Sectoral Business Efficiency Analysis during the Pandemic on IDX (2018-2022): Tourism, Food, and Transportation Logistics via Data Envelopment Analysis

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Abstract: Throughout 2018 and 2022, the COVID-19 pandemic significantly affected several industry sectors on the Indonesia Stock Exchange (IDX). This paper examines the operational effectiveness of three crucial industries—tourism, food, and transportation logistics—during the epidemic. The analysis's findings indicate that these sectors' levels of efficiency during the pandemic varied. Business efficiency is greatly influenced by risk management, operational methods, and adapting to shifting consumer demand. As a result of this examination of company performance during the pandemic, it is clear that adequate policies are required to sustain operational continuity and the expansion of significant sectors in the Indonesian stock market. By taking input into account, the DEA approach is utilized to assess these businesses' relative efficiency. Along with factors like operating costs, total assets, labor, and capital, outputs like revenue and net profit are also considered. The factors that led to the most inefficient performance were determined to be fixed assets (24.62%), total liabilities (19.10%, and COGS expenses (18.98%). This study also advances knowledge of the elements that influence the effectiveness of businesses in the tourism sector. The implications of the study's findings can be used to assist the tourism industry's sustainable expansion in Indonesia and to improve the performance of travel businesses in the future.

Keywords: Tourism industry efficiency, Tourism company finance.

1. Introduction

The tourism industry plays a very important role in the global economy, including in Indonesia. As one of the main sectors in the country's economy, the tourism industry contributes significantly to economic growth, job creation, and the promotion of Indonesia's culture and natural beauty at the international level. The Indonesia Stock Exchange (IDX), as the main financial market in Indonesia, also has an important role in supporting the development of this industry.

The Indonesia Stock Exchange (IDX) is an important institution in facilitating investment in various industrial sectors in Indonesia. Tourism, as one of the prominent sectors, requires special attention from investors. In the period of 2018-2022, Indonesia's tourism industry has experienced various changes and challenges that are very heavy and can affect its efficiency in the capital market. To maintain and improve the competitiveness of the tourism industry in Indonesia, it is crucial to understand its efficiency level. One of the analytical tools that can be used to measure industry efficiency is Data Envelopment Analysis (DEA). DEA is a non-parametric method that allows relative comparison between various entities in an industry. In this context, DEA can be used to assess the efficiency of tourism companies listed on the IDX during 2018-2022.

Several previous studies have used DEA to analyze efficiency in various industry sectors, including tourism. For example, research by Charnes, Cooper, and Rhodes (1978) has introduced the DEA method and applied it in the hospitality industry. In addition, research by Zheng, Zhao & Hui (2011). used DEA to evaluate the efficiency of hotels in China. At the national level, research by the World Bank (2021) has also looked at the efficiency of the tourism sector as part of efforts to improve a country's economic competitiveness.

This research will focus on the period of 2018 to 2022 to identify changes in efficiency in the tourism industry on the IDX during that period. As such, this research is expected to contribute significantly to the understanding of the efficiency of the tourism industry in Indonesia and possibly provide recommendations for future efficiency improvements.

Problem identification are: (1) What is the impact of utilizing Data Envelopment Analysis to assess Relative Efficiency within the tourism sector (E5) and two additional industries (D2 and K3) on the Indonesia Stock Exchange (IDX)?; AND (2) How has the evolution of the tourism industry and two other industry sectors influenced the financial performance of companies listed on the Indonesia Stock Exchange (IDX) between 2018 and 2022?

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2. Methodology

Efficiency Data Analysis through Data Envelopment Analysis (DEA)

Data Envelopment Analysis (DEA) is a statistical method used to measure the relative efficiency of a group of decision-making units, such as firms or organizations. DEA compares the inputs used by a unit with the outputs produced to assess whether or not the unit is operating efficiently. In other words, DEA helps identify units on the "efficiency frontier," which can be considered the best example of maximizing output with given inputs.

DEA in the Context of the Tourism Industry in the IDX. In the context of this article, DEA will be used to measure the efficiency of companies in the tourism industry listed on the Indonesia Stock Exchange from 2018-2022. The data required for this analysis will include relevant inputs and outputs. Inputs may include the amount of labor, capital, or other financial resources used by the company. Outputs may be revenues, profits, or other performance measures that can be used to gauge the company's achievements.

Data analysis will utilize the Data Envelopment Analysis (DEA) mathematical programming technique, which was initially introduced by Charnes, Cooper, and Rhodes (1978). DEA is commonly recognized as a non-parametric analytical method. However, its application hinges on the linearity assumption as proposed by Chang and Guh (1991). This assumption is used either for the DEA type assuming constant return to scale (CRS) introduced by Charnes, Cooper, and Rhodes (1978), making it the CCR model, or assuming variable return to scale (VRS) introduced by Banker, Charnes & Cooper (1984), making it the BCC model.

DEA measurement finds widespread use in various industries for assessing the productivity of a group of test samples, often referred to as Decision Making Units (DMUs). These DMUs employ multiple inputs to generate specific outputs in their production processes. In simpler terms, this measurement is expressed as a ratio between output and input. It can be expressed partially or in its entirety to highlight the most influential input factors contributing to output generation.

The choice of the DEA method in this study is motivated by several advantages it offers. These include its capacity to simultaneously analyze multiple outputs and inputs, its ability to operate without requiring assumptions or a priori definitions of the production frontier's shape, its measurement of relative efficiency based on the best observations, its independence from price information. Furthermore, as a non-parametric approach, DEA does not rely on population parameters and does not necessitate assumptions regarding sample distribution, as observed by Fried et al. (1993).

However, the nature of DEA that does not require a normal distribution creates a bias if not corrected. This non-bias corrected value causes the efficiency value from DEA cannot be used for further parametric analysis. To overcome this shortcoming, Simar & Wilson (2007) came up with the Double Bootstrap method. The first bootstrap is applied to correct the bias in conventional DEA. The second bootstrap is applied to the regression equation where the bias corrected efficiency value will be the dependent variable and the other factors will be the predictors that will be analyzed for their relationship by hypothesis testing.

Data Envelopment Analysis (DEA)

In essence, Data Envelopment Analysis (DEA) is a method used to assess a company's efficiency in comparison to its peers within the same industry. It is considered a relative measurement technique because it evaluates performance relative to the best-performing similar companies. This assessment is based on the ratio of output to input for each work unit within a sample. In simpler terms, inputs are akin to costs, while outputs represent benefits. The unit being evaluated is referred to as a Decision-Making Unit (DMU) within the DEA model. This DMU can be an entire company or sub-units (like departments) within a company as long as they are defined consistently for DEA analysis. DEA establishes a frontier line of efficient DMUs, encompassing other less efficient DMUs below it. This statistical approach is known as Data Envelopment Analysis (DEA) and helps identify the most efficient DMUs and highlight inefficiencies in others.

In contrast, parametric analysis assumes a single optimized regression equation for each DMU, requiring specific functional forms relating independent variables to the dependent variable. However, DEA optimizes the performance measure of each DMU without necessitating assumptions about the functional form, enabling the construction of an efficient frontier. DMUs with an efficiency score of one are on the frontier, while inefficient ones have scores between 0 and 1. The closer the score is to one, the more efficient the DMU is compared to other inefficient ones. Efficiency scores can be calculated with two orientations: input and output. The output-oriented DEA method maximizes output levels with fixed inputs, while the input-oriented DEA minimizes input levels with fixed outputs.

DEA measurement commonly employs two models: constant returns to scale (CRS/CCR) and variable returns to scale (VRS/BCC). The CRS model assumes an equal ratio in maximizing the output-to-input weight when a DMU operates optimally. Input and output changes are always proportional in this case. In contrast, the BCC model assumes that firms typically do not operate at an ideal or optimal scale. The frontier line should exhibit properties such as increasing returns to scale (IRS), decreasing returns to scale (DRS), and constant returns to scale (CRS) as a transition point from IRS to DRS.

Double Bootstrap Technique

One weakness of the DEA method, as highlighted by Banker, Charnes, & Cooper (1984), and Charnes, Cooper & Rhode. (1978) is its failure to consider statistical noise in its measurements, leading to inaccurate outcomes. To address this issue, Simar & Wilson (2007) introduced an algorithm that employs a bootstrap resampling approach to establish confidence intervals for second-stage regression. This algorithm incorporates a bias correction procedure to eliminate bias in the initial efficiency scores, aligning them with the truncated model.

The Double Bootstrap Technique is a statistical approach utilized to estimate the variance of a statistic or parameter by employing a two-tier bootstrap process. Bootstrap, a resampling method, is employed to compute statistical estimates and confidence intervals from sample data by creating numerous bootstrap samples derived from the original data. The Double Bootstrap Technique proceeds through several phases. An outer bootstrap process initially generates multiple distinct bootstrap samples from the original data. In each bootstrap sample, data points are repeatedly selected with replacements from the original data, ensuring that each bootstrap sample matches the original data's size. Subsequently, the inner bootstrap phase, carried out within each bootstrap sample produced in the first step, involves a second bootstrap process. This entails resampling once more from each of the existing bootstrap samples. The inner bootstrap serves to gauge additional variability in the estimation of the statistics under investigation. Within each inner bootstrap sample, the statistic or parameter being estimated (such as mean, median, or regression parameter) is computed using the resampled data, resulting in multiple estimates of that statistic.

After collecting multiple estimates of the statistic through inner bootstrap resampling, we can compute the statistic's variance. This variance serves as an indicator of how much our estimates fluctuate when different samples are used. The resampling or iteration process emulates the data generation process of the actual base model, considering a random model among observations, and computes the deviation from the mean score for each variable. A larger residual variance corresponds to a wider Bootstrap confidence interval established in hypothesis testing. The accuracy of these bootstrap estimates hinges on both the number of repetitions (typically ranging from 100 to 1000 repetitions) and the size of the DMU sample. Failing to account for these factors in the bias correction process can lead to greater errors than the original efficiency scores without employing the bootstrap technique (Simar & Wilson, 2007).

This study employed both non-parametric and parametric approaches to assess efficiency scores. The analysis used the non-parametric approach, followed by the parametric approach in the subsequent stage. Among various non-parametric techniques, data envelopment analysis (DEA) was selected to estimate the production frontier, representing the best outcome achieved or aimed for by the efficient sample compared to the rest of the sample, known as the inefficient sample. Utilizing the production frontier method involves using observed data to construct a frontier for estimating the efficiency score of the entire sample. DMUs positioned on the production frontier are presumed to operate at full technical efficiency (efficiency score equals one or =1), extracting maximum output from available inputs or achieving minimal inputs for a fixed level of output.

On the other hand, DMUs situated below the production line are considered inefficient, with efficiency scores falling below one ($0 < \theta < 1$). Regarding the frontier line, this study presents the target value that an inefficient DMU needs to attain from its initial value to become efficient, or in mathematical terms, to achieve an efficiency score of one. Unless the sample is already efficient, the target value for the inefficient DMU must involve using fewer inputs and/or generating greater outputs compared to the initial input and/or output values.

The Developmental Efficiency Analysis (DEA) was created in connection with the production process, whether it involves the manufacturing of goods or the provision of services. This process includes using inputs as production resources and obtaining outputs in the form of units or services produced. The Variable Return-to-Scale (VRS) model is selected based on the idea that the organization's size, represented by the sample size of the Decision-Making Units (DMU) or DMUs, plays a crucial role in determining their relative efficiency. The relationship between VRS and CRS (constant return-to-scale) is referred to as scale efficiency, which pertains to the presence of economies of scale or diseconomies.

In economies of scale or situations of increasing returns to scale (IRS), when you double the inputs, the output increases by more than double. This is because producers can take advantage of bulk purchasing, leading to enhanced productivity. Conversely, an organization can become overly large if it experiences diseconomies of scale or diminishing returns to scale (DRS). In such cases, doubling the inputs results in less than doubling the output, indicating inefficiency.

In alignment with the chosen approach, this study measures efficiency using the input-oriented DEA method, which involves minimizing inputs while maintaining a fixed output level. The mathematical representation of this model is as follows:

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

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

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

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

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

A bootstrapping procedure proposed by Simar & Wilson (2007) addresses issues associated with sampling noise, which can lead to biased scores. Additionally, it aids in estimating a truncated regression model to identify the factors that influence the efficiency level (referred to as Algorithm II). Simar & Wilson's (2007). Algorithm II is implemented to estimate the regression model through a double bootstrap process involving a total of 2000 iterations. The first bootstrap run uses the maximum likelihood method to compute the bias-corrected efficiency score, while the second bootstrap is employed to estimate the truncated regression model along with its confidence intervals and standard errors.

The bootstrap technique involves iteratively simulating or resampling data, applying conventional DEA measures to each simulated dataset in a manner that replicates the unknown distribution of the original population. The general mathematical formula for a truncated regression aimed at estimating variations in efficiency is provided below.

$$Var(\hat{\theta}) = \frac{1}{B} \sum_{i=1}^{B} \left(\frac{1}{B} \sum_{j=1}^{B} (\hat{\theta}_{i,j} - \hat{\theta}_{\cdot,\cdot})^2 \right)$$

Here, is the statistical or parameter estimate in the jth inner bootstrap sample generated from the i-th bootstrap sample. is the statistical or parameter estimate from the original data. The study relies on linear programming executed using R-package software to derive the DEA results, encompassing deterministic efficiency scores, scale efficiency, and targeted improvement scores. Additionally, bootstrap calculations were performed, yielding bias-corrected and regression-truncated efficiency scores.

In terms of data collection, secondary techniques were employed. The input and output data utilized in the initial stage of DEA analysis were sourced from the official IDX website (https://idx.co.id) and structured in a taxonomy format that encompasses various elements from financial statements, such as the Statement of Financial Position, Statement of Comprehensive Income, Statement of Cash Flows, and Statement of Changes in Equity. Conversely, the explanatory data used for the subsequent stage of bootstrap analysis primarily originated from IDX Statistics spanning from 2008 to 2022, accessible in the Equity Trading Activity - Cumulative Data (January - December) section of the IDX website (https://idx.co.id). It's worth noting that all publicly listed companies are obligated to disclose their financial statements and other significant public information that has undergone a financial audit conducted by an authorized audit institution on the official IDX website (https://idx.co.id).

3. Results and Discussion

The research employs 129 sets of financial performance data from 108 publicly traded companies (Tbk) on the Indonesia Stock Exchange. This study involves a total of 5 variables, comprising three inputs and two outputs. The input variables encompass operating expenses, total assets, inventory (citing Zheng et al., 2011; Nanka-Bruce, 2011; Yu & Han, 2012; Memon & Tahir, 2012), and interest expenses (as indicated by Sumantyo & Tresna, 2017). Conversely, the output variables include operating revenue (referencing Zheng et al., 2011; Memon & Tahir, 2012; Yu & Han, 2012) and the earnings per share ratio (sourced from Powers & McMullen, 2000).

This research specifically focuses on evaluating the financial performance efficiency of 108 listed companies, categorized into three industry groups (IDX code) on the Indonesia Stock Exchange (IDX). The data sources for this study consist of three groups of variables: input variables, output variables, and explanatory variables. The input and output variables are utilized to assess the deterministic efficiency score using the conventional DEA method. The input variables encompass Cost of Goods Sold, Revenue, Operating Expenses, Financial Expenses, and Fixed Assets. Meanwhile, the output variables include Sales, Operating Income, and Operating Profit/Loss.

The subsequent phase of analysis involves employing a left-truncated linear regression approach to identify the factors influencing the Issuer's efficiency score, with a set of explanatory variables such as Debt to Asset Ratio, Closing Stock Price, Stock Price to Book Value Ratio, Company Size (indicated by Total Assets), and Company Age. This analysis encompasses financial statements and annual reports spanning from 2008 to 2022 for all Issuers actively listed or not suspended on the Indonesia Stock Exchange.

Table 1. Group of variables in DEA.

Input Variables	Variable Output
Cost of Goods Sold	Sales and Revenue Business
Fixed Assets	Profit (Loss)
Total Liabilities / Total Assets	

Source: Powers & McMullen (2000).

One method to evaluate the efficiency of various decision-making units (DMUs) using cross-sectional data is the DEA (Data Envelopment Analysis) method, which utilizes multiple inputs to produce desired outputs (Cooper et al., 2006). Changes in the business world impact the structural integrity of companies. From 2008 to 2022, the global COVID-19 pandemic caused a significant transformation among companies, leading to a major crisis in all industries worldwide. In today's digital era, it is important for industries to prioritize efficient performance. With various variables and large amounts of data (commonly called big data), calculations based on cross-sectional data are important. Cross-sectional research, also called transversal research, involves observing independent and dependent variables simultaneously at a single point in time. The next step involves adjusting the technical efficiency score, which serves as the dependent variable in the multivariate regression analysis. This analysis aims to identify the influence of various control variables on determining the bias-corrected efficiency score of technical efficiency.

How is the Relative Efficiency in tourism industry (E5) and two other Industry sectors (D2 AND K3) in IDX with Data Envelopment Analysis approach?

After processing the data using the input variables mentioned earlier, we derive the Efficiency scores for the three groups of Industrial Issuers that were assessed.

Table 2. Results of the efficient score of 3 industry groups.

Sector		EFF Score
D2	Food and Beverages	87,3%
E5	Tourism	87,0%
K3	Logistic and Transportation	83,3%

Source: IDX Jakarta.

What is the anticipated goal of enhancing the values of input and output parameters in order to enhance the future performance efficiency of the three categories of industrial issuers?

Table 3. Average input reduction and maximum output of 3 industry sectors.

Sector	Average Input Reduction	Average Output Maximation
D2	-19,7%	6,2%
E5	-20,2%	12,7%
K3	-22,2%	1,7%

Source: Author's calculation results (2023).

Throughout the pandemic, the tourism industry (referred to as E5) found itself in a unique position. Unlike other sectors that could maintain or even increase their output with the same level of input, E5 could only cut down on its inputs but couldn't boost its production. Consequently, there is a notable potential for E5 to achieve a substantial increase in its maximum output, estimated at 12.7%. These enhancements in input and output capabilities can be achieved by taking into account various factors that may influence the efficiency of these sectors. Below, you will find the projected goals for each sector along with the scientific reasoning behind them.

Sector D2 (Food and Beverages)

The table presents the results of the sector efficiency calculations measured in percentages: (1) Sector D2 reduced inputs by around 19.7% and increased output by 6.2%. This shows that sector D2 can improve its efficiency by reducing the use of resources (inputs) and increasing the output produced; (2) K3 sector reduced inputs by about 22.2% but only managed to increase output by 1.7%. This may indicate that the OSH sector has tried to reduce resource use, but still needs to improve its productivity to achieve higher efficiency.

In general, these results show the potential to improve efficiency in these sectors by better managing their resource use and increasing their output.

Sector E5 (Consumer Services, specific E51 Tourism)

Input Increased 10%, increase in output 6%. Sector E5 has experienced a notable 20.2% reduction in inputs, yet it has seen a positive uptick of 12.7% in output. A modest 10% increase in inputs could be employed to address the substantial input decline. Simultaneously, a 6% boost in output would enhance the sector's performance. These actions reflect Sector E5's potential to enhance efficiency by optimizing resource usage while emphasizing output growth. The rationale behind augmenting inputs and outputs rests on the assumption that augmenting inputs will aid these sectors in countering significant input declines that may arise over time. Conversely, an escalated output is also necessary for achieving heightened efficiency and sustaining business expansion.

Sector K3 (Logistics and Transportation)

Average Input Reduction (-22.2%): The OHS sector had a significant input reduction of 22.2%, indicating the potential to reduce resource use substantially. Average output maximization (1.7%), although there was a 1.7% increase in output, this figure is relatively small compared to the decrease in inputs. This may indicate that the OHS sector may face constraints in increasing production further.

Academic Rationale

These results suggest that the OHS sector may face challenges in improving efficiency. Further study may help in identifying specific issues that need to be addressed in order to improve the sector's performance. Overall, this table provides an initial view of the efficiency level and potential improvements in three different sectors. Further analysis and academic research will be needed to understand the factors underlying these results and develop appropriate improvement strategies for each sector.

What is the degree of comparison between the bias-adjusted efficiency scores derived from input variables and the efficiency scores acquired through traditional or deterministic DEA measurements for the three groups of Industrial Issuers?

Sector D2 (Food and Beverages)

Table 4. Results of efficient score of food and beverage.

Sector	Year	EFF Score
D2	2019	85,78%
D2	2020	85,07%
D2	2021	88,13%
D2	2022	90,14%

Source: IDX Jakarta.

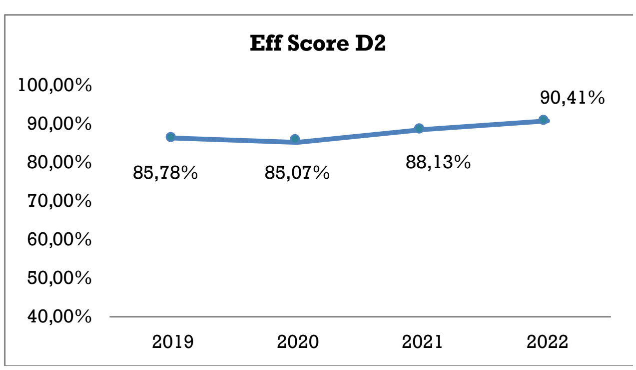

Fig. 1. Diagram of efficient score of food and beverage.

Efficiency Improvement Trend

The table shows the efficiency improvement trend of the D2 sector from 2019 to 2022. In 2019, the efficiency of the sector reached 85.78%, which then increased to 85.07% in 2020, 88.13% in 2021, and reached the highest level of 90.41% in 2022. This indicates significant improvements in resource utilization and sector productivity over the period.

Consistency of Improvement

A consistent trend of efficiency improvement from year to year indicates that the D2 sector has optimized its operations. This may include efficiencies in using labor, capital, or other strategies that have led to better results year-on-year. Above average achievement, over the four-year period, the average efficiency score of the D2 sector was 87.35%. This indicates that the sector has consistently achieved above-average efficiency over time. This success can be considered a good achievement in making good use of resources.

Potential for further improvement, although sector D2 has achieved a good level of efficiency, there is still potential for further improvement. Companies or organizations within this sector can continue to look for ways to improve their efficiency to achieve higher levels of resource utilization and productivity. In an academic context, such an analysis can be used to evaluate the performance of a sector or company over time, as well as to understand the impact of efficiency improvement efforts that have been made. It can also form the basis for further research on the factors contributing to efficiency improvements within the sector.

Sector E5 (Consumer Services, specific E51 Tourism)

Table 5. Results of consumer services, specific tourism.

Sector	Year	EFF Score
E5	2019	88,5%
E5	2020	86,1%
E5	2021	86,8%
E5	2022	86,7%
	Average	87,0%

Source: IDX Jakarta.

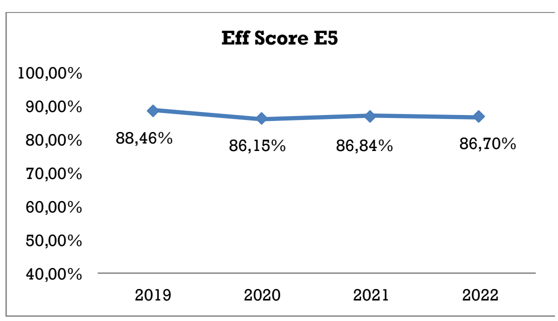

Fig. 2. Diagram of efficient score of consumer services, specific tourism.

The tourism industry, classified as Sector E5, pertains to the economic activities associated with travel, recreation, and the provision of services for travelers. This sector encompasses a wide range of businesses, including hotels, dining establishments, airlines, travel agencies, and tourist destinations. Over the past four years, Sector E5 has consistently maintained an average Efficiency Score of 87.04%, surpassing the average Efficiency Score of all nine industry sectors, which stands at 84.39%. This suggests that Sector E5 demonstrates stronger industry resilience compared to the overall industry average.

In terms of variability in efficiency, this table shows the variation in efficiency of sector E5 from year to year. From 2019 to 2022, the efficiency level fluctuates between 86.1% and 88.5%. This variability could be due to many factors, such as changes in resource utilization, management strategies, or market changes. Average Level of Efficiency: Despite annual fluctuations in efficiency, the average efficiency over the four-year period was 87.0%. This indicates that overall, the E5 sector managed to utilize its resources with a relatively consistent level of efficiency over the period.

Further analysis, while the average efficiency is 87.0%, further research may be needed to understand the factors that influence annual fluctuations in efficiency. This could include a more in-depth analysis of input and output components, changes in industry regulations, or other factors that might affect the performance of the E5 sector from year to year. Importance of Monitoring Efficiency: This table underscores the importance of regular efficiency monitoring. While average efficiency may be adequate, annual fluctuations may affect the long-term performance and sustainability of the E5 sector. Therefore, companies or organizations within the sector should monitor and actively manage their efficiency to ensure optimal business continuity.

Implications for decision making, Efficiency data such as this can be used by managers, shareholders, or other decision-makers within the E5 sector to identify years where efficiency has declined and take corrective action accordingly. This can help the E5 sector to remain competitive and efficient in an ever-changing business environment.

Sector K3 (Logistics and Transportation)

Table 6. Results of logistics and transportation.

Sector	Year	EFF Score
K3	2019	82,1%
K3	2020	81,8%
K3	2021	83,5%
K3	2022	85,7%
	Average	83,3%

Source: IDX Jakarta.

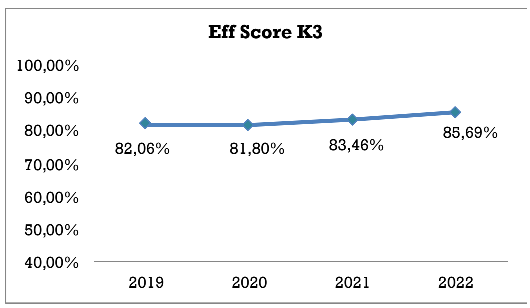

Fig. 3. Diagram of an efficient score of logistics and transportation.

Academic Reasoning

In relation to management and process improvements, there have been improvements in the management and operational processes of the OHS sector from year to year. This could include efficiency in resource use, improvements in planning, and optimization of business processes. Innovation and technology, there may be implementation of innovations or new technologies within the OHS sector that help to improve productivity and efficiency. This could include the use of more advanced information systems or more efficient production technologies.

Experience and learning, the year-to-year experience, can also play a role. OHS sector management and employees may have learned from previous experiences and implemented improvements based on these learnings. Investment and resources, there may be appropriate investments in human resources, infrastructure, or training that help improve efficiency.

Policy Changes: Sometimes, changes in government policies or industry regulations can also affect efficiency scores. If there are changes that favor efficiency, this can be reflected in an improved efficiency score. Competition and competitors, economic theory says that the level of competition in an industry can encourage companies to become more efficient. If the OHS sector experienced an increase in competition during the period, this could be a factor affecting efficiency improvements. With an average efficiency score of 83.3% over the four-year period, it can be concluded that the OHS sector as a whole managed to improve its efficiency.

Efficiency Score of the Tourism Sector (E5) and two other sectors in IDX

Table 7. Results of all sector.

Sector		EFF Score
D2	Food and Beverage	87,3%
E5	Tourism	87,0%
K3	Logistics and Expedition	83,3%

Source: IDX Jakarta.

To compare the efficiency score of the Tourism sector (E5) with the other two sectors, namely Food & Beverages (D2) and Logistics & Delivery (K3) on the Indonesia Stock Exchange (IDX), we need to look at the factors that affect the efficiency of each sector. Efficiency can be affected by various factors such as productivity, operating costs, and resource management.

The Food & Beverage sector (D2) has the highest efficiency score with 87.3%. This could be due to several scientific reasons: (1) Demand stability, food and beverage products are basic necessities, so their demand tends to be stable, regardless of economic fluctuations. This can help the sector to be more efficient in production planning and stock management; (2) Production process efficiency, the sector may have adopted efficient production technologies and processes, including automation in production and distribution; (3) Economies of scale, the sector may have achieved a good level of economies of scale, where production costs per unit can be minimized.

The Tourism sector (E5) has an efficiency score of around 87.0%. While its efficiency is almost comparable to the Food & Beverage sector, there are some scientific reasons why it may be slightly lower: (1) Seasonal nature, the tourism industry is often seasonal, with spikes in tourist visits during certain holiday seasons. This can lead to fluctuations in demand and supply, which are difficult to manage efficiently; (2) Infrastructure costs, tourism often requires investment in infrastructure such as hotels, airports and tourist attractions. These costs may be high and take time for return on investment; (3) Regulation and competition, tourism is often highly regulated and has many competitors. This can affect efficiency in terms of bureaucracy and price competition.

Solutions to improve the efficiency of the Tourism sector (E5) could include: (1) Diversification, increase the variety of tourism products on offer to reduce dependence on a particular holiday season; (2) Technological innovation, adopting the latest technology in reservation management, online marketing, and visitor experience to improve operational efficiency; (3) Partnerships, collaborate with the government, transportation companies, and hotels to reduce infrastructure costs and promote tourism efficiently; (4) Human resource training, improve the qualifications of human resources in the tourism industry to provide better and more efficient services.

4. Conclusion

The global health and economic sectors have faced significant challenges due to the COVID-19 pandemic. In Indonesia, the government has implemented various regulations, including lockdowns, quarantines, and domestic and international travel restrictions. The tourism industry, in particular, has suffered a sharp decline, with international travel numbers plummeting in 2020 and 2021. However, domestic and regional travel started to recover once social restrictions were eased in September 2020. McKinsey & Co. predicts that the tourism sector may return to pre-COVID-19 levels by 2023 or later. Despite widespread vaccination, the pandemic permanently altered people's travel habits.

The Tourism Industry Sector (E5) has faced more significant financial challenges between 2018 and 2022 compared to the other nine sectors listed on the Indonesia Stock Exchange. The marked differences in cost reduction, expenses, and net losses may be attributed to changes in the tourism sector, possibly influenced by factors like the COVID-19 pandemic and shifts in consumer travel preferences.

An increase in a company's stock price can enhance its appeal to investors and boost efficiency. Conversely, a growth in the liability ratio can reduce efficiency. The impact of the steep drop in sales within the tourism industry during the COVID-19 pandemic includes challenges in debt repayment, revenue loss, and reduced profits. To ensure the survival of their businesses, the tourism industry must adopt cost-cutting strategies. These strategies involve adjustments in financial management, workforce, marketing, information and communication technology (ICT), and service quality. Technology and digitalization are pivotal in reducing physical interactions in public spaces.

This study comes with several limitations that should be taken into account for future research. An efficiency analysis using a time series approach rather than cross-sectional techniques could provide more detailed insights. With time series data, it becomes possible to establish a production frontier line for each year during the study period, enabling an analysis of annual productivity growth.

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