1.0000	0.7696	0.7696	1.0000	0.8288	0.8288	1.0000	0.8737	0.8737	1.0000	0.7939	0.7944	0.9988	0.7684	0.8022	0.9549	0.7980	0.8037	0.9923
Average of group 2	0.1850	0.8144	0.2084	0.1763	0.7526	0.2049	0.1653	0.7576	0.1864	0.2757	0.7077	0.3155	0.2006	0.8659	0.2188	0.2597	0.8828	0.2959	0.2104	0.7968	0.2383
Average of 16 ports	0.3982	0.7915	0.5052	0.3988	0.7590	0.5030	0.4141	0.7843	0.4915	0.5000	0.7700	0.5722	0.4231	0.8391	0.5113	0.4505	0.8525	0.5430	0.4308	0.7994	0.5210

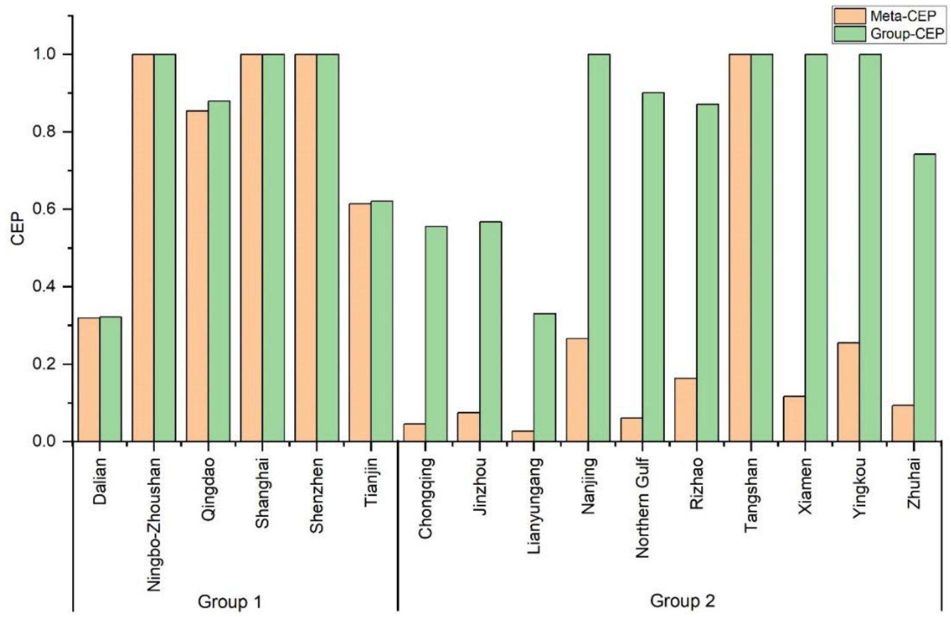

Figure 1 The average Meta-CEP and Group-CEP of 16 ports, 2013–2018

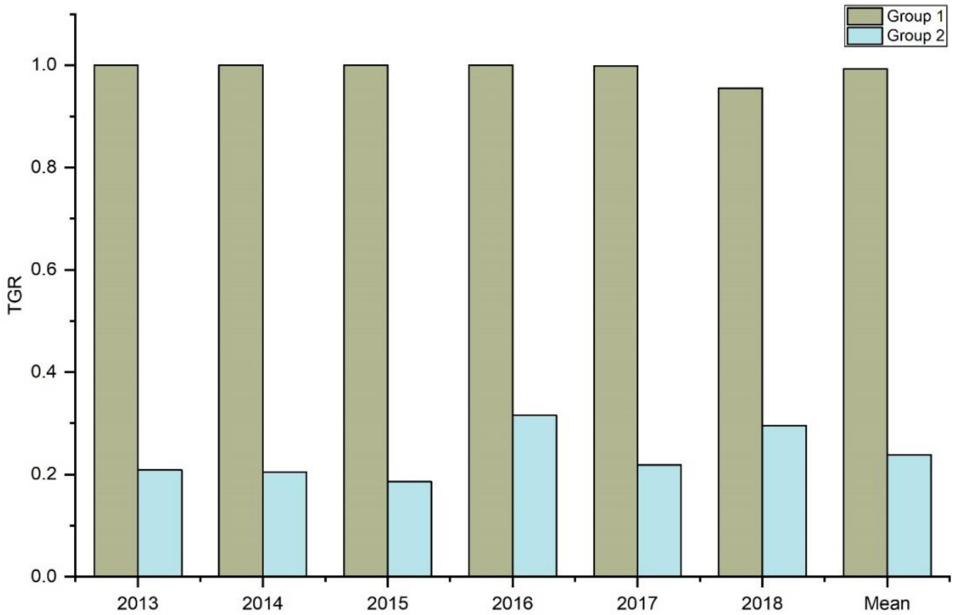

Figure 2 The average TGRs of two groups, 2013–2018

4.3 Results and analysis of the dynamic CEP of ports

In this section, we further examine the dynamic changes in CEP (MNMCEP) and reveal its underlying drivers (EC, BPC, and TGC). As described in Eq. (9), the MNMCEP measures the CEP dynamic changes of a specific DMU with respect to global frontier from time t to t+1. Table 5 gives the results of the MNMCEP of the 16 ports from 2013 to 2018. We can draw several findings from Table 5.

First, it can be seen that the annual average MNMCEP of the 16 ports is 1.2489 over the period of 2013–2018, indicating a 24.89% annual average growth rate of CEP. The average MNMCEP increased in most years except 2014–2015 with a slight decrease by 0.50%. Although the static CEP of whole sample were not well, their CEP has been improved significantly during the investigated time span. This achievement may mainly attributed to the strict implementation of the “energy conservation and emissions reduction” policy from the 12th “Five-Year Plan”.

Second, the average MNMCEP differs significantly between both groups, and MNMCEP of group 2 is higher than that of group 1 exclude 2014 to 2015. The average MNMCEP of group 1 is 1.0451, which means that the CEP of group 1 increased at an average rate of 4.51% per year, lower than the overall average annual growth rate of 24.89%, while the average MNMCEP of group 2 is 1.3713, which means that the CEP of group 2 increased by 37.13% annually, greater than the overall average annual growth rate. Figure 3 shows the trend in MNMCEP for group 2 was same for the whole, and the former is higher than the latter during 2015–2018. Between 2014 and 2015, the MNMCEP for group 2 was less than one (0.9242), indicating a decrease in CEP, while the same phenomenon occurred in group 1 between 2015 and 2016 with MNMCEP being 0.9676.

Third, the average MNMCEP was also differs among ports. Except Tianjin and Shenzhen ports from group 1 with an average MNMCEP being 0.9749 and 1.0000, respectively, the remaining 14 ports have an average MNMCEP over one, showing an increase in CEP during the investigated six years. Tangshan Port from group 2 shows the highest average MNMCEP (1.5331), indicating an increase in CEP by 53.31%. Although ports from group 2 performed worse than ports from group 1 in terms of CEP, they performed better growth in CEP than that of group 1. For example, Qingdao Port from group 1 improved its CEP at an average rate of 14.30% per year, close to 14.04% for Yingkou Port from group 2 who exhibited the smallest growth in CEP.

Table 5 MNMCEP of 16 ports, 2013–2018

Port	13-14	14-15	15-16	16-17	17-18	Average
Group 1						

Dalian	0.9833	0.9469	1.1342	0.8981	1.1692	1.0264
Ningbo-Zhoushan	1.0000	1.0000	0.8061	1.1155	1.1121	1.0067
Qingdao	1.1340	1.6907	0.7624	1.2018	0.9259	1.1430
Shanghai	1.0907	1.0187	1.0358	1.4518	1.0000	1.1194
Shenzhen	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Tianjin	1.1003	1.0220	1.0669	0.7208	0.9643	0.9749
Group 2						
Chongqing	1.1180	0.9635	1.1156	2.5657	0.9039	1.3333
Jinzhou	1.0730	0.9263	0.9492	1.6264	1.4775	1.2105
Lianyungang	0.8505	0.6141	0.1086	2.7315	5.3594	1.9328
Nanjing	1.4322	1.0114	1.6906	1.0636	1.8600	1.4116
Northern Gulf	1.3561	0.6668	1.4580	1.9753	1.6038	1.4120
Rizhao	1.2737	1.0010	0.9545	1.4704	2.1039	1.3607
Tangshan	2.0548	1.0329	1.4491	1.3944	1.7341	1.5331
Xiamen	1.1285	0.7007	0.9446	1.2338	1.7639	1.1543
Yingkou	0.9968	1.0489	1.1710	1.1156	1.3699	1.1404
Zhuhai	0.5568	1.2768	1.2727	1.5349	1.4785	1.2239
Average of group 1	1.0514	1.1130	0.9676	1.0647	1.0286	1.0451
Average of group 2	1.1840	0.9242	1.1114	1.6712	1.9655	1.3713
Average of 16 ports	1.1343	0.9950	1.0575	1.4437	1.6142	1.2489

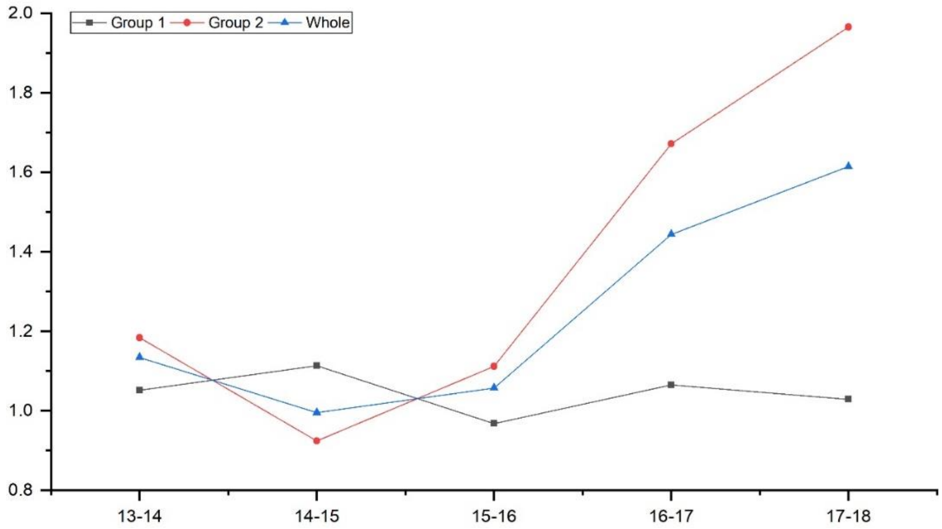

Figure 3 The changes of MNMCEP in both groups and the whole

To further analyse the sources of dynamic changes in port CEP, we decomposes the MNMCEP into three components, named the EC, BPC, and TGC, as described in Eq. (10). The results of EC, BPC, and TGC of the 16 ports over the time of 2013 to 2018 are listed in Table 6. Several conclusions can be drawn from Table 6.

First, the average efficiency change (EC) index of CEP during 2013 to 2018 was 1.1134, indicating an increase in CO_2 emission efficiency by 11.34% annually. The average annual growth rate of 11.34% reveals that ports moved toward the contemporaneous technology frontier obviously, reflecting significant catch-up effect. In addition, port group 2 achieved obvious improvement in the technical efficiency of CEP with an average annual increase of 16.77% compared to a slight average annual growth rate of 2.30% for group 1. Figure 4 clearly illustrate that the EC of group 2 and the whole have the same trend over 2013 to 2018. The EC of group 1 was worse than group 2 and the whole except 2013–2014, and it had a large decrease by 12.34% in 2016–2017, showing a negative impact on CEP change. For individual port enterprise, we can see that Tianjin Port from group 1 exhibited a decrease in EC with an average rate of 0.56%, which means that it moved away the contemporaneous technology frontier. The EC value of Ningbo-Zhoushan, Shanghai, and Shenzhen ports from group 1 and Nanjing, Tangshan, Xiamen, and Yingkou ports from group 2 is constant to one, indicating that their distance to contemporaneous frontier is constant, i.e., they did not show the catch up effect.

Second, the average BPC of the whole from 2013–2018 was 1.1020, which means that the contemporaneous frontier shifted towards the inter-temporal frontier at an annual average rate of 10.20%, reflecting significant technological innovations or technological upgrades. Group 2 had an average BPC of 1.1442. This reveals that the contemporaneous technology frontier of the group 2 moved toward the inter-temporal technology frontier at an average annual rate of 14.42%, indicating obvious technological innovation effect. The average BPC of group 1 (1.0317) is smaller than that in the whole (1.1020), showing slight technology progress. It can be seen from Figure 5 that group 2 and the whole exhibited similar trend in BPC over the sample period, with a large decrease in 2014–2015 and a large increase in 2017–2018. While group 1 had a large increase in 2016–2017. Furthermore, except Shenzhen port from group 1 and Xiamen ports from group 2 had an average BPC being 1, the remaining 14 ports had an average BPC greater than 1, which indicates that they achieved technology progress over the researched time span.

Table 6 EC, BPC, and TGC of 16 ports, 2013–2018

Port	EC						BPC						TGC					
	13-14	14-15	15-16	16-17	17-18	Average	13-14	14-15	15-16	16-17	17-18	Average	13-14	14-15	15-16	16-17	17-18	Average
Group 1																		
Dalian	0.9744	0.9586	1.3225	0.6658	1.2048	1.0252	0.9047	0.9893	0.8331	1.3585	1.0083	1.0188	1.1153	0.9986	1.0294	0.9930	0.9625	1.0198
Ningbo-Zhoushan	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.8090	1.1121	1.1115	1.0065	1.0000	1.0000	0.9964	1.0031	1.0006	1.0000
Qingdao	1.0914	1.5016	1.0000	1.0000	1.0000	1.1186	1.0327	1.0749	0.8053	1.2417	1.0000	1.0309	1.0062	1.0474	0.9467	0.9679	0.9259	0.9788
Shanghai	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0907	1.0187	1.0358	1.4518	1.0000	1.1194	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Shenzhen	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Tianjin	1.0846	1.0537	1.2563	0.5937	0.9838	0.9944	1.0098	0.9747	0.8589	1.1930	1.0370	1.0147	1.0047	0.9950	0.9888	1.0176	0.9453	0.9903
Group 2																		
Chongqing	1.0403	1.1505	1.2699	2.3508	1.0000	1.3623	1.1008	0.8394	0.8507	1.4134	1.0000	1.0408	0.9764	0.9977	1.0327	0.7722	0.9039	0.9366
Jinzhou	1.3443	0.7182	0.7818	1.8194	1.6466	1.2621	0.9898	0.9889	0.9789	0.8671	1.3929	1.0435	0.8063	1.3043	1.2403	1.0309	0.6442	1.0052
Lianyungang	0.7759	3.0552	0.0296	1.7323	2.9893	1.7165	1.1190	0.2240	2.5439	1.0655	1.4421	1.2789	0.9795	0.8974	1.4437	1.4799	1.2432	1.2087
Nanjing	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.3160	1.0000	1.0000	0.7964	1.2556	1.0736	1.0883	1.0114	1.6906	1.3354	1.4814	1.3214
Northern Gulf	1.0000	0.4060	2.4633	1.0000	1.0000	1.1738	1.3746	1.2408	0.5441	1.2718	1.6720	1.2207	0.9865	1.3238	1.0878	1.5532	0.9592	1.1821
Rizhao	1.0000	1.0000	0.5541	1.8048	0.6745	1.0067	0.9314	0.7520	1.5067	0.8481	2.6685	1.3413	1.3675	1.3310	1.1433	0.9607	1.1689	1.1943
Tangshan	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	2.0464	0.8033	1.2449	1.0000	1.0000	1.2189	1.0041	1.2858	1.1640	1.3944	1.7341	1.3165
Xiamen	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.1285	0.7007	0.9446	1.2338	1.7639	1.1543
Yingkou	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9215	0.9896	1.0972	1.0965	1.7308	1.1671	1.0817	1.0599	1.0673	1.0174	0.7915	1.0036
Zhuhai	0.3134	1.3025	1.7987	1.3621	1.0000	1.1553	1.2397	1.0917	0.7136	0.9682	1.2734	1.0573	1.4331	0.8980	0.9916	1.1639	1.1611	1.1295
Average of group 1	1.0251	1.0857	1.0965	0.8766	1.0314	1.0230	1.0063	1.0096	0.8904	1.2262	1.0261	1.0317	1.0210	1.0068	0.9936	0.9969	0.9724	0.9982
Average of group 2	0.9474	1.1632	1.0897	1.4069	1.2310	1.1677	1.2039	0.8930	1.1480	1.0327	1.4435	1.1442	1.0852	1.0810	1.1806	1.1942	1.1851	1.1452
Average of 16 ports	0.9765	1.1341	1.0923	1.2081	1.1562	1.1134	1.1298	0.9367	1.0514	1.1053	1.2870	1.1020	1.0611	1.0532	1.1105	1.1202	1.1054	1.0901

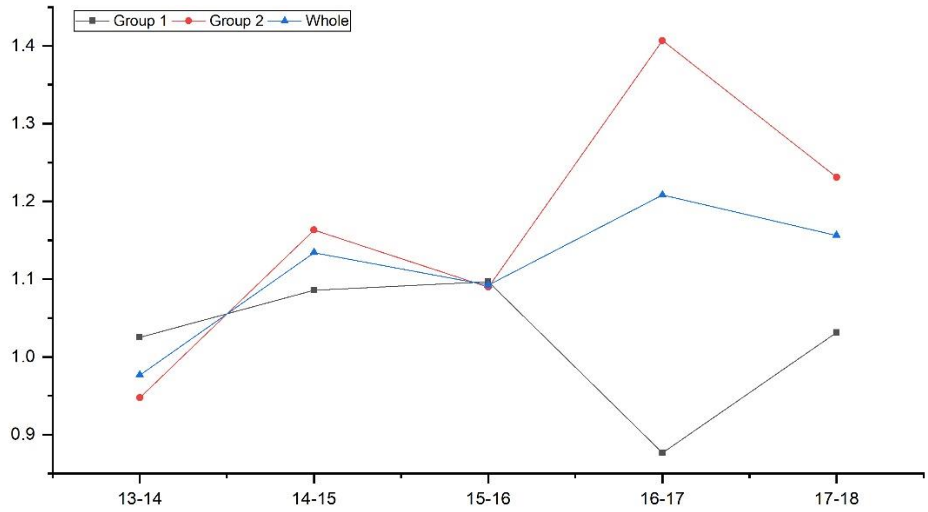

Figure 4 The changes of EC in both groups and the whole

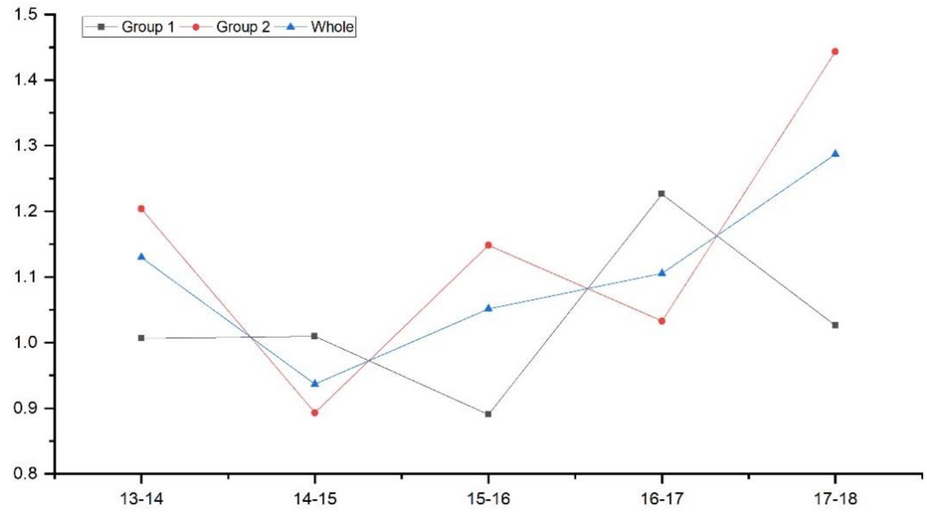

Figure 5 The changes of BPC in both groups and the whole

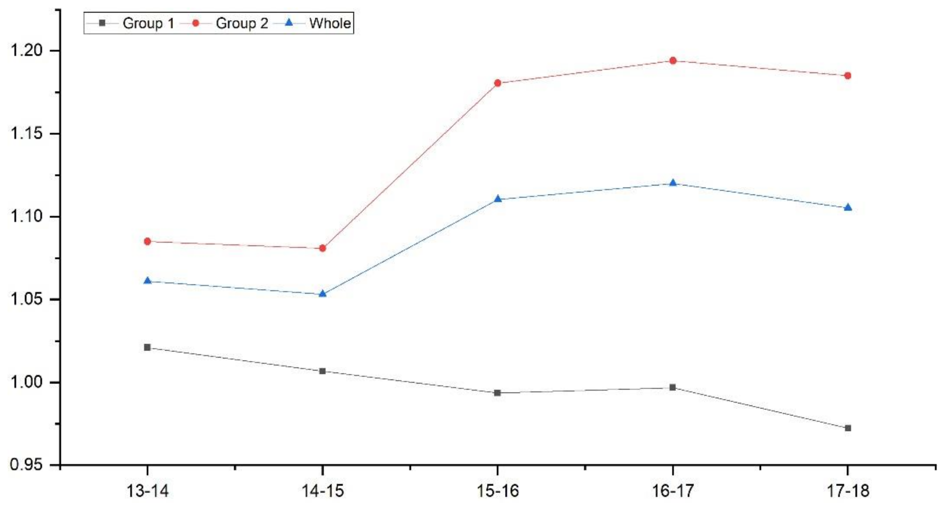

Figure 6 The changes of TGC in both groups and the whole

Third, the average TGC value is 1.0901, which implies the inter-temporal technology frontier approached to the global technology frontier at a rate of 9.01% annually. The averages TGC of group 1 and group 2 are 0.9982 and 1.1452, respectively, which means that the inter-temporal frontier shifted away from the global frontier at an annual average rate of 0.18% for group 1, whereas the inter-temporal frontier moved toward the global frontier at an annual average rate of 14.52% for group 2. The results reflect that there is lack of technological leadership among ports in group 1. Figure 6 shows that the TGC of group 2 and the whole have the same trend and always above one, while group 1 exhibited the declined trend over the sample period, in particular, it’s inter-temporal frontier deviates from the global frontier at a rate of 0.64% in 2015–2016, 0.31% in 2016–2017, and 2.76% in 2017–2018, respectively.

Combing Table 5 with Table 6, we have the following findings.

First, the average MNMCEP of the whole is 1.2489, indicating an annual average growth rate of 24.89%. The annual average growth rate of EC, BPC, and TGC indices are 11.34%, 10.20%, and 9.01%, respectively, which means that the growth of CEP of the whole is attributed to the combination of EC (catch-up effect), BPC (innovation effect), and TGC (leadership effect).

Second, the annual average growth rate of MNMCEP in group 1 is 4.51%, while the EC and BPC increased by 2.30% and 3.17% annually, respectively, but TGC has a slight negative growth rate of 0.18%, which implies that the growth of CEP is mainly driven by catch-up effect and innovation improvement. MNMCEP of Ningbo-Zhoushan and Shanghai ports grow at annual average rates of 0.67% and 11.94%, respectively, but their EC and TGC equalled to 1, which indicates that the growth of CEP in them were all driven by technology innovation. MNMCEP of Qingdao Port increase at an average rate of 14.30% per year. The average annual growth rate of EC and BPC are 11.86% and 3.09%, respectively, but its TGC decreased by 2.12%, indicating the growth of CEP was mainly driven by catch-up effect and innovation improvement. The average MNMCEP of Tianjin Port is 0.9749, showing an average annual decrease rate of 2.51%. Although it’s BPC increased by 1.47%, the average EC and TGC were less than 1, thus leading to the negative growth of CEP. In addition, we can see that the combination of catch-up effect, innovation effect, and leadership effect contributes to the growth of CEP in Dalian Port.

Third, in group 2, MNMCEP, EC, BPC, and TGC increase at an annual average rate of 37.13%, 16.77%, 14.42%, and 14.52%, respectively, which implies that the combination of catch-up effect, innovation effect, and leadership effect contributes to the growth of CEP. The average MNMCEP, EC, and BPC of Chongqing Port is 1.3333, 1.3623, and 1.0408, respectively, but TGC decreased at rate of 6.34% per year, which indicates that catch-up effect (EC) played a key role in the growth of CEP. Xiamen Port presents different pattern which its CEP increased at an annual average rate of 15.43%, while EC and BPC equalled 1, showing no catch-up effect and innovation effect. However, the annual average growth rate of TGC (leadership effect) is 15.43%, indicating the CEP growth of Xiamen Port was mainly due to leadership effect. MNMCEP of Nanjing, Tangshan, and Yingkou ports increased at annual average rates of 41.16%, 53.31%, and 14.04, respectively, but their EC equalled 1, which indicates that the CEP improvement of them was mainly driven by innovation improvement and leadership effect. Additionally, the combination of catch-up effect, innovation effect, and leadership effect contributes to the CEP growth of other ports (e.g., Jinzhou, Lianyungang, Northern Gulf, Rizhao, and Zhuhai).

4.4 Regression analysis

To further explore the determinants that explain the CEP and CEP changes (MNMCEP) of Chinese port enterprises, Feasible Generalized Least Squares (FGLS) estimation is applied. Both internal and external environmental factors are included in the regression method. The former is mainly related to port input and output, while the latter refers to factors that may influence the port CEP but they are not under the control of the port, mainly including the natural environment and the socio-economic environment factors.

Internal factors include both specialization indices of various outputs and total assets. The specialization index measures the degree of specialization of a certain output by the port (Tovar and Wall, 2019a). Chinese ports have formed a specialized transportation system for coal, oil, ore and containers. Thus, following Tovar and Wall (2019a), the indices of specialization in coal (SI_{coal}), oil (SI_{oil}), ore (SI_{ore}), and containers ($SI_{containers}$) are calculated, respectively. Moreover, port size is an important indicator that affects port CEP, total assets is selected to capture the scale of the port and it is normalized in the regression.

On the other hand, we selected environmental regulation (ER) and openness as two external factors. ER is a constraint on the whole process of ecological prevention and governance. It represents the investment and operation of pollution facilities and the pollution discharge, which may positively influence environmental performance (Song and Wang, 2014). Referring to Ouyang et al. (2019), we select the environmental indicators of port hinterland enterprises to construct a comprehensive index of ER intensity. The openness influences the cargo flow of the ports (Cui, 2017). We use the actual use of foreign capital of port hinterland to represent the openness and we normalized it in the regression.

Table 7 Regression analysis results: FGLS estimation

	(1) Meta-CEP	(2) MNMCEP
SI_{coal}	0.1140^{***}	0.0348
	(0.0343)	(0.0955)
SI_{oil}	0.0578	-0.1350
	(0.0423)	(0.1150)
SI_{ore}	0.1030^{***}	0.2280^{**}
	(0.0355)	(0.0955)
$SI_{container}$	5.4760^{***}	-1.4210
	(0.3770)	(1.2030)
Port size	-0.1430	0.7510^{***}
	(0.1170)	(0.2670)
ER	0.0074^{***}	0.0014
	(0.0018)	(0.0055)
Openness	-0.0865	-0.8860^{***}
	(0.0972)	(0.3060)
constant	-0.2190^{***}	1.1990^{***}
	(0.0812)	(0.2590)
N	96	80
Wald test	848.52^{***}	1020.06^{***}

Note: z statistics shows in bracket; *, **, and *** represent the variable is significant at 10%, 5% and 1%, respectively.

Regression results are presented in Table 7. Columns 1 and 2 of Table 7 shows the effects of determinants on CEP with respect to meta-frontier (meta-CEP) and dynamic changes in CEP (MNMCEP), respectively. It can be seen that specialization in coal, ore, and container have significantly and positively impacts on CEP at the level of 0.01, while specialization in ore positively and significantly influence the MNMCEP. In addition, the effect of port size on CEP is negative but insignificant, while its effect on MNMCEP is significantly positive, indicating expand the scale of ports conducive to the growth of CEP. The impact of ER on CEP is positive and significant, which implies that strict environmental regulations can improve CEP. The effect of openness on MNMCEP is negative and significant. It means that increasing the degree of openness has a deteriorating effect on the growth of CEP.

5. Discussion and conclusion

5.1 Findings and discussion

In this study, using the panel data of 16 port enterprises in China during the period of 2013–2018, we apply a modified non-radial DDF in the meta-frontier framework to evaluate their CO_2 emission performance (CEP) and its dynamic changes (MNMCEP) as well as driving forces (e.g., EC, BPC, and TGC). Considering the heterogeneity may exist among ports, we classified 16 ports into two groups based on the criterion of size and complexity, i.e., group 1 contains 6 ports while group 2 contains 10 ports. We draw the following findings from our empirical analysis.

First, with respect to meta-frontier, the meta-CEP of port enterprises in China was poor during 2013–2018, with an average value of 0.4038, which in line with the results obtained from Sun *et al*., (2017). Port group 1 performed better in terms of meta-CEP with an average score of 0.7980 than that of port group 2 with an average score of 0.2104. Four ports, namely, Ningbo-Zhoushan, Shanghai, and Shenzhen ports from group 1 and Tangshan Port from group 2, achieved efficiency in meta-CEP. On the other hand, both groups performed well in CEP with respect to their specific group frontiers, with average group-CEP of 0.8037 and 0.7968, respectively. 4 out of 6 ports from group 1 and 7 out of 10 ports from group 2 had average group-CEP over 0.7.

Second, we examine the dynamic changes in CEP (MNMCEP) and reveal its driving forces, namely, EC, BPC, and TGC. Although the port enterprises performed not well in CEP, their CEP increased at an annual average rate of 24.89%, and the CEP of group 1 and group 2 increased by 4.51% and 37.13%, respectively, indicating the policy of developing green port promotes the improvement of port's CEP (Wu *et al.*, 2017; Li *et al.*, 2020). In addition, the growth of CEP differs among ports. We find that the average EC, BPC, and TGC of the whole are 1.1134, 1.1020, and 1.0901, implies obvious catch-up effect, innovation effect, and leadership effect. The growth of CEP in group 1 is mainly driven by catch-up effect and innovation improvement, while for group 2, the combination of catch-up effect, innovation effect, and leadership effect contributes to the growth of CEP.

Third, via a regression approach of FGLS, we find that the effects of specialization in coal, ore, and container on CEP are positive and significant, while the effects of specialization in ore and port size on MNMCEP are positive and significant, which implies that expanding port scale and having specialization in some certain outputs are conducive to the growth of CEP, consistent with Tovar and Wall (2019a) who found that port size and specialization are conducive to the productivity growth. This is because large ports with specialization are more likely to have comparative advantages in economies of scale, introduction of advanced and cleaner equipment, and technological innovation ability (Chang and Tovar, 2017; Sun *et al.*, 2017; Tovar and Wall, 2019a). Moreover, the impact of ER on CEP is positive and significant, indicating stronger environmental regulation policies are necessary for ports (Song and Wang, 2014; Ouyang *et al.*, 2019). It should be noted that openness has a significantly negative effect on the MNMCEP in this study. Al-Mulali *et al.* (2013) pointed out that the impact of openness on environmental performance is not uniformly positive. On one hand, the increase of openness will attract more foreign direct investment. Foreign direct investment has "technology spillover effect", which brings advance technology, clean equipment and mature management experience, thus leading to the improvement of port environmental performance (Wang *et al.*, 2013; Seker *et al.*, 2015). On the other hand, the strict environmental regulations in developed countries pushed multinational companies to shift industries with high pollution and high energy consumption to countries with less strict environmental regulations. Thus, increasing openness and attracting more foreign investment in the port will increase CO_2 emission of ports, which deteriorate the improvement of environmental performance (Copeland and Taylor, 1994; Tamazian *et al*., 2009). Additionally, higher degree of openness would increase operational expectation of port practitioners and thus result in more CO_2 emission (Cui, 2017).

5.2 Policy suggestions

According to the empirical results, some suggestions are provided as follows.

First, environmental regulation is necessary for the ports. On one hand, the government can use "control" environmental regulation tools such as setting up the emissions control zones and emission limits to strengthen the strictness of environmental regulation. On the other hand, the government can also apply the "incentive" environmental regulation policies such as establishing a reward and punishment system to encourage ports to use clean energy equipment and stimulate ports toward self-governance.

Second, due to the unbalanced development of ports, differentiated operation strategies should be adopted. If the size of port is large enough, more attention should be paid to the degree of specialization. If the port has already been in specialization in several outputs, the port can make more investments to enlarge the size.

Third, the results of CEP show that smaller and less complex ports have low CEP on the basis of meta-frontier, but achieve relative high CEP with respect to their specific group frontiers. Therefore, it is necessary to compare ports of similar size and complexity, and the government or industry association can share the best practices among the same type of ports to stimulate the effects. Additionally, the Chinese government could set carbon emission reduction targets and allocate initial quota for individual port based on both meta-CEP and group-CEP.

5.3 Limitations

This study is not free of limitations and can be further researched in several directions: First, considering the availability of data, we evaluate the CEP of 16 port enterprises from 2013 to 2018 in this study, more port enterprises and longer period could be taken into account in future studies to better evaluate the CEP of ports in China. Second, we only include the CO_2 emission from land side in the analysis, the lack of data on CO_2 emission from sea side is one limitation that should be addressed. Third, bootstrapped parametric techniques can be incorporated to analyse the statistical inference for CEP and CEP dynamic changes as well as its driving forces.

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