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Genevieve M. Nouyrigat, Elena M. Barbu

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Efficiency Measurement of Tourism and Recreation Companies (Industry Code E51) Listed on the Indonesia Stock Exchange

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COVID-19, IDX E51, DEA, efficiency score, left-truncated regression

ABSTRACT

COVID-19 pandemic which the first outbreak was found on December 2019 in Wuhan, China, has given great impact to tourism industries worldwide. Since then, most countries implemented lockdown and quarantine system, issued tight regulations about travel restriction. In order to survive the COVID-19 pandemic, which the ending has yet to be determined, every tourism industry must be able to work efficiently to maintain the usage of operating costs as low as possible since the revenue could not be optimized. This research aims to measure efficiency score of 41 companies in Tourism and Recreation Industry (code E51) listed on Indonesia Stock Exchange (IDX) from 2018 to 2021. At the first stage, data envelopment analysis (DEA) method with variable-return-to-scale (VRS) input-oriented approach is employed to estimate technical efficiency scores. At the second stage, left-truncated regression estimation with double-bootstrap is employed to test the significance of some explanatory factors. Cost of Sales and Revenue, Operating expenses, Interest expenses, and Fixed Assets are chosen as input variables, while Sales and Revenue, Profit (Loss) from Operation, and Asset Turnover Ratio as output variables of DEA. The result shows that efficiency score dropped by 20.42% in 2020 compared to the score in 2019. A slight increase of 2.39% in 2021 compared to the score in 2020. Another result also denotes that several explanatory factors such as Stock Price positively affected efficiency score of, meanwhile Liability to Asset Ratio gave negative influences. Finally, this research may contribute to the development of operation and management science in hospitality and tourism field as well as to support the business operators to adjust their strategic plans, especially in financial budgeting, to face the long-impact of COVID-19 pandemic. Efficiency measurement using advanced DEA Double Bootstrap method with selected financial parameters that are different from any previous studies in tourism provides novelty to this research.

1. INTRODUCTION

On December 8, 2019, the government of Wuhan, China, announced a brand-new disease identified as coronavirus 2019 or COVID-19 [1]. Since then, COVID-19, which is a novel variant of the SARS virus (SARS-CoV-2), quickly developed into a global pandemic and spread to various countries in the world. The first COVID-19 case in Indonesia was detected on March 2, 2020 and since then COVID-19 has been officially declared as national pandemic. Efforts to limit the spread of COVID-19 are carried out globally by issuing travel restrictions, working or studying from home, and applying social or physical distancing. Most countries in the world have also implemented a lockdown system that broadly restricts international arrivals and departures, especially from and to various places with high confirmed positive cases of COVID-19, suspended all international commercial flights as well as tourist's visa issuance. An unavoidable international trip required at least 14 days self-quarantine [2]. In the first and second quarters of 2020, the study [3] reported that 93% of destinations in Europe had completely closed their borders for international travels. In America this proportion reaches 82%, Asia and the Pacific 77%, Middle East 70%, and Africa 60%.

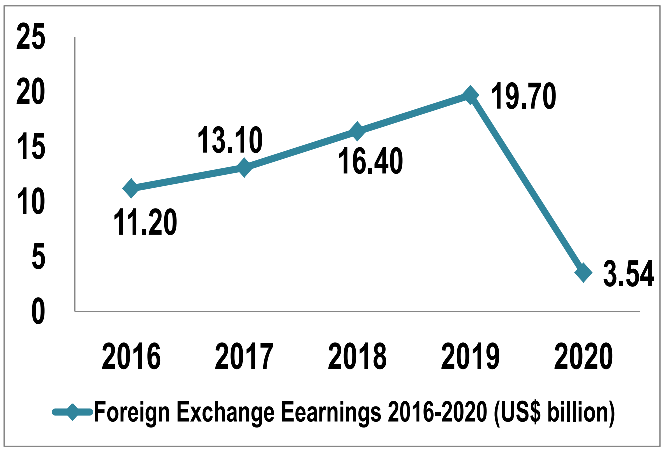

Figure 1. Indonesia's foreign exchange earnings from the tourism sector, 2016-2020

UNWTO also reported that the COVID-19 pandemic has caused a 22% decline in international tourist arrivals globally during the first quarter of 2020 and continues to decline by 60-80% throughout 2020. It calculated that the number of tourist arrivals in March 2020 fell by 57% after the lockdown came into effect, and also as a result of the closure of international airports in many countries [3]. The Indonesian Hotel & Restaurant Association stated that from January to April 2020, the tourism industry in Indonesia lost potential income from international tourists around US$ 4 billion or IDR 60 trillion compared to the previous year. In 2019, this sector contributed in foreign exchange earnings around US$ 19.7 billion [4]. Total foreign exchange earnings in the tourism sector were recorded at only US$ 3.54 billion or around 18% of the value in 2019 [5]. Its changes from 2016 to 2020 are shown in Figure 1.

To be able to survive during COVID-19 pandemic, which has yet to be determined, tourism industry (including hotels and restaurants) must be able to work efficiently to keep operating costs at the lowest level. The definition of efficiency used in this study refers to technical efficiency, which is a proportional reduction of inputs at a certain level of outputs [6]. The smaller the input value used to produce the same output, the more efficient is the operational performance. Data analysis was carried out using the mathematical programming technique named Data Envelopment Analysis (DEA), which was first introduced by Charnes, Cooper, and Rhodes in 1978. DEA measurement is widely used in various types of industries to show the productivity of a sample group known as Decision Making Units (DMUs). Simply, efficiency score is measured as a ratio between output(s) and input(s), where the result can be expressed as efficient or inefficient DMUs in the data set [7].

In this study, DEA method is selected for its several advantages, e.g. DEA is able to analyze many outputs and inputs simultaneously, does not require assumptions or a priori to define the shape of the production frontier line, measures the relative efficiency obtained from the best observations, does not require price information [8-10], and as a method with a non-parametric approach DEA does not require a normal distribution of and correlation between the samples tested [11]. However, the original type of DEA still contains bias if it is not corrected. This uncorrected bias causes the efficiency score of DEA cannot be used for further parametric analysis. To overcome this shortcoming, Simar and Wilson [12] introduced complementary method called Double Bootstrap. The first stage of bootstrapping was applied to correct the bias in the efficiency score resulted from conventional DEA measurement. The second stage of bootstrapping is applied to the regression equation, where the bias-corrected efficiency score will become the dependent variable, to measure the influence of some explanatory variables as predictors on it.

DEA is now becoming a more popular method with non-parametric approach to measure relative productivity and efficiency by using a production frontier line as reference [13]. In general, DEA evaluates the efficiency of a company compared to other similar companies that have the best performance in the same industry. Thus, it makes DEA is mentioned as a relative measurement method. The efficiency scores are determined based on the outputs to inputs ratio for each work-unit of the entire samples. Simply, inputs can be equated with costs, whereas outputs with the benefits. This evaluated work-unit is known as DMU (decision making unit) in DEA model. A DMU can be a single whole company or a sub-unit (or department) within the same company, as long DMUs are defined equally as dataset for DEA measurement. With the DEA method, a frontier line will be formed from the efficient DMU and enveloping other inefficient ones which are distributed below it [11, 13]. Therefore, this statistical method is known as Data Envelopment Analysis (DEA). By referring to the frontier line, DEA indicates which DMU is more efficient and identifies inefficiencies from other DMUs [13]. In parametric analysis, a single optimized regression is assumed to apply to each DMU and requires the imposition of a specific functional form that relates the independent variable to the dependent variable [11]. In contrast, DEA optimizes the performance measures of each DMU and does not require any assumptions about its functional form to build efficient frontiers [14, 15]. All DMUs with an efficient score equal to one will fall on the frontier line. Inefficient DMUs will have a score between 0 and 1. Closer the score efficiency to one reflects a certain DMU performs more efficiently compared to other inefficient DMUs.

One of the drawbacks of the DEA method is that it does not take into account the statistical noises in its measurement which leads into inaccurate results. Toward this issue, Simar and Wilson [12] proposed an algorithm, based on bootstrap resampling scheme, to construct confidence intervals for being used in the second stage regression. This algorithm incorporates bias-correcting procedures to remove the bias in the original efficiency score so it will be fitted to a truncated model later. Resampling or iteration scheme imitates the process of generating data from the actual base model and it deals with redistribution, assumes a random model among observations, and calculates deviation from the mean score of each variable. The higher the residual variance, the greater the Bootstrap confidence interval built in hypothesis testing. Accuracy of bootstrap estimation depends on the number of repetitions as well as DMU sample size otherwise bias-correction process may produce additional errors that are larger than the original efficiency score without bootstrap technique [12].

This study aims to measure the efficiency of the tourism and recreation sector in Indonesia in 2018-2021 using forty-one (41) public companies listed on the Indonesia Stock Exchange (IDX) as DMU with the input-oriented DEA VRS (variable return-to-scale) method [16]. Several financial parameters and ratios are selected to measure the efficiency of the company's performance. Left-truncated regression is employed to analyze some explanatory variables which have significant effects for determining the efficiency scores (bias-corrected) [12]. This research is expected to contribute to the development of science, strategic management in particular, and be useful in providing information to investors regarding the technical efficiency score which is able to reflect operational performance of several tourism and recreation companies in Indonesia that have been severely affected by the COVID-19 pandemic.

2. METHODOLOGY

Both non-parametric and parametric approaches are used in this research to measure efficiency score, where the former is employed in the first stage of analysis and the latter is for the second stage. Among several types of non-parametric technique, data envelopment analysis (DEA) is selected to estimate production frontiers, constructed by the efficient samples, as the best results achieved or targeted by the rest or inefficient samples. Analysis using the production frontier method uses observed data to build a boundary line to estimate the efficiency score of all samples. DMUs that fall on the production frontier are assumed to operate with full technical efficiency (efficiency score equal to one or=1), producing maximum output from available inputs or minimal inputs for a fixed output level [15]. Meanwhile, DMUs that fall below the production line are inefficient, where the efficiency score is less than one (0<θ<1). With reference to that frontier line, this study displays the target value that must be achieved by an inefficient DMU from its initial value to become efficient or mathematically the efficiency score is one [16]. Unless the sample is efficient, the targeted value of inefficient DMUs shall have less or reduced inputs and/or greater or increased outputs compared to the initial input and/or output value.

DEA is developed in relation to production process, goods or services, involving inputs as production resources and outputs as units or services produced. Variable return-to-scale (VRS) model is selected based on assumption that size organization of DMU samples or DMUs is considered to relevant in determining its relative efficiency. Ratio between VRS and CRS (constant return-to-scale) is called scale efficiency which involves the presence of economies or diseconomies of scale. In economies of scale or increasing return-to-scale (IRS), doubling the inputs will lead to more than a doubling of output because producers get benefit by purchasing items in bulk. Vice versa, organization might become too large in diseconomies of scale or decreasing return-to-scale (DRS). In consequence, doubling the inputs will lead to less than a doubling of outputs [14]. According to its type of orientation, efficiency score in this study is measured using the input-oriented DEA method by minimizing input at a fixed output level [13]. The mathematical formulation of DEA VRS input-oriented model for estimating DMU's efficiency score is given below.

$$Min\theta + \varepsilon\left[\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right]$$

$$s.t. \sum_{j=1}^{n} x_{ij}\lambda_j = \theta x_{io} - s_i^-, i = 1,2,\dots,m;$$

$$\sum_{j=1}^{n} y_{rj}\lambda_j = y_{ro} + s_r^+, r = 1,2,\dots,s;$$

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

$$\lambda_j, s_i^-, s_r^+ \geq 0$$

where, there are n samples producing s different outputs (y_r denotes the observed amount of output r) and using m different inputs (x_i denotes the observed amount of input i). The λ_j are weights applied across n samples and θ are the score efficiency. For a full set of efficiency scores, the cosntraints listed above have to be solved n times, once for each sample.

In the second stage, bootstrapping procedures proposed by Simar and Wilson [12] correct the problem associated with the sampling noise which generates biased score as well as to estimate truncated regression model in determining the explanatory character that affect efficiency levels (Algorithm II). Simar and Wilson's Algorithm II has been applied to estimate regression model using the double bootstrap procedures for 2000 times of iteration in total. Using the maximum likelihood method, the first bootstrap is executed to calculate the bias corrected efficiency score while the second one is employed to estimate the truncated regression model with its confidence interval and standard errors. Bootstrap technique performs repeated simulations or data resampling, applies the conventional DEA measurement for each simulated sample so that the results will mimic distribution of original population which is not previously known [12]. The mathematical general formulation of truncated regression to estimate efficiency variations is given below:

$$\theta_{it} = \beta Z_{it} + \varepsilon_{it}$$

where, particularly in this study, θ_{it} denotes the independent variable that reflects the bootstrapped bias-corrected efficiency score (BCES) of DMU_i in year t; Z_{it} denotes a vector of explanatory variables to explain changes in efficiency score; ε_{it} denotes an independent error term that follows normal distribution, with parameters $\mu=0$ and σ, left-truncation at $1-\beta Z_{it}$.

DEA results (deterministic efficiency score, scale efficiency, and targeted value of improvement) as well as its bootstrap calculations (bias-corrected efficiency score and truncated regression) in this study are based on linear programming run by the R-package software. The secondary data collection technique is employed in this study. Both input and output data used in the first stage of DEA analysis are obtained from IDX official website (https://idx.co.id), prepared and presented in a formatted taxonomy that contains financial statements elements, including Statement of Financial Position, Statement of Comprehensive Income, Statement of Cash Flow, and Statement of Changes in Equity. Meanwhile, explanatory data used for bootstrap analysis in the second stage are mainly obtained from IDX Statistics 2018 to 2021 in the section of Equity Trading Activity – Cumulative Data (January - December) (https://idx.co.id). All listed companies are required to publish all financial statements and other important public information that has passed a financial audit by an authorized audit institution on the IDX official website (https://idx.co.id). This is not only for reporting purposes, but also for public offerings or to accommodate potential investors to monitor the company's financial performance and share price fluctuations compared to a certain composite index. Thus, the secondary data used in this study has a credible authenticity and correctness. Reconfirmation is not required.

The companies listed on IDX are classified based on industry and market exposure similarity. IDX-IC (IDX Industrial Classification) has four levels of categorization, i.e. 12 sectors, 35 sub-sectors, 69 industries, and 130 sub-industries. Each sector will be given a code in the form of letters A to Z, while sub-sectors, industries and sub-industries will be given integer numbers sequentially 1 to 9. Based on IDX-IC, tourism and recreational industry is coded E51 where the letter E denotes the Consumer Cyclicals sector and E5 denotes the Consumer Services sub-sector. Therefore, industry E51 becomes the main object of this study. There are a total of 41 listed companies included in E51, which are classified into 4 sub-industry categories, namely E512 Hotel, Resort, and Ship (28 companies); E513 Travel Agent (3 companies); E514 Recreation and Sport Facilities (4 companies); and E515 Restaurant (6 companies). All listed companies are used as samples or DMUs (decision making unit) in this study.

Three groups of variables are employed for mathematical measurement, namely input, output, and explanatory variables. Input is defined as resources to produce the same type of products, in the form of goods and/or services, as the output. Input and output variables are used to calculate deterministic efficiency score using conventional DEA method. The input variables selected in this study consist of Cost of Sales and Revenue, Operating Expenses, Finance Expenses, and Fixed Assets. Meanwhile, the output variables consist of Sales and Operating Income, Operating Profit/Loss, and Assets Turnover Ratio [17-22]. The explanatory variables used in the left-truncated regression analysis consist of the Liability to Asset Ratio, Stock Price (Closing), Market to Book Ratio, Company Size (reflected through Total Assets), and Company [23-28]. Those variables in each different category are selected with reference to several previous studies. All research data for each variable are obtained from financial statement and equity trading activity of active or not-suspended E51 Listed Companies from 2018 to 2021, accessed through the official website of Indonesia Stock Exchange (https://idx.co.id).

Specifically, 3 (three) models are presented in the truncated regression analysis. Model 1 covers periods before or pre COVID-19 pandemic, i.e. 2018 and 2019. Model 2 covers periods during COVID-19 pandemic, i.e. 2020 and 2021. Model 3 covers the entire research year, i.e. 2018 to 2021. This division is made with the aim of seeing changes in efficiency scores during the transition period, especially from 2019 to 2020, where 2020 was the year COVID-19 discovered. The rest, analysis is carried out using a common cross-sectional method without any division of the research model.

3. RESULT

This section consists of two parts. First, the results obtained from DEA measurement combined with bootstrap technique which produce efficiency score, scale efficiency score, and improvement target for the entire sample of listed companies. Second, estimation of explanatory variables that significantly affect (bias-corrected) efficiency score analyzed with left-truncated regression.

3.1 Efficiency scores of tourism and recreational companies listed on IDX (Code E51)

In the measurement of efficiency score, this study adopts an input-oriented variable-return-to-scale DEA approach [16]. A single bootstrap technique with 2000 iterations was then used to correct for the bias in the deterministic efficiency scores [12]. Removal of the bias causes bias-corrected efficiency score to be slightly lower than the deterministic or original one. Average efficiency scores per year (2018 to 2021) for both deterministic and bias-corrected of E51 are shown in Figure 2.

Meanwhile, the average efficiency score for each Sub-industry of E51 during 2018 to 2021 is shown in Table 1. Lambda score will reveal the type of either increasing (IRS), constant (CRS), or decreasing (DRS) return-to-scale [29].

This study covers two conditions, before COVID-19 in 2018-2019 and during COVID-19 in 2020-2021. In general, this pandemic has caused the performance of global tourism industry to decline drastically from 2019 to 2020, where the Indonesian government officially declared COVID-19 a pandemic in March 2020. At the same time, travel restrictions were immediately imposed. No airlines serving domestic and foreign flights are permitted to operate. Similar conditions are experienced by the tourism, hotel and recreation industries which must be completely closed following the government regulations. Overall, changes in bias-corrected efficiency scores (BCES) from 2018 to 2021 for each Sub-industry of E51 Tourism and Recreational Industry on IDX are shown in Figure 3.

Sorted by bias-corrected efficiency score, E515 Restaurant Sub-industry has the highest score of 0.830, followed by E513, E512, and E514. In correlation with the efficiency score, projecting the target to improve inefficiency of each DMU can also be estimated by DEA Software. Those targets reflect expected increase in outputs and reduction in inputs as research variables. For the input variable, average initial value is always greater than the target. It shows that inefficiency does exist, thus cost reduction is expected. On the contrary, greater target value of output variable denotes that total revenue or profit, in general, should be increased to perform more efficiently. The average improvement target of selected input and output variables (in percentage) for each Sub-industry during 2018 to 2021 is shown in Table 2.

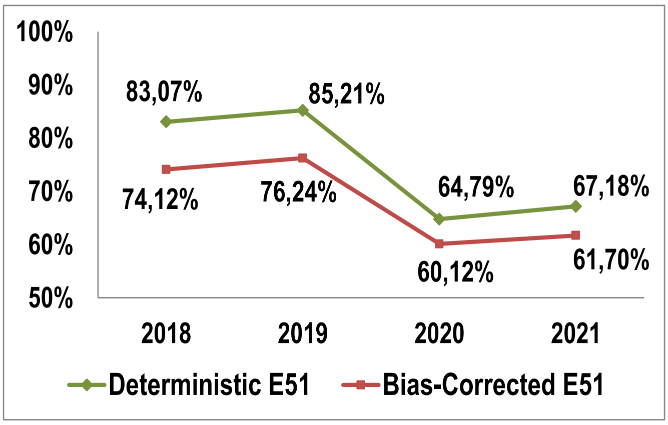

Figure 2. Efficiency score of E51 per year, 2018-2021

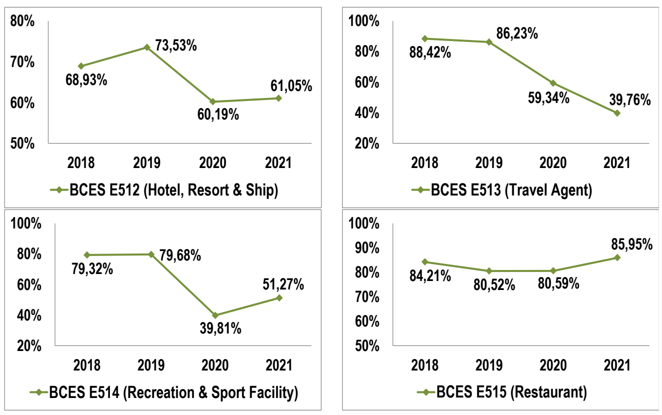

Figure 3. Bias-corrected efficiency score (BCES) of sub-industry E51, 2018-2021

Table 1. Average efficiency score & type of RTS of each sub-industry of E51 (2018-2021)

Sub-Industry of E51	Deterministic Efficiency Score	Bias-Corrected Efficiency Score	Scale Efficiency Score	∑ Lambda	RTS
512	0.708	0.646	0.972	1.818	DRS
513	0.748	0.684	0.901	4.427	DRS
514	0.685	0.629	0.978	1.873	DRS
515	0.957	0.830	0.908	4.413	DRS
Average	**0.745**	**0.673**	**0.958**	**2.394**	**DRS**

Table 2. Average improvement target of each sub-industry of E51 (2018-2021)

No	Sub-Industry of E51	Cost of Sales & Revenue*	Operating Expenses*	Finance Expenses*	Fixed Assets*	Sales & Operating Income**	Operating Profit/Loss**	Assets Turnover Ratio**
1	512	-25,98%	-31,10%	-68,87%	-72,83%	+0,02%	+465,30%	+51,45%
2	513	-7,80%	-17,18%	-74,83%	-28,44%	0,00%	+372,53%	+19,04%
3	514	-24,09%	-25,99%	-56,71%	-62,38%	0,00%	+1046,96%	+17,24%
4	515	-3,34%	-3,92%	-43,25%	-4,98%	+0,03%	+97,60%	+2,83%

* Input Variables; ** Output Variables

3.2 Left-truncated regression to estimate significant explanatory variables

Truncated regression is employed to analyze the impact of explanatory variables on efficiency score of Industry E51. This procedure is also known as the second stage of Simar and Wilson's algorithm [12]. The general model of truncated regression used in this study is written as follows:

$$RBCES_{i,t} = \beta_0 + \beta_1 LTAR_{i,t} + \beta_2 LnPrice_{i,t} + \beta_3 MTBR_{i,t} + \beta_4 LnAsset_{i,t} + \beta_5 LnAge_{i,t} + \varepsilon_{i,t}$$

where, RBCES stands for Resiprocal Bias-Corrected Efficiency Score; LTAR for Liability to Asset Ratio; Price for Closing Stock Price; MTBR for Market to Book Ratio; Asset for Total Asset to reflect company size; Age for Company Age after IPO; $\beta_0, \beta_1, \beta_2, \ldots, \beta_5$ are the parameters to be determined, and ε is the error term or sigma value. All variables apply to each DMU_i in the t-period. Price, Asset, and Age are expressed in logarithmic value. Descriptive statistics of those explanatory variables, captured within year 2018 to 2021, are shown in Table 3.

Table 3. Descriptive statistics of explanatory variables

Statistics	LTAR	LnPrice	MTBR	LnAsset	LnAge
Max	0.879	8.896	117.221	31.052	3.638
Min	0.001	3.912	0.186	24.828	0.000
Mean	0.390	5.902	4.471	27.564	2.039
Std Dev	0.217	1.367	11.894	1.333	1.180

Reciprocal value of bias-corrected efficiency score (RBCES) is used to simplify DEA measurement so that the range becomes wider [1,~). In RBCES, one is the smallest value where a listed company is in the most efficient state. The larger the RBCES, the more inefficient the company's performance will be. This condition gives the meaning of left-truncated in linear regression.

The truncated regression function is run using R-statistics software. Three types of analysis are provided to describe conditions before the pandemic of COVID-19 (model 1: 2018-2019), during the pandemic of COVID-19 (model 2: 2020-2021), and throughout entire research year (model 3: 2018-2021). The results of left-truncated regression models with 95% confidence interval (α=0.05) in hypothesis testing are shown in Table 4. With this model separation, explanatory variables that have a significant effect on the efficiency score in each model can be identified. It will help in discovering any differences in significant determinants of model 1 (before COVID-19 pandemic), model 2 (during COVID-19 pandemic), and model 3 (throughout the entire research year).

Before COVID-19 pandemic emerged, shown as model 1 (2018 and 2019), Stock Price was the only significant determinant that affects RBCES with a negative coefficient. The higher the Stock Price, the lower the RBCES of a listed company (close to 1) which indicates it performs more efficiently. During COVID-19 pandemic, shown as model 2 (2020 and 2021), only Liability to Asset Ratio (LTAR) has a significant effect on RBCES. Positive LTAR coefficient indicates that the greater the LTAR, the greater the RBCES or the lower the efficiency of the listed company's performance. Lastly, throughout entire research year (2018 to 2021), model 3 raises those two variables as significant determinants at different confidence interval (CI). Those are Liability to Asset Ratio (LTAR) at CI=99.9% (α=0.001) and Stock Price at CI=99% (α=0.01).

Table 4. Results of left-truncated regression models

Variables	Model 1			Model 2			Model 3		
	Beta	Std. Error	p-Value	Beta	Std. Error	p-Value	Beta	Std. Error	p-Value
Intercept	1,978	1,799	0,272	-2,193	3,089	0,478	0,659	1,977	0,739
LTAR	-0,231	0,408	0,572	2,855***	0,725	0,000	1,845***	0,451	0,000
LnPrice	-0,162**	0,058	0,005	-0,143	0,125	0,255	-0,196**	0,073	0,007
MTBR	0,002	0,011	0,879	0,000	0,011	0,982	0,005	0,008	0,522
LnAsset	0,019	0,065	0,772	0,133	0,116	0,249	0,047	0,073	0,516
LnAge	-0,005	0,063	0,939	-0,026	0,158	0,871	0,014	0,084	0,871
Sigma	0,577***	0,055	0,000	1,059***	0,122	0,000	0,936***	0,076	0,000

Sig, codes: 0 '***' 0,001 '**' 0,01 '*' 0,05 ',' 0,1 ' ' 1

4. DISCUSSION

The impact of the COVID-19 pandemic is very influential on changes in tourist's behavior, especially in traveling. Throughout 2020, the tourism industry experienced a very significant decline due to travel restrictions at national and international level. Almost all countries in the world implement border closures, cancellations of public events, and strict post-foreign travel quarantine requirements [30]. This severe impact could not be ended faster before the discovery of the COVID-19 vaccine [31]. Changes in behavior are evident in the choice of vacation destinations due to the COVID-19 pandemic. Tourists prefer destinations with low human density and good sanitary facilities. To avoid crowded places, tourists prefer to do outdoor activities which are in direct contact with nature and away from big cities [32]. In relation to the duration or travel period, tourists prefer a shorter visit period or with the same duration but divided into several small trips [33-35]. In the context of business travel, recovery is predicted to occur more slowly than travel for leisure purposes. With the presence of advancement in ICT (information and communication technology) can provide high quality of application, with its sophisticated features, to support full virtual online or hybrid meeting. Muller and Wittmer [36] stated that process of decision making of business travelers is different to leisure ones, as options for face-to-face (FtF) communication or video conferencing are available for business purposes. Many FtF meetings or business gatherings, as one of the MICE-industry targets (meetings, incentives, conferences, and exhibitions), can be held virtually with technology devices and applications after the breakout of COVID-19 pandemic. Furthermore, it also contributes to lessen carbon emission issues associated with hypermobile lifestyles [36].

New human behavior to reduce physical contact has had an unfavorable impact on the global tourism industry, especially hotels, travel agencies, and local recreational activities [37]. Marquez et al. [38] stated that there are at least three main factors that cause a shift in travel behavior patterns. First, the government regulation factor related to health protocols and new normal habits; second, the human psychological factor with fear of the risks and dangers of COVID-19 transmission; and third, the economic factor where travel is considered a tertiary need that can be delayed due to financial instability during the pandemic. In this study, technical efficiency is used to predict how sharp the performance decline of the tourism industry in Indonesia by selecting samples of Listed Companies which are classified as E51 (Tourism and Recreational) on the IDX Industrial Classification (IDX-IC).

Figure 2 depicts a sharp decline in efficiency scores from 2019 to 2020 which then gradually improves in 2021. COVID-19 was officially declared by the Indonesian government as a national pandemic in March 2020. At that moment, all tourism and recreational activities had to temporarily stop operating to prevent the spread of COVID-19. The gradual reopening of some local tourist destinations with the implementation of the new normal and CHSE (Cleanliness, Health, Safety, Environment Sustainability) certification in the fourth quarter of 2020 has made the industry slowly bounce back as indicated by an increase in efficiency score in 2021. This increase may also occur because various countries in the world have stretched travel restrictions, accompanied by mandatory vaccinations since early 2021, at least twice for each person. Regarding the type of RTS or return-to-scale [29], E51 Listed Companies are DRS or decreasing return-to-scale in general. The emergence of the COVID-19 pandemic since March 2020 requires most E51 listed companies to reduce their business scale in order to optimize their efficient performance. Downsizing the business scale will be in line with reducing the operating costs when revenue cannot be maximized anymore. This is considered as the most suitable survival strategy to be applied during the pandemic crisis.

Figure 3 shows changes in business performance as reflected by the efficiency scores of each Sub-industry E51. It can be seen that E515 (restaurant) is the only sub-industry that remains stable during 2020 and 2021. Research conducted by Google et al. [39] in a report entitled “e-Conomy SEA 2021 Roaring 20s: The SEA Digital Decade” stated that the three highest-income of internet economy sectors during the COVID-19 pandemic, i.e. e-commerce, food delivery, and online entertainment media. Many offline customers are transforming into digital buyers, and restaurants into digital merchants. Food and drinks are easily ordered through the online application. Delivery-services make customers do not have to leave their homes. Kusumaningsih et al. [40] stated that there was an increase in the intention to shop online during the pandemic, which was mainly mediated by health concerns. Candra et al. [41] added that the F&B sector can survive better than other industries because food is a basic, functional, and primary need to support human life. In Indonesia, revenue from food delivery and online transportation reached $5.7 Bio in 2019 and increased to $6.9 Bio in 2021 due to the prohibition of dine-in at the restaurant during COVID-19 pandemic [39].

Sub-industry E512 (Hotels, Resorts, and Ships) and E514 (Recreation and Sport Facilities) show a similar trend in efficiency scores, a sharp decline in 2020 followed by a slight increase in 2021. This promising improvement possibly occurred after the issuance of Indonesian government’s regulations to gradually reopen some tourist destinations for the locals in September 2020 which were completely closed before. Besides that, Ministry of Tourism and Creative Economy promulgated CHSE (Cleanliness, Health, Safety, and Environment) certification to be applied by most of commercial tourism and hospitality industries in Indonesia, mainly accommodations and food services. This phenomenon was also confirmed by IDX Composite Index (or more well-known as Jakarta Composite Index) that showed significant trading volume rise in the sector of Trade, Services, and Investments, in which the tourism and hospitality industries are included, in September 2020 after experiencing a spiky downturn in March 2020 when the first positive case of COVID-19 was found in Indonesia.

Le and Phi [42] found that domestic tourism dominated almost the entire travel industry as local people book staycations within their own borders. Staycation has become a popular tourism activity amid the period of social restrictions and national borders closures. It is usually a short trip, both in terms of time and distance. Hence, a staycation may become one of the low-risk travel alternatives [43]. Until mid-2021, recreational activities carried out in confined spaces with low mobility, e.g. cinemas, are still not allowed to operate. The local government allows reopening of outdoor recreation areas in some locations with low confirmed cases of COVID-19.

The E513 sub-industry experienced the worst negative impacts in the E51 group. The trend of efficiency scores in 2021 is still decreasing compared to 2020. The high number of global confirmed positive cases of COVID-19 makes people afraid to travel internationally for any purpose, e.g. vacation, business, study, religion, etc. This particular result is in line with the research findings conducted by Google, Temasek, Bain and Co. [39] in measuring total revenue obtained from online travel businesses, where the value of $10.1 Bio in 2019 dropped sharply to $2.6 Bio in 2020 and relatively remains flat $3.4 Bio in 2021. Great losses were suffered by most of travel agents because they must process refunds to customers due to massive tour and accommodation cancellations [37]. Sub-industry E513 is predicted to bounce back faster when demands for international business travel live up across regions. The resilience in travel business is highly dependent on national travel regulation, including vaccination policies, and recovery of the economic situation due to unavoidable spending of travel-related costs such as tickets, accommodation, meals, etc. Health concerns and cost-cutting become the main reasons to suspend all non-essential business travel for most of global companies. However, there are some benefits of business travel that can't be replaced by video conferencing, such as the formation of social contacts and networks; the access to globalized market, international supply chains, knowledge exchange, and innovation; and the development of cultural leadership skills and global mindset. Those irreplaceable benefits will also foster the recovery of international business travel around the world [36].

4.1 Influences of stock price and liabilities on E51's efficiency

This study employs three models to distinguish period before and during COVID-19 pandemic (model 1 and model 2), as well as a combination of those two models (model 3). The result of the left-truncated regression analysis in model 1, before the COVID-19 pandemic (2018-2019), shows that Stock Price is the only explanatory variable which has a significant effect on Reciprocal Bias-Corrected Efficiency Score (RBCES). Its coefficient with a negative sign indicates that Stock Price has an inverse proportion on RBCES. The larger the Stock Price, the smaller the RBCES, the more efficient the Listed Company's performance is. A company with higher stock price reflects better financial performance. Hence, it will be more attractive to investors thus encourage increases in stock prices [44-50]. These findings prove that there is a positive relationship between financial performance and stock price. Therefore, it is important for company management to improve the efficiency of its financial performance [51, 52].

Model 2, during the COVID-19 pandemic (2020-2021), shows that the Liability to Asset Ratio (LTAR) is the only explanatory variable which has a significant effect on the Reciprocal Bias-Corrected Efficiency Score (RBCES). The positive sign indicates that LTAR has a direct proportion on RBCES. The greater the LTAR, the greater the RBCES, the more less-efficient the Listed Company's performance is. This ratio can be used to assess the extent to which the company's assets are financed with debt [53, 54]. The smaller the liabilities, the better the condition of a company will be. Ideally, equity investments should be greater than the debts [55]. Devi et al. [56] stated that a significant decline in sales during the COVID-19 period affected the company's profit as well as its cash flow. This severe condition also affected the company's ability to pay its debts. Rofiqoh [57] stated that an increase in the Liabilities to Assets Ratio may indicate a decline in the financial performance of Listed Companies on the Jakarta Stock Exchange when facing monetary crisis in 1998. Increased financial risk will arise during an economic crisis, especially those related to a great number of uncontrollable costs, including the interest expenses.

Combination of the data analysis in model 1 and model 2 results Stock Price and Liability to Asset Ratio (LTAR) as two explanatory variables with significant effects on RBCES. Sign of each coefficient remains similar to the previous two models, Stock Price with a negative sign while LTAR with a positive sign. Higher Stock Price and smaller value of Liabilities will increase efficiency score of Listed Companies E51.

4.2 Tourism strategies in enhancing efficiency during COVID-19 pandemic

Dealing with the impacts of the COVID-19 crisis, most of tourism industries are trying to survive by implementing various alternative strategies to reduce their operational costs. Various adjustments were made in finance, human resources, marketing, ICT, and service quality standards to adapt to a new-normal era [58]. Low facility occupancy, e.g. in a hotel, requires the companies to make adjustments to several operational costs, both direct and overhead costs. Cash flow savings are emphasized on reducing electricity consumption, maintenance, promotion, and employee development costs.

The biggest cost component of any companies engaged in services is the employee wages. During the crisis, management takes action to streamline company's organizational structure by laying off all non-permanent workers, as well as not extending employee contracts which are about to expire. For those who are still working, many of them have experienced reduction in salary or omission in benefits and compensation [59]. In order to work in accordance with the new normal regulations, active employees are required to receive additional training on health protocols to serve the guests more safely. In 2020, the Ministry of Tourism and Creative Economy of the Republic of Indonesia has provided detailed operational guidelines for the implementation of cleanliness, health, safety, and environmental sustainability (CHSE) which must be applied in every tourist destination, e.g. hotels, restaurants, games and sports arenas, during COVID-19 pandemic. These guidelines are not only useful for regulating and controlling human movement, but also modulating minimum sanitation facilities that must be available in public spaces.

The high rate of COVID-19 transmission has created pressure on strict social distancing practices and physical contact reduction, both among people and with objects in public facilities [60]. This is where technology and digitalization play a role to diminish any excessive interaction. Development of technology in tourism industry can accelerate recovery of this business after COVID-19 pandemic. Fipra [61] provides several examples of digital application usage in tourism business, such as contactless hotel check-in, mobile room key, online food order, online reservation, and touchless payment. With advances in technology, all of these features can be accessed only by using the customer's mobile phone. In addition, some luxury hotels in several countries have even implemented the use of artificial intelligence (AI) and robotics before the emergence of COVID-19 to carry out most guest service activities, such as housekeeping, food production, room service, waiters, bellboys, receptionists, and others [62]. Since AI and robotics are high-cost technologies, companies need to conduct thorough financial analysis before making decision to invest [63].

5. CONCLUSION

The COVID-19 pandemic has been a health and economic crisis with devastating effects all around the world. Indonesian government had also implemented several emergent regulations, such as lockdowns, quarantines, and major restrictions on national and international mobility. A sharp contraction occurred in tourism sector, where the number of international tourist arrivals declined drastically throughout 2020 and 2021. Meanwhile, domestic and regional travel started to recover faster after the relaxation of social restriction in September 2020. McKinsey and Co. [31] stated that tourism industry is estimated a return to pre-COVID level at least in 2023 or later. Though most people are now vaccinated, their behaviors towards travelling have totally changed after the pandemic.

In dealing with the long-impact of pandemic crisis, tourism sectors are required to operate more efficiently. Employing double bootstrap DEA VRS input-oriented method [12, 16], this study aims to reveal the score efficiency of Tourism and Recreation Industry, coded E51 on IDX (Indonesian Stock Exchange), as well as some explanatory variables that affect it. The average score efficiencies of E51 industry in 2018 to 2021 respectively are 0.831, 0.852, 0.648, and 0.672. Based on the type of DEA return-to-scale, E51 shows a decreasing return-to-scale (DRS) trend with an average Lambda value of 2.394 during 2018-2021. This indicates that the operating scale of most Listed Companies in the E51 group is still too large which contributes to their inefficient performance. Downsizing the business scale will affect reduction in operating expenses when revenue cannot be maximized anymore.

Based on the Sub-industry category, E515 (Restaurant) has the highest average efficiency score, followed by E513 (Travel Agent), E512 (Hotel, Resort, and Ship), and E514 (Recreation and Sport Facility) the lowest during 2018-2021. Although it ranks second, E513 shows a downward trend in 2021. In fact, not many people are willing to travel internationally for non-urgent purposes. E512 and E514 were dropped in 2020 but started to recover slightly in 2021 as Indonesian government decided to reopen some tourist destinations with low confirmed positive cases of COVID-19 for domestic arrivals since September 2020. Among all, only efficiency scores of E515 remain stable before and during the pandemic. Google et al. [39] reported most of food services go online today. Food delivery along with e-commerce is predicted to make the biggest contribution to the current and future development of internet economy. Since foods are human's primary needs, food business will survive better than any other ones in the tourism industry. The need for vacations and recreation can be postponed, but not so for food.

Using truncated regression analysis as part of double bootstrap technique [12], this study finds two explanatory variables, i.e. Stock Price and Liability to Asset Ratio, which significantly affect the score efficiency of Listed Companies E51. Increase in stock price improves efficiency. A company with higher stock price will be more attractive to investors. Adversely, increase in liability ratio decreases efficiency. A sharp decline in tourism sales during the COVID-19 period affected the company's ability to pay its debts as well as loss in revenue and profits. To keep its business alive, tourism industry must implement some strategies with costs reduction as the ultimate goal. Various adjustments were made in finance, human resources, marketing, ICT, and service quality standards. Technology usage and digitalization play important roles to diminish any physical contact or interaction between human or with an object mainly in public area. Certification in CHSE (cleanliness, health, safety, environmental sustainability) is mandatory to obtain an operating license from government, especially for chain businesses such as chain hotels or chain restaurants.

This research has some limitations that can be taken into considerations in conducting future research. Efficiency analysis might generate more detailed results if it is treated in a time-series instead of a cross-sectional technique. Data processed through a time series approach will produce a production frontier line every year during the study period so that its annual productivity growth can be analyzed.

It is also realized that companies listed in E51 Tourism and Recreation Industry have some sub-industries with totally different business fields (E512-E515). By still adhering to the sub-industry classification that has been determined by the Indonesia Stock Exchange, future research is suggested to add research samples not only limited to listed companies but also private companies to meet the minimum DMU requirements, at least three times the total input and output variables. Moreover, it will represent industry population much better by involving both public (listed) and private companies into DEA measurement.

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