

Environmental efficiency analysis of port cities: slacks-based measure data envelopment analysis approach

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Abstract

Because ports have been rapidly expanding, port cities have been exposed to air pollution. Air pollution in port cities that has resulted from the intense expansion of ports has become a pressing concern. Although several studies have discussed the relationship between port and city functions and a few studies have attempted to consider ports' environmental performance using the data envelopment analysis (DEA) approach, none have examined emerging port city issues like their environmental influence in great detail. To address these gaps, a slacks-based data envelopment analysis (SBM-DEA) model was used in this paper to assess the

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environmental efficiency of port cities. The labor population in respective port cities was selected as the input variable, and gross regional domestic product (GRDP) and container throughput were used as the desirable output variables. As the undesirable output variables, nitrogen oxide (NO_x), sulfur oxide (SO₂), and carbon dioxide (CO₂) emissions were selected in the model. The results showed that Singapore, Busan, Rotterdam, Kaohsiung, Antwerp, and New York are the most environmentally efficient port cities, while Tianjin is the least environmentally efficient. The social and opportunity costs for air pollutants emissions in low efficient port cities were calculated as well.

Keywords: Port City, Environmental Efficiency, Slacks-Based Measure Data Envelopment Analysis, Social Cost, Opportunity Cost

1. Introduction

Ports have been developed naturally in many areas, and the industries related to ports have been organized in the same areas; thus the developed places with port industries are called port cities in the geographical economics context (Bird, 1980; Bassett and Hoare, 1996). A port city is commonly defined as a city that is closed to a port and depends on pure port functions, logistics, and derived functions such as trade and activities related to the port. Most related studies have been comprised by the geographical pattern changes in port cities (Ducruet, 2006; Ducruet and Lee, 2006; Lee and Ducruet, 2009). In particular, Hoyle (1989) was concerned with Western port cities' evolutionary phases, and Lee et al. (2008) studied Asian port cities' development model as exemplified by both Singapore and Hong Kong. Port cities have been increasing in size because of the expansion of port activities. Port cities have improved their local economies as a result of such activities. Studies have highlighted the existence of ports could have positive effect on national as well as regional economies (Fujita and Mori, 1996; Tan, 2007; Deng et al., 2013).

As the same time, however, they are more exposed to air pollutants. Lin and Lin (2006) insisted that air pollution deteriorates the health of residents in port cities because it is comprised of carcinogenic substances. Environmental pollutants, including CO₂, SO₂, NO_x, and sulfur oxide (SO_x), have a negative impact on port cities. These emissions generated from sulfur burning are some of the air pollutants produced from ships berthing and are detrimental to human health. Although the emerging research issues in ecological economics have focused on their environmental impact on OECD countries (Zhou et al., 2006; Zhou et al., 2007), industry sector (Zhang et al., 2008; Li et al., 2010; Mao et al., 2010), energy field (Hu and Wang, 2006; Hanoma and Hu, 2008; Li and Hu, 2012). Some studies have merely highlighted ports' environmental performance (Chin and Low, 2010; Chang, 2013). Similarly,

numerous researchers have attempted to measure air pollutant emissions in ports (Joseph et al., 2009; Chang et al., 2013; Merk, 2012) and from oceangoing vessels (Eyring et al., 2005; Enderson et al., 2003; Corbett and Koehler, 2003). There has, however, been little concerns with the environmental impact on port cities.

To address these research gaps, we measured the environmental efficiency using the SBM-DEA model in this study. Based on the result, the most environmentally efficient port cities will be identified and recommendations will be made accordingly. This paper is thus organized into six sections. The next section reviews relevant previous studies. The research methodology is then described, followed by data analysis. Section five then suggests managerial and academic implications. Finally, this paper concludes with a discussion on future research directions.

2. Literature review

To evaluate the environmental influence of ports, the contingent valuation method (CVM) and cost benefit analysis (CBA) have been adopted by several ecological economists (Yoo and Chae, 2001; Jorgensen et al., 2001; Huppel and Ishikawa, 2005). In particular, Zhang et al. (2008) argued that DEA could easily be considered derivative coefficients weighted, normal judgments, and valuation for measuring environmental influence compared to CVM or CBA.

DEA can be defined as a nonparametric method of measuring the efficiency of a decision making unit (DMU) with multiple inputs and/or multiple outputs, without a clear identification of the relation between them. Among other models in the context of DEA, the two most widely used DEA models are the Charnes, Cooper and Rhodes (CCR), and Banker, Charnes and Cooper (BCC) models. The DEA-CCR model allows multiple inputs and

outputs of each DMU to be represented. It can also be represented as a ratio of the abstract input to abstract output, and the resulting efficiency value can then be used for comparison with other DMU in the set. The DEA-BCC model, on the other hand, allows for variable returns to scale.

DEA has been used to measure the efficiency and productivity of many institutions such as universities, banks, and hospitals (Fukuyama, 1993; Sherman, 1984; Chen, 1997). With regard to the port industry, several previous studies have been conducted using the DEA model (Tongzon, 2001; Cullinane et al., 2006; Wang and Cullinane, 2006). Tongzon (2001) applied DEA to analyze the operational efficiency of 16 ports in Australia and Europe. Cullinane et al. (2006) also attempted to compare the efficiency results between DEA and the stochastic frontier approach (SFA) on the port industry.

Looking at the environmental issue, the DEA-based approach has been widely used to measure the environmental impact on many areas. Similar to the DEA approach, the SBM-DEA model was introduced by Tone (2001). The SBM-DEA model can show over weighted input resources and deficient output variables directly in contrast to CCR and BCC models, which do not considering slacks; the two classical models can only show reductions or enlargements proportionally. The SBM-DEA model was expanded by Zhou et al. (2006), incorporating undesirable output variables in both objective and constraint functions the given SBM-DEA model.

In the ecological economics context, most economists have taken into account air pollutant emissions as undesirable output variables in the SBM-DEA model. Zhou et al. (2006) measured the 30 OECD countries using the SBM-DEA model from 1998 to 2002. They used two input variables, the total primary energy supply and population, a desirable output variable as gross domestic product (GDP), and CO₂ emissions were used as undesirable output variable. In 2007, Zhou et al. adopted the same model, taking into account the labor

force and primary energy consumption as input variables, GDP as a desirable output variable, and CO₂, SO_x, and NO_x were used as undesirable output variables. Choi et al. (2012) also used SBM-DEA model to evaluate 30 Chinese provinces' CO₂ emission efficiency and energy efficiency. They concluded that CO₂ emissions should be reduced by 56.1 million tons per each province and by 1,683 million tons nationwide. In addition to these studies, several application studies have been done, including the industry side (Zhang et al., 2008) and ports' environmental performance (Chin and Low,2010; Chang, 2013).

Chin and Low (2010) compared ports' productivity and their environmental efficiency using the DEA and SBM-DEA models, respectively, then, they did a sensitivity analysis of output resources, determining that the vessel capacity is greater than the current. Chang (2013) attempted to analyze environmental efficiency of 23 Korean ports, and as a result of his study, Sokcho, Yeosu, Daesan, Gohyun, and Jeju are the most environmentally efficient ports in Korea.

On the one hand, undesirable output has been used to measure social efficiency. Oum et al. (2013) found a proper methodology rather than the DEA model to measure social efficiency. They conducted an application study about both Japanese rail and airlines' social efficiency adopting input variables of labor, capital cost, variable cost, and passengers' time; an output variable of equivalent passenger-kilometers; and an undesirable output variable of life-cycle CO₂ emissions. As a result, the overall rail firms show higher indices than airlines' performance. Lozano and Gutiérrez (2011) adopted the SBM-DEA model for 39 Spanish airports, taking into account airplane delay time as an undesirable output factor. A summary of the application studies using the SBM-DEA model is shown in Table 1.

[INSERT TABLE 1]

3. Methodology

3.1. Description of the SBM-DEA model

Generally, the principle of the SBM-DEA model is similar to the classical DEA model, which assumes that producing more desirable outputs relative to less inputs and undesirable outputs is a key factor for higher efficiency (Chang, 2013; Lozano and Gutiérrez; Zhou et al., 2006). The SBM-DEA model can be summarized as follows:

Data

i : index of inputs

g : number of good (i. e. , desirable) outputs

k : 1, 2, ..., g index of desirable outputs

b : number of bad (i. e. , undesirable) outputs

r : 1, 2, ..., g index of undesirable outputs

N : number of port cities

j : 1, 2, ..., N index of port cities

0 : index of specific port city whose efficiency is being assessed

x_{ij} : observed amount of input i of port city j

y_{kj} : observed amount of desirable output k of port city j

z_{rj} : observed amount of undesirable output r of port city j

Variables

$(\lambda_1, \lambda_2, \dots, \lambda_n)$: Nonnegative multipliers used for computing a linear combination of the port cities in the data sample

λ_{k0}^+ : Slack (i.e., potential increase) of desirable output k of port city 0

λ_{r0}^- : Slack (i.e., potential reduction) of undesirable output r of port city 0

α : Auxiliary variable due to joint weak disposability of desirable and undesirable outputs

The proposed SBM-DEA model (1) can be summarized as below (Lozano and Gutiérrez, 2011):

$$\text{Min } \lambda_{k0} = \frac{1 - (1/\alpha) \sum_{r=1}^s (\lambda_{r0}^- / \lambda_{r0})}{1 + (1/\alpha) \sum_{k=1}^m (\lambda_{k0}^+ / \lambda_{k0})}$$

s.t.

$$\sum_{j=1}^n \lambda_j x_{kj} \leq \lambda_{k0} \quad \forall k$$

$$\alpha \cdot \sum_{k=1}^m \lambda_k x_{kj} = \lambda_{k0} + \lambda_{k0}^+ \quad \forall k$$

$$\alpha \cdot \sum_{r=1}^s \lambda_r x_{rj} = \lambda_{r0} - \lambda_{r0}^- \quad \forall r$$

$$\sum_{j=1}^n \lambda_j = 1$$

$$0 \leq \alpha \leq 1$$

$$\lambda_j \geq 0 \quad \forall j \quad \lambda_{k0}^+ \geq 0 \quad \forall k \quad \lambda_{r0}^- \geq 0 \quad \forall r \quad (1)$$

The proposed SBM-DEA model (1) can be summarized as below (Lozano and Gutiérrez,

2011):

The above model can be regarded as a fractional non-linear program; thus, it needs to be transformed into a linear program using two stages. In the first stage, it needs define the new variables $\theta_j = \theta \cdot \lambda_j \cdot \forall_j$ removing the nonlinear oriented constraints. The revised linear program (2) thus is as follows:

$$\begin{aligned} \text{Min } \theta_0 &= \frac{1 - (1/\theta) \sum_{j=1}^n (\bar{\theta}_0 / \theta_0)}{1 + (1/\theta) \sum_{j=1}^n (\theta_0^+ / \theta_0)} \\ \text{s.t.} & \\ \theta & \\ \theta \theta_j \lambda_{jj} &\leq \theta \cdot \theta_0 \quad \forall j \\ \theta & \\ \theta \theta_j \lambda_{jj} &= \theta_0 + \theta_0^+ \quad \forall j \\ \theta & \\ \theta \theta_j \lambda_{jj} &= \theta_0 - \theta_0^- \quad \forall j \\ \theta & \\ \theta \theta_j &= \theta \\ \theta & \\ 0 &\leq \theta_j \leq \theta \\ \theta_j &\geq 0 \quad \forall j \quad \theta_0^+ \geq 0 \quad \theta_0^- \geq 0 \quad \forall r \end{aligned} \quad (2)$$

In the second stage, the model can be organized into a typical linear program using the classical DEA model, the DEA-CCR model, using a similar method as in the original SBM model (Tone, 2001), i.e., generating several new variables $t > 0 \hat{\theta} = \theta \cdot \theta_j \lambda_{jj} \quad \forall j = \theta \cdot \theta_0^+ \theta_0 = t \cdot \theta_0^+ \quad \forall j \quad \hat{\theta}_0^- = \theta \cdot \theta_0^- \quad \forall j$. The revised model (3) is as follows:

$$\text{Min } \theta_0 = \theta - \frac{1}{\theta} \sum_{j=1}^n \frac{\hat{y}_{j0}^-}{\theta_{j0}}$$

s.t.

$$\theta + \frac{1}{\theta} \sum_{j=1}^n \frac{\hat{y}_{j0}^+}{\theta_{j0}}$$

θ

$$\theta \hat{y}_{j0} \leq \theta \cdot \theta_{j0} \quad \forall j$$

θ

$$\theta \hat{y}_{j0} = \theta \cdot \theta_{j0} + \hat{y}_{j0}^+ \quad \forall k$$

θ

$$\theta \hat{y}_{j0} = \theta \cdot \theta_{j0} - \hat{y}_{j0}^- \quad \forall ?$$

θ

$$\theta \hat{y}_j = \theta$$

$$0 \leq \theta \leq 1$$

$$\hat{y}_j \geq 0 \quad \hat{y}_{j0}^+ \geq 0 \quad \hat{y}_{j0}^- \geq 0 \quad (3)$$

Additionally, the SBM efficiency measure θ_0 , the optimal solution to model (3) taking into account $\theta^*, \hat{y}_j^*, \theta^*, (\hat{y}_{j0}^+)^*, (\hat{y}_{j0}^-)^*$ provides the following summation of the target outputs for port city 0 as:

$$\theta_{j0}^* = \theta^* \cdot \sum_{j=1}^n \hat{y}_{j0} \theta_{j0} = \theta^* \sum_{j=1}^n \hat{y}_{j0} \theta_{j0} = \frac{1}{\theta^*} \sum_{j=1}^n \hat{y}_{j0}^* \theta_{j0}$$

$$= \frac{1}{\theta^*} \theta^* \cdot \theta_{j0} + (\hat{y}_{j0}^+)^* = \theta_{j0} + \frac{(\hat{y}_{j0}^+)^*}{\theta^*} \quad \forall ?$$

$$\theta_{j0}^* = \theta^* \cdot \sum_{j=1}^n \hat{y}_{j0} \theta_{j0} = \theta^* \sum_{j=1}^n \hat{y}_{j0} \theta_{j0} = \frac{1}{\theta^*} \sum_{j=1}^n \hat{y}_{j0}^* \theta_{j0}$$

$$= \frac{1}{\lambda^*} \cdot \lambda_0 - \lambda_0^* = \lambda_0 - \frac{(\lambda_0^*)^*}{\lambda^*}$$

3.2. Research design

In this paper, we chose the world's top container ports whose throughput was above 4,000,000 TEUs in 2011. The total sorted ports were 27 ports. Wang and Cullinane (2006) insisted that when selecting variables for the DEA-based approach, all variables should accurately represent the research topic.

As for desirable output variables, product and/or service value-related determinants are needed. Ducruet (2006) and Wang et al. (2007) studied clustering port cities in Europe and Asia using several classification indicators such as the number of logistics facilities, container throughput, and the number of direct calls. Among these indicators, container throughput can show the degree of port activity and how much a city depends on port activity from a regional economic perspective. Thus, container throughput is also used as an output variable in this study. In addition, Zhou et al. (2007) and Hu and Wang (2006) used GDP as an output variable to measure a country's environmental efficiency. To reflect cities' economic conditions, GRDP was also used as the output variable instead of GDP in this study. We collected container throughput data for each city from the Containerization International Online while, GRDP data were multiplied by GDP per capita and city population.

In general, NO_x, SO₂, particulate matter (PM), unburned hydrocarbons (UHC), SO_x, and carbon monoxide (CO) generated from sulfur burning are the main air pollutants produced during ship berthing. These air pollutant emissions have negative effect on ports and port city areas like depleting the ozone layer, increasing the green-house effect, and producing acid rain. To measure the environmental efficiency of port cities, these air pollutant emissions

could explain port cities' environmental impact, the SBM-DEA model's undesirable output variables should be these specific emissions. The European Commission and ENTEC UK Limited (2002) also highlighted that NO_x, SO₂, hydrocarbon (HC), PM, and CO₂ are mainly generated by ship engines. Many studies, however, have measured these emissions' portions; both HC and PM have accounted for small portion of cargo vessels' emissions (Corbett and Koehler, 2003; Enderson et al., 2003; Eyring et al., 2006). Corbett and Koehler (2003) found that CO₂, NO_x, and SO₂ accounted for 95.8%, 2.5%, and 1.5%, respectively. HC and PM have low portions, 0.1% and 0.2%. Thus, "CO₂, NO_x, and SO₂ emissions" were selected as undesirable output variables. There are no official statistics on CO₂ emissions for ports and cities. CO₂ emissions were calculated by the authors. We multiplied the CO₂ emissions per capita and city population. Both SO₂ and NO_x emissions data were extracted from Merk (2012). His study followed the below equation to estimate the extent to how much vessels generate air pollutants in ports.

$$E = P \times LF \times EF \times T$$

Where:

E: emissions in units of pollutant

P: maximum power output of auxiliary engine in kW

LF: load factor for auxiliary engines, as a fraction of maximum installed power capacity

EF: emission factor (pollutant specific) in mass emitted per work output of the auxiliary engine in sailing mode, g/kWh

T: time in sailing mode in hours

As an input variable, Oum et al. (2013), Choi et al. (2012), Zhou et al. (2006), and Zhou et

al. (2007) have taken into consideration social and environmental efficiency using labor population; thus we can select the variables of labor population in each port city. Labor population is multiplied by the labor participation rate and city population.

In 27 sorted ports whose container throughput were above 4,000,000TEUs, we excluded 16 ports (Shanghai, Shenzhen, Ningbo, Guangzhou, Qingdao, Dubai, Tanjung Pelepas, Xiamen, Dalian, Long Beach, Leam Chabang, Lianyungang, Jawajrlal Nehru, Tokyo, Valencia and Yingkou) that do not provide air pollutant emissions data, and then 11 port cities were finally selected for DMUs. The R package software was employed to evaluate the environmental efficiency of the selected port cities. Table 2 provides a summary of data in this study, while Figure 1 demonstrates the process of measuring the environmental efficiency of port cities.

[INSERT FIGURE 1]

[INSERT TABLE 2]

4. SBM-DEA results

Table 3 shows the results of the environmental efficiency analysis of port cities. It can be seen from Table 3 that Singapore, Busan, Rotterdam, Kaohsiung, Antwerp, and New York (1.000) are the most environmentally efficient port cities. However, Los Angeles (0.846), Hong Kong (0.727) and Hamburg (0.796), Tianjin (0.067) and Jeddah (0.396) were ranked relatively low in terms of environmental efficiency.

We can make the assumption that most environmental port cities, such as Singapore, Rotterdam, and Kaohsiung (Chang and Wang (2012)), have engaged in environmentally

friendly activities, that is they have established green task force early to mitigate air pollutants and complied with relevant regulations of the International Maritime Organization (IMO).

To optimize the efficiency of port cities, Hong Kong should mitigate their NO_x, and CO₂ emissions of 183.808 and 6221,514.111 tons, respectively.

Tianjin has an excessive labor population of 8,043,826 persons; NO_x, SO₂, and CO₂ should be reduced by 1,817.005, 1,452.918, and 67,145,097.336 tons, respectively. In Hamburg, the excessive labor population is 135,646 persons, and the city should reduce its NO_x, SO₂, and CO₂ emissions by 218.821, 129.289, and 5,356,191.319 tons, respectively. Los Angeles still needs to reduce its air pollutant emissions, although its port has been adopting strong green port planning. NO_x, SO₂, and CO₂ emissions need to be reduced by 9.542, 23.804, and 208,065,838.905 tons, respectively. In addition, the excessive labor population is 20,041 persons. Jeddah has an excessive labor population of 807,172 persons, and its shortfall container throughput is 3,342,781 TEUs. Both SO₂, and CO₂ emissions need to be reduced by 132.101, and 49,244,083.654 tons, respectively.

Given the SBM-DEA model results, CO₂ is the most urgent form of emissions that needs to be treated in each port city. We now present the social costs of handling potential CO₂ emissions in 2011. In Oum et al. (2013), they regarded that CO₂ emissions' price is 30€ per ton when they measured social costs; we can thus estimate the social cost for port cities' excessive CO₂ emissions. Hong Kong exposed its social cost for treating CO₂ emissions being 18,645,423€. Tianjin has a social cost for CO₂ emissions of 2,014,352,920€, and Hamburg has a cost of 160,685,740€. Los Angeles has a social cost of 6,241,975,167€, and Jeddah has a cost of 1,477,322,510€ for treating CO₂ emissions.

Zhou et al. (2006) presented the opportunity cost for measuring the loss of desirable output and excessive input and undesirable output. They measured opportunity cost using this

formula; $(1 - \text{?}) \times \text{?}$. In this study, we can use GRDP instead of GDP. Hong Kong has an opportunity cost of 68,406,912,488 USD. Tianjin's is 65,781,764,847 USD, Hamburg's is 16,249,232,456 USD. Los Angeles and Jeddah have opportunity costs of 102,902,096,070 and 50,347,780,333 USD, respectively.

[INSERT TABLE 3]

[INSERT TABLE 4]

5. Academic and managerial implications

This study has both academic and managerial implications. First, the need for more environmentally friendly shipping and port operations has become increasingly urgent in recent years. The need to reduce the impact of ship emissions on port cities is seen as a central research topic. In this respect, this study contributes to setting the foundation for this research agenda by revealing the current environmental efficiency performance of port cities worldwide. The use of the SBM-DEA model to examine the extent to which environmental influences reduce the environmental efficiency of port cities was pioneered in this paper and thus can lead to further refinement and application of this method in the area of environmental efficiency research. The topic of the environmental efficiency of port cities has gained little attention until now, despite its significance, and several studies only show ports' environmental efficiency results (Chin and Low, 2010; Chang, 2013). This research is therefore meaningful and can open up directions for future research, not only for the port city discipline, but also for the ecological economics area. The analysis of the environmental efficiency of port cities has the potential to be effective methodology to evaluate the influence of air pollution generated from ocean vessels.

There are many managerial implications of this research. First, the findings confirm that most environmentally efficient port cities are those with ports implementing proactive and early measures to tackle the effects of ship emissions in ports. As one example, New York especially has established action plans to mitigate air pollution and has developed an alternative marine power system for container ships well ahead of other ports in this study. Such findings also justify the need to develop green shipping and port operations measures according to IMO regulations since the air pollutants derived from ocean vessels could have a negative impact on residents living near ports. In addition to the existing MARPOL 73/78 instruments to regulate used oil, sewage, and overall waste material from ocean vessels, the IMO has recently developed the Energy Efficiency Design Index (EEDI), Energy Efficiency Operational Indicator (EEOI), and Ship Energy Efficiency Management Plan (SEEMP) to mitigate air pollution from ships. In fact, leading companies in the maritime industry have already taken action to enhance the environmental efficiency of their operations. A remarkable example is the introduction of the Maersk's Triple-E class vessels in 2011. The A. P. Moller-Maersk Group announced that they ordered the greenest vessel, the Triple-E class, which achieves the three Es: economy of scale, energy efficiency, and environment friendly. The vessel not only emits air pollutants less than existing vessels by 50%, but it also loads more than 2500 containers. Thus, the trend of mega ships would have both economic and environmental benefits. Lastly, the present findings also advocate for the green supply chain (GSC) concept to be implemented in port cities. The GSC concept entails carrying products and services from suppliers and manufacturers to the end customers through product, information, and cash flows, taking into account environmental concerns. In this respect, it is argued that contemporary supply chain managers only think about how to supply products to the customers effectively. GSC managers, on the other hand, collaborate with supply chain parties to engage in green purchasing, cooperation with customers, and reverse logistics to

enhance environmentally friendly operations. Several studies have validated in the manufacturing and textile industries that conducting GSC would affect supply chain performance positively (Wu et al., 2012; Zhu et al., 2007). It is therefore time for port operators (and port city developers) to think about various operational measures in respect to GSC to enhance their environmental efficiency.

6. Conclusions

Generally, ocean vessels are known to be the most environmentally friendly mode of transportation. Nevertheless, they still emit numerous air pollutants, especially CO₂, NO_x, and SO₂. These emissions are being measured more in terms of their impact on port cities than in general cities. To measure the environmental efficiency of port cities, we used GRDP and container throughput as desirable output variables and, NO_x, SO₂, and CO₂ emissions as the undesirable output variables. The labor population for each port city is regarded as an input variable in this study.

The results show that Singapore, Busan, Rotterdam, Kaohsiung, Antwerp, and New York are highly environmentally efficient port cities. Meanwhile, the port cities of Hong Kong (0.727), Tianjin (0.067), Hamburg (0.796), Los Angeles (0.846), and Jeddah (0.396) are relatively less environmentally efficient. To optimize the DMUs, NO_x emissions should be reduced an average of 743.055 tons, SO₂ emissions should be reduced 434.528 tons, and CO₂ emissions should be reduced 66,086,545.065 tons. The average excessive labor population is 2,026,269 persons, and shortfall container throughput is 3,342,781 TEUs. We then present the social cost for treating CO₂ emissions and the opportunity cost for dealing with all air pollutant emissions in the following inefficient port cities; Hong Kong, Tianjin, Hamburg, Los Angeles, and Jeddah. Their average social cost is 1,982,596,351€, and their average

opportunity cost is 60,737,557,238 USD.

This study has several limitations because some air pollutant emissions data, such as PM and HC, were not accessible. We excluded 16 ports consisting of DMUs due to the limitation of gathering data for all variables. To expand the targeted ports and variables, future researchers will need to conduct environmental efficiency analysis of port cities.

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List of Tables and Figures

Table 1

Summary of application studies of environmental and social efficiency

Researcher	Main concept	Objective area	Input variables	Desirable output variables	Undesirable output variables
Zhou et al. (2006)	Environmental efficiency	30 OECD countries	Total primary energy supply, population	GDP	CO ₂ emissions
Zhou et al. (2007)	Environmental efficiency	26 OECD countries	Labor population	GDP	CO ₂ , SO _x , NO _x , CO emissions
Zhang et al. (2008)	Eco-efficiency	Industrial system in China	Water resource, raw mining resource, energy consumption	Value-added of industry	COD, NO _x , SO ₂ , soot, dust emissions, industrial solid wastes produced
Chin and Low (2010)	Environmental efficiency	World's 13 ports	Frequency of shipping services, bilateral trade flows	Container vessel capacity flow	NO _x , SO ₂ , CO ₂ , PM ₁₀ emissions
Lozano and Gutiérrez (2011)	Slacks-based measure of efficiency	39 Spanish airports	Total runway area, apron capacity, number of baggage belts, number of check-in counters, number of boarding gates	Annual passenger movements, aircraft traffic movements, cargo handled	Percentage of delayed flights, average conditional delay of delayed flights
Choi et al. (2012)	Eco-efficiency	30 Chinese cities	Capital, labor population, energy consumption	GDP	CO ₂ emissions
Chang (2013)	Environmental efficiency	Korean 23 ports	Labor force, quay length, terminal area, energy consumption	Vessel, cargo handled	CO ₂ emissions
Oum et al. (2013)	Social efficiency	Three rail firms and two airlines in Japan's domestic market	Labor force, capital cost, variable cost, passengers' time	Equivalent passenger-kilometers	Life-cycle CO ₂ emissions

Table 2

Descriptive statistics for DMUs

	Container throughput (TEU)	GRDP (US\$)	Labor population (Persons)	NO_x (Ton)	SO₂ (Ton)	CO₂ (Ton)
Minimum	4,010,448.00	8,257,652,000.00	469,910.00	2,280.00	1,800.00	9,399,200.00
Maximum	29,937,700.00	1,014,628,608,000.00	11,600,640.00	12,300.00	9,300.00	235,752,000.00
Average	12,607,282.18	235,387,329,506.00	3,863,867.45	5,056.36	3,861.82	49,713,791.98
Standard deviation	7,983,994.41	318,934,194,895.19	3,808,594.70	3,056.01	2,284.30	65,731,561.99

Authors: All variables are from 2011 without CO₂ emissions which are from 2010.**Table 3**

Efficiency optimization

	????	Excessive labor population	Shortfall container throughput	Shortfall GRDP	Potential NO_x emissions reduction	Potential SO₂ emissions reduction	Potential CO₂ emissions reduction
Singapore	1.000	0.000	0.000	0.000	0.000	0.000	0.000
Hong Kong	0.727	1,124,661	0.000	0.000	183.808	0.000	621,514.111
Busan	1.000	0.000	0.000	0.000	0.000	0.000	0.000
Rotterdam	1.000	0.000	0.000	0.032	0.000	0.000	0.000
Tianjin	0.067	8,043,826	0.000	0.000	1,817.005	1,452.918	67,145,097.336
Kaohsiung	1.000	0.000	0.000	0.005	0.000	0.000	0.000
Hamburg	0.796	135,646	0.000	0.000	218.812	129.289	5,356,191.319
Antwerp	1.000	0.000	0.000	0.000	0.000	0.000	0.000
Los Angeles	0.846	20,041	0.000	0.000	9.542	23.804	208,065,838.905
New York	1.000	0.000	0.000	0.000	0.000	0.000	0.000
Jeddah	0.396	807,172	3,342,781	0.000	0.000	132.101	49,244,083.654

Table 4
Social and opportunity costs

DMU	2011	
	Social cost for treating CO ₂ emissions (€)	Opportunity cost (USD)
Hong Kong	18,645,423	68,406,912,488
Tianjin	2,014,352,920	65,781,764,847
Hamburg	160,685,740	16,249,232,456
Los Angeles	6,241,975,167	102,902,096,070
Jeddah	1,477,322,510	50,347,780,333

Figure 1
Process of environmental efficiency analysis of port cities

