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Analyzing the Effect of COVID-19 on the Operational Efficiency of Asia's Major Container Ports: A Data Envelopment Analysis

Tae-Hyung KIM* · Sang-Duk CHOI**†
* Researcher, Institute of Fishing village & Aquaculture, Chonnam National University, Yeosu, 59626, Korea
** Professor, Faculty of Marine Technology, College of Fisheries & Ocean Science, Chonnam National University, Yeosu, 59626, Korea

COVID-19 위기가 아시아 주요 컨테이너항만의 운영효율성에 미치는 영향

김태형* · 최상덕**†
* 전남대학교 어촌양식연구소 연구원, ** 전남대학교 교수

Abstract : *The COVID-19 virus has generated major shockwaves in all spheres of human life since its outbreak. Maritime transport (both cargo and passenger) is one of the industries most heavily affected, yet over 80% of the world cargo is transported by sea. This study analyzes maritime port operational efficiencies before and after the start of the COVID-19 pandemic to determine whether the pandemic has caused major differences in the operational efficiencies of many leading Asian maritime container ports via data envelopment analysis (DEA). The results of both the CCR and BCC models reveal that overall, efficiency during the COVID-19 pandemic has been higher than before the pandemic despite a few inefficiencies. This implies that the pandemic has so far not has major consequences for the operational efficiency of maritime ports. However, two ports (Busan and Guangzhou) should adjust the scale sizes and technical capacities of their operations to improve performance.*

Key Words : *DEA (Data envelopment analysis), CCR, BCC, Port Efficiency, Container Ports, DMU (Decision Making Unit)*

요 약 : COVID-19가 전 세계를 강타하면서 각 국가는 대혼란에 빠졌다. 전 세계 화물교역은 80% 이상이 해상운송을 통해 이루어지고 있어 화물과 여객을 포함한 해상운송업은 COVID-19의 큰 영향을 받는 산업으로 예측되었다. 따라서 본 연구의 목적은 코로나 팬데믹(Coronavirus Pandemic) 발생 전후로 아시아 주요 항만 컨테이너 항구의 팬데믹 전후 운영효율성을 분석하는 것이다. 항만의 운영효율성을 분석하기 위해서 자료포락분석(DEA)을 이용하였다. 본 연구의 분석 기간은 5년(2016~2020년)으로 2016년, 2017년, 2018년, 2019년을 코로나 이전으로 하고, 2020년을 포스트 코로나 시대로 설정하였다. 또한, 분석 대상으로는 아시아 상위 10개 항구 중 동종 DMU의 DEA 요건을 충족시킨 상하이, 광저우, 선전, 닝보-저우산, 부산 및 싱가포르 총 7개 항구를 선택하였다. DEA의 CCR 및 BCC 모델의 결과는 몇 가지 비효율성이 확인되었음에도 COVID-19 팬데믹 발생 시점에서 몇 개월 이후부터는 전반적으로 운영효율성이 코로나 이전 몇 년 동안보다 상대적으로 높았음을 확인하였다. 하지만 일부 항만 (부산, 광저우)의 경우에는 더욱 나은 운영효율성을 위해서 항만의 규모와 운영의 기술적 능력 등을 제고 할 필요가 있다.

핵심용어 : 자료포락분석, CCR, BCC, 효율성분석, 컨테이너항만, DMU

1. Introduction

Since its outbreak in late 2019, the Coronavirus pandemic has generated notable shockwaves in all spheres of human life (Abous et al., 2021; UNCTAD, 2020). Millefiori et al. (2021) describes this pandemic as one of the worst world global crises since World War II, currently causing over 145 million infections worldwide, and over 3 million deaths. Consequently, at the start of 2020, the World Health Organization (WHO) declared the Coronavirus as a pandemic and as a result recommended containment and suppression measures to slow down the spread of the virus in the

* First Author : timothytaehyung@gmail.com, 061-659-7578
† Corresponding Author : choisd@jnu.ac.kr, 061-659-7100

quest to safeguard health and safety. As a result of these measures, during the months right after the COVID-19 outbreak, maritime transport (both cargo and passenger) was most affected (Abous et al., 2021) with significant disruptions to shipping and maritime activity along established transport routes (Oyenuga, 2021).

In a world of global supply chains and complex industrial development processes, seaports and port operators have played an integral role of utmost importance and acted as an incentive to the development of the marine economy and particularly, the national economy in general (Wang et al., 2021). Hitherto, over 80% of the world cargo is moved by maritime transport (UNCTAD, 2018). However, due to the pandemic, all economic and trade expectations for 2020 and the near future were affected. For example, a forecast of 3.6% growth in container trade worldwide in the last quarter of 2019 was reduced to 2.5% in January 2020 and later on to -4.9% (United Nations, 2020). In general terms, world trade was expected to fall by between 13% and 32% in 2020 as the COVID-19 pandemic disrupted normal economic activity and life globally (Millefiori et al., 2021). Fig. 1 shows the effect that COVID-19 has had on the maritime industry in terms of inactive container capacity.

However, not all operations at ports have been reduced. For example, China's imports and exports steadily increased in 2020 (COSCO Shipping Ports Limited, 2020). According to the General Administration of Customs of the PRC, China's imports and exports reached RMB32 trillion in 2020, increased by 1.9% year-on-year. In particular, exports increased by 4.0% year-on-year to RMB18.6 trillion and imports decreased by 0.7% year-on-year to RMB13.4 trillion.

Thus, the pandemic has generally caused supply chain and demand shocks on the container shipping industry which has intensified competition among maritime players including terminal operators (Wang et al., 2021). The maritime port facilities (both tangible and intangible) have remained constant and yet the productivity has dwindled in part in the early months of the pandemic, and showing uncertainty, thereby creating the need for industry survival (Abous et al., 2021). Thus, managers must evaluate the operating efficiency of their port facilities aimed at identifying those gaps that will need to be bridged. One of the most important ways to measure port performance is the method of data envelopment analysis (DEA) (Pjevčević et al., 2012).

In this context, the objective of this paper is to analyze Asia's maritime ports operational efficiencies before and after the occurrence of the COVID-19 pandemic. We seek to determine whether the pandemic has caused major differences in the operational efficiencies in some of Asia's best maritime container ports. The academic contribution of this paper is to pave way for the comparison of port efficiency since the COVID-19 outbreak.

2. Literature Review

Data envelopment analysis (DEA) is a mathematical programming-based technique applied in evaluating the relative performance of organizations (Thanassoulis, 2001). While the main applications were originally been in the evaluation of not-for-profit organizations, the technique has recently been widely successful in applying to other situations (for-profit organizations) such as in the

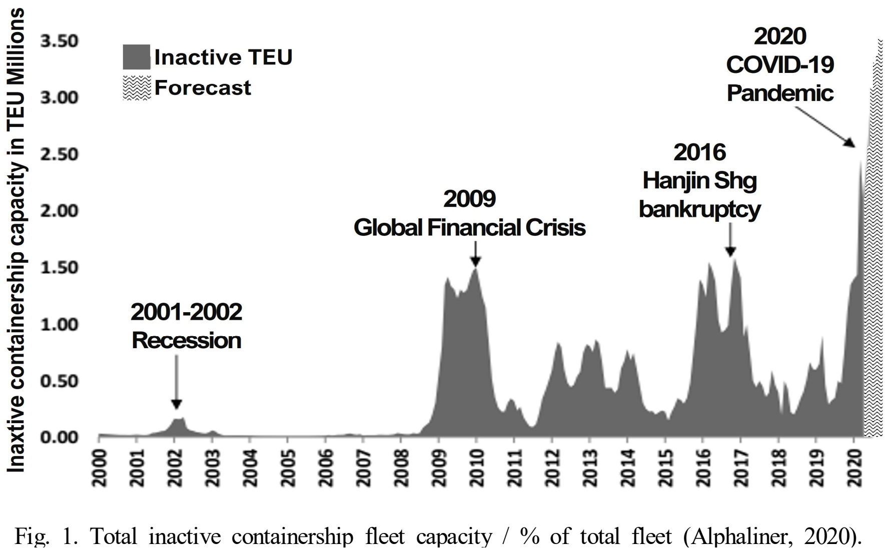

Fig. 1. Total inactive containership fleet capacity / % of total fleet (Alphaliner, 2020).

financial, insurance sectors (Santos and Grilo, 2013), private medicare (Jia and Yuan, 2017), maritime sector (Kutin et al., 2017).

The objective of the DEA methodology is to present efficient and inefficient decision-making units (DMUs) with the latter benchmarking the former DMUs for performance improvement as they make adjustments in inputs and outputs (Kutin et al., 2017). To be specific, DEA methodology identifies the best practice DMU without a priori knowledge of which inputs and outputs are crucial in determining efficiency measures (Charnes et al, 1978). It also measures the level of inefficiency for the DMU that is not in the best-practice category (Andersen and Petersen, 1993). These DMUs are groups of private firms, nonprofit organizations, administrative units with similar goals, purposes, standards and, market segments (Charnes et al., 1978; Sherman and Zhu, 2006; Thanassoulis, 2001; Zhu and Cook, 2007).

A DMU is deemed efficient (operates along the efficiency frontier) if and only if none of its inputs or outputs can be improved without deteriorating some of its other inputs or outputs (Cooper et al., 2011). DEA has a strength of delineating the least efficient DMU from the set of all DMUs whereby the best-practice (most efficient) DMUs are awarded efficiency scores of one, whereas the less efficient DMUs are awarded values somewhere between zero and one (Charnes et al., 1978). The Charnes, Cooper, and Rhodes (CCR) model was introduced with an assumption of constant returns to scale (CRS) in assessing relative productive efficiencies of the DMUs with multiple inputs and outputs (Charnes et al., 1978). This implies that any change in inputs should produce a proportional change in output.

With the CCR model, the measure of the efficiency of any DMU is obtained as the maximum of a ratio of weighted outputs to weighted inputs subject to the condition that the similar ratios for every DMU be less than or equal to unity (Charnes et al. 1978). CCR model is based on constant return scale (CRS) and could only give out the technical efficiency (TE) in practical use. Technical efficiency (TE) can be divided into two categories: input-guided and output-guided (Kumar and Gulati, 2008). The former indicates the achievement of a given output level by reducing inputs, the latter indicates the achievement of the highest output level by using the given inputs.

The CCR model assumes that there is perfect competition (but in the real world this situation is unreal). Imperfect competition, financial constraints, control steps, and other factors can cause DMUs not to operate at their optimal size. A DEA model that allows for calculations with a variable return to scale has been developed to overcome this problem. This model is the BCC model (Banker, Charnes, Cooper) and it is used to measure the so-called "pure technical efficiency". The BCC model is "more" realistic because it takes into account the existence of imperfect competition. The overall technical efficiency (CCR) can be decomposed into pure technical efficiency (BCC) and scale efficiency (SE). The value of scale efficiency indicates whether the DMU operates under increasing or decreasing return to scale, in other words, if the DMU is too big or too small. The objective of the BCC model was to give account to interpret the fact that, at different scales, the DMUs could have different productivities and still be considered efficient (Benicio and de Mello, 2015). Under the CRS model, efficient DMUs have the same productivity whereas under the BCC model, however, DMUs need not have the same productivity.

The concept of the CCR model is to identify the overall inefficiency, whereas the BCC model differentiates between technical efficiency and scale efficiency (Wang et al., 2021). Technical efficiency is defined as the ratio of the input of the firm concerning the input of a fully efficient firm producing the same output (Taib et al., 2018). This implies that technical efficiency is the capability of a firm to produce output with the specified inputs. On the other hand, scale efficiency can be thought of as the parameter at which level of average productivity a firm can achieve on operating at optimum scale size (Sherman and Zhu, 2006). Scale efficiency can be represented by the equation;

○ Scale efficiency
  = Technical efficiency / Pure technical efficiency

Meanwhile, the BCC efficiency index represents the local pure efficiency (PTE) under the assumptions of the variable returns to scale, and it is indicated as;

○ Technical Efficiency
  = Pure Technical Efficiency × Scale Efficiency

Finding the right mix of inputs to produce specific output(s) is an important part of the DEA methodology (Zhu and Cook, 2007; Thanassoulis, 2001). Therefore, in this study of port efficiency, we considered the quay length, yard area, and the number of gantry cranes as input variables. These inputs were chosen under the pretext that they determine the number and size of container vessels that can be accommodated at the port terminal and determine the number of containers that could be transferred and stored within the port area in the case of no direct ship-to-ship loading or transferring container out of the port area on rail/road vehicles, respectively. These inputs can also easily be manipulated to ensure a certain level of performance from the DMUs (ports). On the other hand, we adopted the container throughput as the only output variable. Roll and Hayuth (1993) were the first to study the efficiency of maritime ports and they made a major contribution in literature as they introduced the throughput of port facilities as an output variable that is mostly used to date. Several studies (as indicated in Table 1) on ports' and/or terminals' efficiency have approached the studies with a similar mix of input and output variables (Den et al., 2016; Kutin et al., 2017).

This study focuses on selected Asia's best maritime container ports. These were selected based on the DEA's homogenous DMUs assumption and the availability of their data.

Table 1. Previous studies that have focused on port/ terminal efficiency

No	1) Authors 2) Domain 3) DMU		
1	1) Kutin et al.(2017) 2) ASEAN 3) Port	Input	· Maximum depth of berth · Size of container yard · Length of Quay · Number of gantry cranes · Number of RTGs
		Output	· Container Throughput
2	1) Den et al.(2016) 2) Russia & Korea 3) Terminal	Input	· Total terminal area · Total quay length · Quay equipment · Yard equipment · Storage capacity · Depth · Handling capacity
		Output	· Annual Container Throughput
3	1) Pjevčević et al.(2012) 2) Sebia 3) Ports	Input	· Total area of warehouses · Quay length · Number of cranes
		Output	· Port throughput
4	1) Almawsheki and Shah(2015) 2) Middle East Region 3) Terminal	Input	· Terminal area · Quay length · Quay crane · Yard equipment · Maximum draft
		Output	· Throughput
5	1) Li et al.(2015) 2) Northeast Asia 3) Container Ports	Input	· Berth length · Total terminal area · Number of container gantries · Quay cranes · Floating cranes · Mobile cranes · Number of straddle carriers
		Output	· Annual container throughput
6	1) Guimaraes et al.(2019) 2) Brazil 3) Container Terminals	Input	· Total energy · Non-renewable energy · Sewage emission · Office supplies consumption · Total emission · Water consumption per worker
		Output	· Container throughput
7	1) Bichou(2012) 2) World 3) Container terminals	Input	· Terminal area · Max draft · Quay length · Quay crane index · Yard stacking index · Gates
		Output	· Container throughput
8	1) Bray et al.(2014) 2) Europe 3) Container ports	Input	· Number of cranes · Container Berths · Number of tugs · Terminal area · Delay time · Number of port authority employees
		Output	· Container throughput · Ship rate · Ship calls · Crane productivity
9	1) Lim et al.(2011) 2) China 3) China	Input	· Quay length · Total area · Gantry cranes
		Output	· Container throughput
10	1) Hung et al.(2010) 2) Asia-Pacific 3) Container ports	Input	· Terminal area · STS · Container gantry cranes · Berths · Total quay length
		Output	· Container throughput
11	1) Current study 2) Asia 3) Container ports	Input	· Quay length · Yard area · Number of quay cranes
		Output	· Cargo Throughput

3. Methodology

3.1 Windows Analysis

To apply DEA in a study, it is an important rule of thumb that the number of DMUs is at least twice (Golany and Roll, 1989) or thrice (Bowlin, 1998) the sum of the number of inputs and outputs. Short of this, the model may produce numerous relatively efficient units and decrease the discriminating power of the analysis. Using few container ports (DMUs) would yield this problem.

To solve this challenge, DEA window analysis will be adopted. The DEA window analysis was introduced by Charnes et al. (1985) as they tried to analyze the optional efficiency of the United States Air Force Base (USAFB). Through this technique, a DMU's performance in any period can be compared with its performance in other periods as well as the performance of other

DMUs (Charnes et al., (1985). In this context, the window has to be as small as possible to reduce the unfair comparison over time, but still large enough to have a sufficient sample size (Asmild et al., 2004).

Consider N DMUs ($n = 1, \cdots, N$) that all use r inputs to produces outputs and are observed in T ($t = 1, \cdots, T$) periods. Let represent an observation n in period t with input vector $X\frac{t}{n}$ and output vector $Y\frac{t}{n}$ which are, respectively, given by:

$$X_n^t = \begin{bmatrix} x_n^{1t} \\ \vdots \\ x_n^{rt} \end{bmatrix} \quad Y_n^t = \begin{bmatrix} y_n^{1t} \\ \vdots \\ y_n^{st} \end{bmatrix} \tag{1}$$

If the window starts at time k($1 \leq k \leq T$) with width w($1 \leq w \leq T-k$), then the matrices of inputs and outputs are written as;

$$X_{kw} = \begin{bmatrix} x_1^k & x_2^k & \cdots & x_N^k \\ x_1^{k+1} & x_2^{k+1} & \cdots & x_N^{k+1} \\ \vdots & \vdots & \ddots & \vdots \\ x_1^{k+w} & x_2^{k+w} & \cdots & x_N^{k+w} \end{bmatrix}$$
$$Y_{kw} = \begin{bmatrix} y_1^k & y_2^k & \cdots & y_N^k \\ y_1^{k+1} & y_2^{k+1} & \cdots & y_N^{k+1} \\ \vdots & \vdots & \ddots & \vdots \\ y_1^{k+w} & y_2^{k+w} & \cdots & y_N^{k+w} \end{bmatrix} \tag{2}$$

Substituting inputs and outputs of $DMU\frac{t}{n}$ into CCR model or BCC model will produce the results of DEA window analysis.

3.2 Sample and source of data

The criterion adopted for the selection of the ports comprised of the following main dimensions.

① The port should have been operated for a significant number of years. ② It should be the prominent and in the top 10 ranking of the world's port. ③ A significant amount of data should be available for the prospective ports at their official website and other reliable government sources.

For the successful and reliable execution of this study, we choose seven (7) out of Asia's best ports. These are Shanghai, Guangzhou, Shenzhen, Ningbo-Zhoustan, Busan, and Singapore ports. These were selected to satisfy the DEA requirement of homogeneous DMUs. For each of the 7 Asian ports identified, we searched for data on quay length, yard area, number of cranes (inputs), and container throughput (output). These were chosen because they are the only variables that had available data throughout the five years (2016-2020). All the port inputs are considered as one-time investments, thus, they are assumed constant for the five years under study. Previous studies have studied the same variables, thus, they are valid (Lim et al., 2011).

Table 2. Summary statistics of the sampled container port

Ports	Container Throughput (000s)					Quay Length (m)	Yard Area (000㎡)	Number of Quay Cranes
Year	2016	2017	2018	2019	2020	2016-2020		
Busan	19,456	20,493	21,662	21,992	21,813	31,165	2,610	208
Shanghai	37,130	40,233	42,010	43,303	43,501	8,293	6,730	155
Shenzhen	23,970	25,209	25,736	25,771	26,533	14,279	6,400	144
Ningbo-Zhoustan	23,300	24,607	26,351	27,535	28,734	7,948	4,750	85
Guangzhou	18,850	20,372	21,920	23,236	23,191	2,096	2,960	47
Tianjin	14,490	15,069	16,007	17,301	18,356	3,390	2,500	70
Singapore	30,903	33,667	36,599	37,195	36,870	15,500	6,000	204

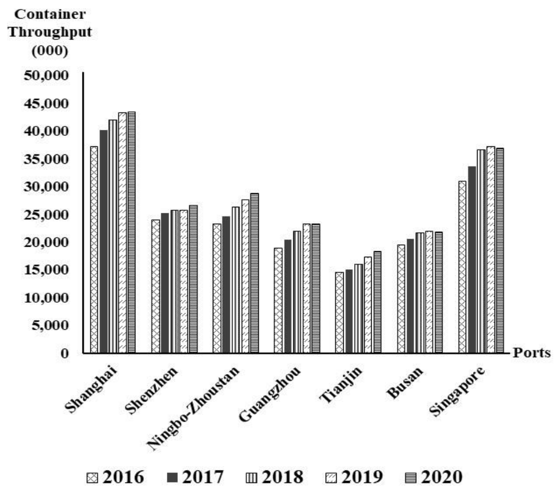

Fig. 2. Container throughput for the selected Asia's container ports under study.

All the data were collected from various sources ranging from port annual reports, Port-MIS, ports' official websites, and other published works. The data chosen was from 2016-2020. Table 2 shows the summary statistics of the data used while Fig. 2 is a bar graph that displays only the container throughput for the whole period.

DEA measures and evaluates the relative operational efficiency of various ports. Therefore, since the efficiency is analyzed in the relative relationship between ports, it is difficult to evaluate the efficiency of ports only with Table 2. Therefore, the operational efficiency was analyzed through DEA.

4. Results and discussion

Data analysis was executed using of DEA-Solver-Pro software developed by Cooper, Seiford, and Tone (1999). For this study, a five years (2016-2020) were selected for the analysis of which the pre-covid era was 2016, 2017, 2018, and 2019 whereas 2020 represents the post-covid era. The data were obtained for selected 7 of the top 10 container ports (n = 7). According to Cooper et al. (2007), the number of data points can be determined as: w = k - p + 1, where, k = number of periods, p = length of the window, w = number of windows. Number of windows (w) = 5 - 3 + 1 = 3. Number of data points = n * p * w = 7 * 3 * 3 = 63. Thus, there are 63 different data points; the first window was formed by the three years (2016-2018). In the second window, in this manner, the analysis is carried out for the next DMUs of the set from 2017-2019, and so on. My study will show the short-term effects of the COVID-19 Pandemic on the technical, pure technical, and scale efficiencies of maritime ports. Table 3 shows the descriptive statistics of the selected data set.

Table 3. Descriptive statistics for the inputs and outputs for 2020

	Quay Length (m)	Yard Area (000㎡)	Number of Quay Cranes	Throughput (000s)
Max	31,165	6,730,000	208	43,501,000
Min	2,096	2,500,000	47	18,356,000
Average	11,810.143	4,564,285.7	130.4286	28,428,285.71
SD	9,156.3453	1,724,204.6	59.6343	8,235,610.234

As mentioned before, the motivation for this study is to examine the impact of the COVID-19 pandemic on the efficiency of Asia's major ports in comparison to the efficiency of the ports before the outbreak of the pandemic. The width for the window analysis in this study is set at three (3).

Table 4. Correlation results for the inputs and output for 2020

	Quay Length	Yard Area	Number of Quay Cranes	Throughput
Quay Length	1	-0.030	0.841	-0.038
Yard Area	-0.030	1	0.392	0.840
Number of Quay Cranes	0.841	0.392	1	0.432
Throughput	-0.038	0.840	0.432	1

From the Table 4, there is a strong positive correlation between container throughput and yard (0.84). The correlation between container throughput and number the of quay cranes is medium and positive (0.43). However, the relationship between quay length and container throughput is negative and weak (-0.038), implying that the bigger the quay length, the lower the efficiency of the port due to the underutilization of the quay area.

The results in Table 5 below indicate windows DEA-CRS model results based on an assumption of constant returns to scale. The average of the DEA efficiency scores per window is presented in the column denoted "Average". The column C-average indicates the overall average of each port for all 5 years combined. The column labeled GD denotes the greatest difference in DEA scores for the entire period. The positive score implies an increase in efficiency while negative values mean a decline in efficiency. The DMU with an efficiency score equal to 1 is considered to be efficient amongst the DMUs included in the analysis. The DMU with an efficiency score of less than 1.000 is deemed to be relatively inefficient.

Table 5. Window DEA-CRS model results

Ports	2016	2017	2018	2019	2020	avg.	C-avg.	GD
Shanghai	0.741	0.803	0.838	-	-	0.794	0.798	0.080
	-	0.759	0.793	0.817	-	0.789		
	-	-	0.793	0.817	0.821	0.810		
Shenzhen	0.500	0.525	0.536	-	-	0.520	0.513	0.025
	-	0.498	0.508	0.509	-	0.505		
	-	-	0.508	0.509	0.524	0.514		
Ningbo-Zhoustan	0.660	0.697	0.746	-	-	0.701	0.713	0.109
	-	0.658	0.705	0.737	-	0.700		
	-	-	0.705	0.737	0.769	0.737		
Guang zhou	0.860	0.929	1	-	-	0.930	0.950	0.138
	-	0.877	0.943	1	-	0.940		
	-	-	0.943	1	0.998	0.981		
Tianjin	0.777	0.808	0.859	-	-	0.815	0.836	0.154
	-	0.765	0.812	0.878	-	0.818		
	-	-	0.812	0.878	0.931	0.874		
Busan	0.898	0.946	1	-	-	0.948	0.971	0.094
	-	0.932	0.985	1	-	0.972		
	-	-	0.985	1	0.992	0.992		
Singapore	0.682	0.743	0.807	-	-	0.744	0.756	0.092
	-	0.706	0.768	0.780	-	0.751		
	-	-	0.768	0.780	0.773	0.774		
avg.	0.731	0.760	0.801	0.817	0.830	-	-	-

The above results were obtained from the use of DEA-Solver-Pro software developed by Cooper, Seiford, and Tone (1999). The first row (with values of 0.741, 0.803, and 0.838) shows the relative technical efficiency of DMU 1 in 2016, 2017, and 2018, respectively. The second row (with values of 0.759, 0.793, and 0.817) shows the relative technical efficiency of DMU 1 in 2017, 2018, 2019). The third row (with values of 0793, 0.817, 0.821) shows the relative technical efficiency of DMU 1 in the years 2018, 2019, and 2020, respectively, and so on. The scores in different years within the same windows show how the efficiency changes from one year to another. Tianjin port has the positive and highest quantity of GD (0.154), which means improving efficiency.

The results show that whereas two ports achieved technical efficiency in the pre-covid era, none of the ports achieved efficiency in 2020. The ports of Guangzhou and Busan recorded an efficiency score of 1 (100%) in 2019. However, these two ports lost their efficiency in 2020 from 1 (100%) to 0.998 and 0.992, respectively. However, only four ports registered a slight increase in their efficiency after the outbreak of the pandemic (in 2020) compared to their performance in 2019. These are; Shanghai (0.004), Shenzhen (0.015), Ningbo-Zhoustan (0.032), and Tianjin (0.054). This is consistent with Si (2020) who noted that Chinese ports such as Shanghai and Shenzhen reported increases in container volumes towards the end of 2020. This can be explained by Chinese firms that have rushed to grab market share as their rivals grapple with reduced manufacturing capacity (World Economic Forum, 2020). Also, analysts have indicated that sustained demand for medical supplies and work-from-home products from coronavirus-hit trading partners have underpinned the outlook for Chinese exports (Qiu and Crossley, 2021). Also, COSCO Shipping Ports Limited reported that not all operations at ports have been reduced. For example, China's imports and exports steadily increased in 2020. Also, the Chinese imports and exports increased by 1.9% annually reaching RMB 32 trillion in 2020. In particular, exports increased by 4.0% year-on-year to RMB18.6 trillion and imports decreased by 0.7% year-on-year to RMB13.4 trillion.

Furthermore, the world's top best three ports, that is, Shanghai, Singapore, and Shenzhen have not operated efficiently before and after the pandemic broke out. This implies that the sheer volume of container throughput generated by a port does not necessarily reflect its operating efficiency, despite its opportunity to exploit economies of scale.

The column "average" depicts the collective mean efficiency score of the DMU from 2016 through 2020. Much as none of the DMU achieved technical efficiency in the post-Covid era, Shanghai, Shenzhen, Ningbo-Zhoustan, and Tianjin ports registered a slight improvement in efficiency from the previous year's scores. This indicates that the effects of the COVID-19 pandemic were not uniform for all the ports that move containers. Overall, except for Guangzhou and Busan ports, the relative efficiency scores of other ports ranged from 0.500 to 0.931, suggesting that there is ample room for substantial improvement in container throughput.

According to the analysis of the average efficiency (as seen in Table 6 and Fig. 3), none of the studied DMUs have an efficiency score of 1. Two container ports (Guangzhou and Busan) are close to the efficiency frontier since they have average scores above 0.9 (90%). Four ports (Shanghai, Ningbo-Zhoustan, Tianjin, and Singapore) showed average scores ranging between 0.713 and 0.836. Shenzhen port had the lowest average efficiency score overall. On a good note, none of the studied DMUs were highly inefficient (with average scores below 50%).

Table 6. Average technical efficiency for the sampled ports under CCR model

Ports	2016	2017	2018	2019	2020	avg.
Shanghai	0.741	0.781	0.808	0.817	0.821	0.793
Shenzhen	0.500	0.512	0.518	0.509	0.524	0.512
Ningbo-Zhoustan	0.660	0.678	0.719	0.737	0.769	0.712
Guangzhou	0.860	0.903	0.962	1	0.998	0.945
Tianjin	0.777	0.787	0.828	0.878	0.931	0.840
Busan	0.898	0.939	0.990	1	0.992	0.964
Singapore	0.682	0.724	0.781	0.780	0.773	0.748

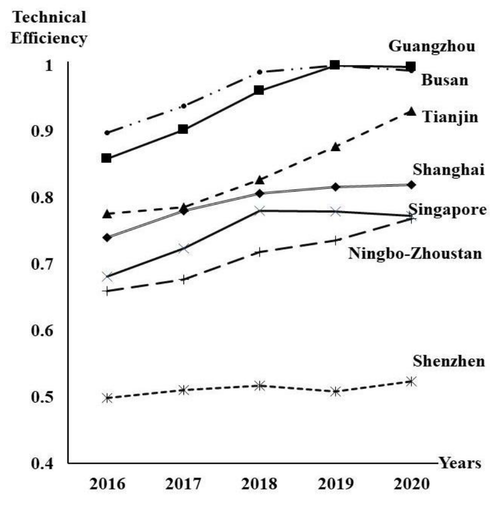

Fig. 3. Average technical efficiency for the sampled ports for the period.

When annual efficiency is analyzed as shown in Fig. 4, the overall efficiency for 2020 was found to be highest than for other years. This implies that, on average, the COVID-19 situation did not largely stop the selected Asian best ports from improving the utilization of quay length, yard area, and quay cranes to achieve higher container volumes as compared to the previous years.

The CCR model assumes that there is perfect competition (but in the real world this situation is unreal). Imperfect competition, financial constraints, control steps, and other factors can cause DMUs not to operate at their optimal size. The BCC (Banker, Charnes, Cooper) model allows for calculations with a variable return to scale. This model is used to measure so-called pure technical efficiency. The BCC model is "more" realistic because it takes into account the existence of imperfect competition. Table 7 shows significant changes in the BCC (VRS) model efficiency scores as compared to the CCR model scores of the 7 selected ports under study.

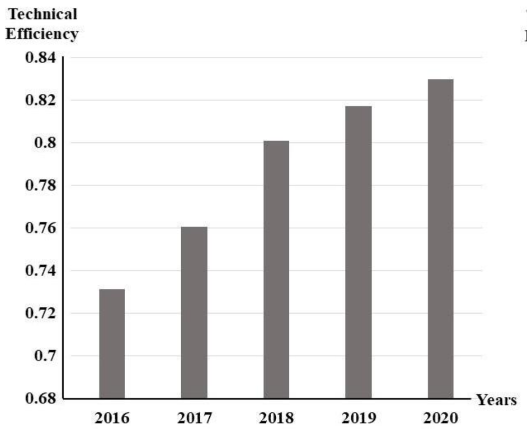

Fig. 4. Overall average efficiency (VRS) for the five years.

In BCC analysis the number of efficient ports is increased as compared to the CCR analysis (as depicted in Table 7), which is a demonstration of the lower total technical efficiency subject to the scale inefficiency. DEA model with CRS assumption provides information on technical efficiency alone while DEA model with VRS assumption identifies pure technical efficiency (BCC) and scale efficiency (SE) taken together. Unlike under the CCR model, two ports (Shanghai and Tianjin) were fully efficient only in 2020 based on the BCC analysis. Other ports like Guangzhou and Busan which had previously operated efficiently in 2019 had a drop in efficiency due to the pandemic, which implies that they are not operating on the right scale as the two efficient ports during the pandemic in 2020. Just like Shanghai and Tianjin, other ports-Shenzhen and Ningbo-Zhoustan registered increases in their efficiencies albeit were not fully efficient. Overall, the relatively bigger number of efficient ports in the BCC model justifies the statement that scale inefficiency is the reason beyond lower CCR efficiency. No port in our sample was fully efficient with a score of 1 in both BCC and CCR models for the two periods under study. Table 8 and Fig. 5 displays the average VRS efficiency for each of the years considered in the study.

Table 7. VRS Efficiency scores according to the BCC model

Ports	2016	2017	2018	2019	2020	avg.	C-avg.
	0.863	0.950	1	-	-	0.938	
Shanghai	-	0.914	0.964	1	-	0.959	0.961
	-	-	0.959	0.995	1	0.984	
	0.518	0.555	0.570	-	-	0.548	
Shenzhen	-	0.519	0.534	0.535	-	0.529	0.539
	-	-	0.533	0.53	0.557	0.542	
	0.677	0.729	0.833	-	-	0.746	
Ningbo-Zhoustan	-	0.677	0.750	0.825	-	0.751	0.773
	-	-	0.748	0.823	0.898	0.823	
	0.999	0.999	1	-	-	0.999	
Guang zhou	-	0.999	0.999	1	-	0.999	0.999
	-	-	0.999	1	0.999	0.999	
	0.999	0.999	0.999	-	-	0.999	
Tianjin	-	0.999	0.999	1	-	0.999	0.999
	-	-	0.999	0.999	1	0.999	
	0.984	0.991	1	-	-	0.992	
Busan	-	0.987	0.997	1	-	0.995	0.995
	-	-	0.996	1	0.998	0.998	
	0.762	0.848	0.939	-	-	0.850	
Singapore	-	0.815	0.907	0.925	-	0.882	0.881
	-	-	0.902	0.921	0.911	0.911	
avg.	0.829	0.856	0.887	0.897	0.909	-	-

Table 8. VRS Average efficiency scores for the sampled ports under study under BCC model

Ports	2016	2017	2018	2019	2020	avg.
Shanghai	0.863	0.932	0.974	0.997	1	0.953
Shenzhen	0.518	0.537	0.546	0.535	0.557	0.538
Ningbo-Zhoustan	0.677	0.703	0.777	0.824	0.898	0.776
Guangzhou	0.999	0.999	0.999	1	0.999	0.999
Tianjin	0.999	0.999	0.999	0.999	1	0.999
Busan	0.984	0.989	0.998	1	0.998	0.994
Singapore	0.762	0.832	0.916	0.923	0.911	0.869

It is evident from Tables 6 and 8 that the overall average efficiency for the CCR model is 0.788, which is lower than that of the BCC model having a value of 0.876. Therefore, it could be summarized that the scale efficiency of the selected ports in this scenario is relatively higher. The result that the DEA-BCC model yields more efficient ports are not surprising since a DEA model with an assumption of constant returns to scale provides information purely on technical and scale efficiency taken together, while a DEA model with the assumption of variable returns to scale identifies technical efficiency alone (Cullinane and Wang, 2006).

Like is the case for the CCR model seen before, the BCC model efficiency score of 2020 is still the highest compared to the previous. Therefore, this confirms the assertion that Covid-19 pandemic did not have devastating effects on the port efficiency after all as compared to the previous years. The differences between the CRS and VRS model efficiency scores for the particular ports indicate that the ports have inadequate operating scales.

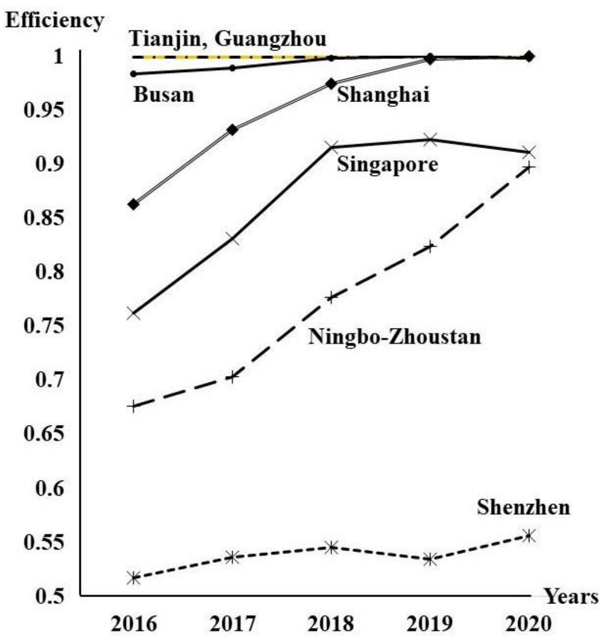

Fig. 5. Average VRS efficiency for each of the years considered in the study.

As seen from the Table 9, none of the ports was operating at the required optimal size in 2020. However, in 2019, Guangzhou and Busan ports operated under optimum scales. Table 10 indicates the average scale efficiency of the selected Asia's ports.

Table 9. Scale Efficiency scores for the selected ports

Ports	2016	2017	2018	2019	2020	GD
	0.858	0.845	0.838	-	-	
Shanghai	-	0.830	0.822	0.817	-	-0.038
	-	-	0.827	0.821	0.821	
	0.965	0.947	0.941	-	-	
Shenzhen	-	0.960	0.952	0.951	-	-0.023
	-	-	0.953	0.953	0.942	
	0.976	0.956	0.896	-	-	
Ningbo-Zhoustan	-	0.973	0.940	0.893	-	-0.119
	-	-	0.942	0.896	0.857	
	0.860	0.929	1	-	-	
Guang zhou	-	0.877	0.943	1	-	0.138
	-	-	0.943	1	0.998	
	0.777	0.808	0.859	-	-	
Tianjin	-	0.765	0.812	0.878	-	0.154
	-	-	0.812	0.878	0.931	
	0.913	0.954	1	-	-	
Busan	-	0.945	0.988	1	-	0.081
	-		0.989	1	0.994	
	0.894	0.876	0.860	-	-	
Singapore	-	0.866	0.847	0.843	-	-0.045
	-	-	0.852	0.847	0.849	

Table 10. Average scale efficiency for the selected ports

Ports	2016	2017	2018	2019	2020	avg.
Shanghai	0.858	0.838	0.829	0.819	0.821	0.833
Shenzhen	0.965	0.954	0.948	0.952	0.942	0.952
Ningbo-Zhoustan	0.976	0.964	0.925	0.894	0.857	0.923
Guang zhou	0.860	0.903	0.962	1	0.998	0.945
Tianjin	0.777	0.787	0.828	0.878	0.931	0.840
Busan	0.913	0.950	0.992	1	0.994	0.970
Singapore	0.894	0.871	0.853	0.845	0.849	0.863

On average, there are slight increases in the port efficiencies after the outbreak of COVID-19 compared to the period before the Pandemic as shown in Table 11.

Table 11. Overall average efficiency scores pre and Post COVID-19

Efficiency	Pre-Covid Regime	Post-Covid Regime
TE	0.777	0.830
PTE	0.867	0.909
SE	0.901	0.913

The average scale, VRS, and CRS technical efficiency of the ports were estimated to be 90.1%, 86.7%, and 77.7% respectively before the COVID-19 situation. On a surprising note, there was a slight increase in all the efficiencies after the occurrence of the pandemic, that is, 91.3%, 90.9%, and 82.9%, for scale, VRS, and CRS efficiencies, respectively.

5. Conclusion

The shipping industry had predicted that COVID-19 would negatively impact it. On the contrary, mixed effects engendered by the pandemic on to the shipping industry have been reported worldwide. According to the Korea Transport Institute (2021), container throughput tended to decline from March when the COVID-19 pandemic was declared but reported a gradual increase from May. It is important to note that, before the outbreak of COVID-19, ship freight in the shipping industry continued to fall due to a decrease in global volume owing to the global economic recession, which resulted in the global shipping industry to undertake Mergers and Acquisitions (M&A) as well as alliances to realize "economies of scale" to reduce transportation costs. However, in the beginning months of the COVID-19 outbreak, the world's shipping volume seemed to be swept away by a big shock, but the activation of online shopping has increased the world's volume, and a new environment is being created in the shipping industry as ship freight has soared (Hankookilbo, 2021). COVID-19 caused a decrease in port volume due to port closures in the early stages of the pandemic. However, the volume and fares (freight) have exploded since the second half of 2020 due to the growth of online purchases and pent-up demand, therefore, are currently recording the largest boom ever.

Therefore, we undertake an assessment of port efficiency through the data envelopment analysis through which we determine how Asia’s major ports make use of their inputs to achieve a certain amount of container throughput before and after the Covid-19 outbreak. Overall, the results from both the CCR and BCC model reveal that overall efficiency during the COVID-19 pandemic has been relatively higher than the years prior. Most specifically, the DEA-CCR identified only Busan and Guangzhou that were the only fully efficient in 2019 but registered a reduction in their efficiency in 2020. The rest of the ports registered annual increases in their technical efficiency. On the other hand, VRS results were somewhat different as Shanghai and Tianjin ports were considered fully efficient during the pandemic. According to the results of this study, the pandemic caused a short-term reduction in port efficiency soon after it had broken out. However, in the months that followed, the effect of the pandemic was less consequential to the port efficiency of Asia‘s best ports. This implies that the shipping industry tended to turn the crisis into an opportunity. In addition, the current largest-ever boom in the shipping industry can be understood macroscopically as a process of "Shipping market cycle" by "Trough-Recovery-Peak-Collapse".

On the other hand, this study has academic contributions in that it examined the macroeconomic relationship between the operational efficiency performance indicators of major ports and the period of COVID-19. Additionally, this paper is to pave way for the comparison of port efficiency since the COVID-19 outbreak as mentioned early. In this respect, this study can be evaluated as the first attempt at related analysis.

Nevertheless, this study was not without limitations. Firstly, it was based on two periods, that is, before and after the outbreak of the COVID-19 pandemic. However, only one year (2020) was considered to represent the second period, which might not be sufficient to explain the effect of the pandemic on Asia’s ports’ efficiency. Future studies need to incorporate more years after the outbreak of the pandemic. Secondly, only 7 Asian ports were used for the study citing a gross absence of data on all the input and output variables for the majority of ports, thus, were not considered for the study. Future researchers need to increase the study scope by increasing the number of ports. Thirdly, this study was limited in the number of inputs and outputs. This was due to the absence of data on many other variables such as the size of the labor force, yard equipment. Future researchers need to address this.

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