The Impact of Company Size, Beta, and ESG Ratings on the Efficiency of Palm Oil Companies Listed on the IDX during Crisis Periods

Dampak Ukuran Perusahaan, Beta, dan Peringkat ESG terhadap Efisiensi Perusahaan Kelapa Sawit yang Terdaftar di IDX Selama Periode Krisis

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Abstract The palm oil industry proves to be a resilient sub-sector of agriculture, particularly during the COVID-19 crisis, contributing significantly to Indonesia's national GDP and supporting financial recovery in the post-pandemic period. This research examines the influence of company size, Beta (stock volatility), and ESG ratings on the efficiency scores of palm oil companies. A total of 20 entities listed on the Indonesia Stock Exchange (IDX) are analyzed over a 5-year period (2019–2023), including 9 ESG-rated companies. A DEA double bootstrap with left-truncated linear regression at 1 is employed to estimate the model. The results show that company size does not significantly affect efficiency, while Beta negatively impacts efficiency, indicating that higher volatility reduces performance. ESG-rated companies consistently outperform non-rated counterparts, demonstrating the positive effects of sustainable practices. This study provides a novel contribution, as no previous research explores these variables in Indonesia's palm oil industry. The findings offer valuable insights for industry practitioners and policymakers, emphasizing the importance of ESG integration for improved efficiency and sustainable growth, and supporting the formulation of policies to enhance the sector's resilience in future crises.

Keywords: double bootstrap DEA, efficiency score, ESG ratings, palm oil industry, stock volatility (beta)

Abstrak Industri kelapa sawit terbukti sebagai sub-sektor pertanian yang tangguh, terutama selama krisis COVID-19, dengan memberikan kontribusi signifikan terhadap PDB nasional Indonesia dan mendukung pemulihan ekonomi pasca-pandemi. Penelitian ini mengkaji pengaruh ukuran perusahaan, Beta (volatilitas saham), dan peringkat ESG terhadap skor efisiensi perusahaan kelapa sawit. Sebanyak 20 entitas yang terdaftar di Bursa Efek Indonesia (IDX) dianalisis selama 5 tahun (2019–2023), termasuk 9 perusahaan berperingkat ESG. Model ini diestimasi menggunakan metode DEA double bootstrap dengan regresi linier tertrunkasi pada 1. Hasil penelitian menunjukkan ukuran perusahaan tidak berpengaruh signifikan terhadap efisiensi, sementara Beta berdampak negatif, yang menunjukkan bahwa volatilitas yang lebih tinggi menurunkan kinerja. Perusahaan berperingkat ESG secara konsisten memiliki kinerja efisiensi lebih baik dibandingkan yang tidak berperingkat, menunjukkan dampak positif dari praktik keberlanjutan. Studi ini memberikan kontribusi baru, karena belum ada penelitian sebelumnya yang mengeksplorasi variabel ini di industri kelapa sawit Indonesia. Temuan ini memberikan wawasan berharga bagi praktisi industri dan pembuat kebijakan, menekankan pentingnya integrasi ESG untuk meningkatkan efisiensi dan pertumbuhan berkelanjutan, serta mendukung kebijakan yang memperkuat ketahanan sektor ini di masa krisis mendatang.

Kata Kunci: double bootstrap DEA, skor efisiensi, peringkat ESG, industri kelapa sawit, volatilitas saham (beta)

INTRODUCTION

The agricultural sector plays a significant role in Indonesia's economy (Annas and Izaati, 2022; Bancin *et al.* 2022), as evidenced by its substantial

Penulis yang tidak disertai dengan catatan kaki instansi adalah peneliti pada Pusat Penelitian Kelapa Sawit

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Naskah masuk: 12/09/2024; Naskah diterima: 03/04/2026

contribution to the national Gross Domestic Product (GDP), accounting for approximately 12.40% in 2022. This places it as the third-largest contributor, following the manufacturing sector at 18.34% and the wholesale and retail trade sector at 12.85%. One of the key sub-sectors within agriculture is the plantation sub-sector, which contributed 3.76% to the total GDP and 30.32% to the agriculture, forestry, and fisheries sector, making it the largest contributor within this category (BPS, 2023).

Crude Palm Oil (CPO) is one of the most important commodities produced by the plantation sub-sector due to its significant role in the economy and its wide industrial applications (Purnomo et al. 2020; Syahza 2019). Its high oxidation stability under pressure, ability to dissolve chemicals that are insoluble in other solvents, and superior coating ability make palm oil versatile for various uses, including cooking oil, industrial oil, and biodiesel fuel (Cong and Loh, 2023; Wibowo, 2023). In terms of production, CPO in Indonesia is produced by three entities: government enterprises, private sector enterprises, and smallholders. Based on these producer categories, Table 1 shows the total production volume of CPO in Indonesia from 2018 to 2022.

Table 1. CPO Production Volume by Producer Categories, 2018–2022
Tabel 1. Volume Produksi CPO menurut Kategori Produsen, 2018–2022

Year	CPO Production by Category of Producers			Total CPO Production	% Changes in Production
	Government (mt)	Private Sector (mt)	Smallholder (mt)	(mt)	(y.o.y.)
2018	2,147,136	25,439,694	15,296,801	42,883,631	
2019	2,134,367	30,060,003	14,925,877	47,120,247	9.88%
2020	2,310,612	27,935,806	15,495,427	45,741,845	-2.93%
2021	2,256,134	27,361,506	15,503,840	45,121,480	-1.36%
2022	2,295,975	28,213,089	16,310,607	46,819,672	3.76%

Source: BPS (2023)
Sumber: BPS (2023)

Visually, the production volume of Indonesia's CPO from 2018 to 2022, categorized by producer, is presented in Figure 1.

In terms of volume, palm oil exports from 2018 to 2019 tended to increase. However, from 2020 to 2022, palm oil export volumes experienced a decline. The largest decline occurred in 2020, with export volumes reaching 25.94 million metric tons, a decrease of 8.29% compared to 2019. Despite the drop in export volumes, this decline was not reflected in the export value of palm oil, which tended to increase in 2020. This was due to the rise in the average price of Indonesian CPO, from USD 520/mt to USD 670/mt in 2020. This unit price continued to rise, reaching its highest point in 2022 at USD 1,110/mt. The consistent price increase since 2020 led to a significant rise in export value, despite the decline in export volume. The largest price surge occurred in 2021, with an increase of 55.95% compared to 2020. This sharp rise also led to a parallel increase in Indonesia's total CPO export value, which grew by 54.08% compared to 2020. In 2022, the value of Indonesia's CPO exports reached its highest level at USD 27.74 billion, marking a slight increase of 3.68% compared to 2021 (BPS, 2023).

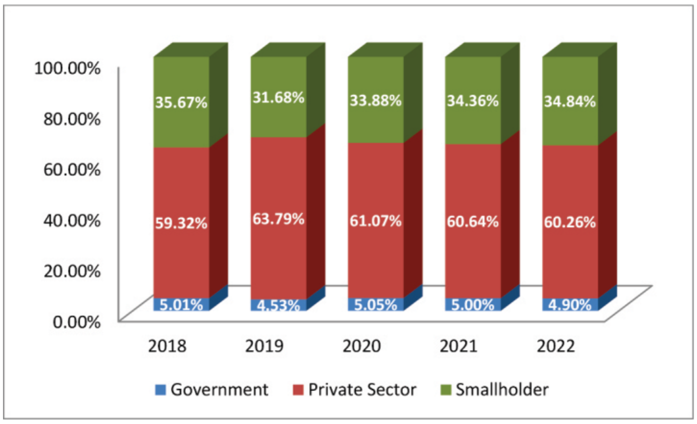

Figure 1. Indonesia's CPO Production in Volume, 2018-2022
Gambar 1. Produksi Minyak CPO Indonesia dalam Volume, 2018-2022

Table 2. Export Volume and Value of Indonesian CPO, 2018–2022
Tabel 2. Volume dan Nilai Ekspor Minyak CPO Indonesia, 2018–2022

Year	Export Volume (mt)	Export Value (thousand US$)	% Changes in Volume (y.o.y.)	% Changes in Value (y.o.y.)	Average Unit Price (US$/mt)	% Changes in Unit Price (y.o.y.)
2018	27,898,875	16,530,212	-	-	593	-
2019	28,279,350	14,716,275	1.36%	-10.97%	520	-12.17%
2020	25,935,257	17,363,921	-8.29%	17.99%	670	28.66%
2021	25,624,258	26,755,136	-1.20%	54.08%	1,044	55.95%
2022	24,989,929	27,738,517	-2.48%	3.68%	1,110	6.31%

Source: BPS (2023)
Sumber: BPS (2023)

The majority of Indonesia's palm oil production is exported overseas, with the remainder marketed domestically. Indonesian palm oil exports reach five continents: Asia, Africa, Australia, the Americas, and Europe, with Asia being the primary market (Azahari *et al*. 2024; Bogheiry *et al*. 2023; Ulfah *et al*. 2019). In 2022, the top five importers of Indonesian CPO were India, Italy, Malaysia, Kenya, and the Netherlands. Exports to these five countries accounted for 95.38% of Indonesia's total CPO exports. India was the largest export destination, with a volume of 2.88 million metric tons, representing 83.45% of Indonesia's total CPO export volume, valued at USD 2.85 billion (BPS, 2023).

As shown in Figure 2, the majority of national CPO production is carried out by the private sector. Smallholder palm oil plantations are largely managed by private companies, either through purchasing smallholder harvests or utilizing a cooperative management model. Therefore, the performance of these private sector companies can be used to predict the contribution of palm oil trade to the national GDP. Companies with higher efficiency in managing inputs to produce optimal production outputs will achieve better performance. Given the critical contributions of private sector companies to

Indonesia's CPO trade, this study aims to analyze the efficiency of palm oil companies listed on the Indonesian Stock Exchange (IDX) by using financial variables that reflect their main operational activities. The efficiency scores obtained will demonstrate whether this measurement is sufficiently relevant to predict the cumulative role of the palm oil plantation sub-sector in supporting economic growth.

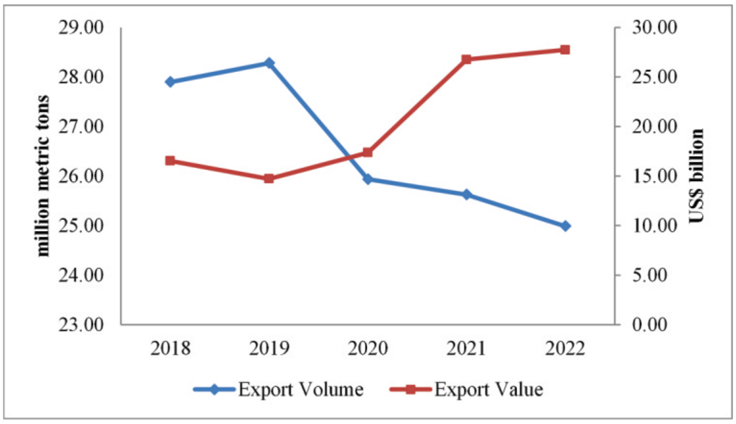

Figure 2. Indonesia's CPO Production in Volume, 2018-2022
Gambar 2. Produksi Minyak CPO Indonesia dalam Volume, 2018-2022

To enhance the significance of the research, several explanatory variables, including company size, beta (systematic risk), and ESG ratings (rated or unrated), are added as predictors to estimate efficiency scores as the outcomes or dependent variables. ESG ratings serve as a variable to categorize whether a company has standardized ESG procedures and is certified, with ESG scores published on the IDX website. As no previous studies have closely resembled this research, it is expected to offer academic novelty and benefit regulators and policymakers by providing insights to create a more supportive business climate, particularly for palm oil farmers and industries in Indonesia.

METHODOLOGY

A total of 20 palm oil companies listed on the IDX are selected as the research population for this study. This group represents the entire sample, with all companies engaged in palm oil cultivation and related industries as their main business activities. The research population, sorted alphabetically by the IDX four-letter company codes, includes: AALI, ANDI, ANJT, BWPT, CSRA, DSNG, FAPA, GZCO, JAWA, LSIP, MGRO, PGUN, PSGO, SGRO, SIMP, SMAR, SSMS, TAPG, TBLA, and UNSP.

The analysis uses secondary data for both the efficiency score measurement in the first stage and linear regression in the second stage. The secondary data come from annual financial reports (Q4) and annual reports of the selected palm oil companies listed on the IDX (https://www.idx.co.id/), as well as from Yahoo Finance (https://finance.yahoo.com/) for daily stock price changes of each listed company, which are used to calculate the beta in comparison with the market portfolio, the Jakarta Stock Exchange (JKSE).

The first stage of this study measures the efficiency score of each listed company, referred to as the Decision Making Unit (DMU), using the non-parametric Data Envelopment Analysis (DEA) method. Efficiency scores are calculated using various input and output variables from the annual financial reports. Input variables represent costs incurred to produce goods or services, with lower values being preferable for achieving a given level of output. Conversely, output variables represent benefits gained from company activities, with higher values being preferable for a given level of input (Coelli *et al*., 2005; Cooper *et al*., 2007; Wybawa *et al*., 2023). DEA is particularly preferred over other methods for analyzing efficiency because it can simultaneously incorporate multiple input and output variables. Both input and output variables are selected based on previous research on efficiency across industries such as banking, manufacturing, healthcare, and tourism (Soetanto *et al*., 2014; Siew *et al*., 2018; Zhang and Zhang, 2018; Wybawa *et al*., 2023).

The input variables (x) consist of four components: COGS (Cost of Goods Sold), Operating Cost, Finance Cost, and PPE (Plant, Property, Equipment). On the other hand, the output variables (y) include Operating Revenue, Finance Income, and Net Income. Each variable for efficiency measurement is selected based on the financial report nomenclature established by the IDX. COGS includes all direct and indirect expenses incurred to run the main business activities and produce goods or services. Operating Cost is the sum of marketing, promotion, and general administrative expenses. Finance Cost consists of interest expenses from bank loans and other liabilities, as well as bank provisions and administrative costs. Operating Revenue reflects the total income generated from core business activities, while other income unrelated to the main operations is separately reported in the company's income statement. Finance Income is derived from interest on demand deposits and fixed-term deposits. Net Income represents the earnings remaining after all operating and non-operating expenses, such as taxes, interest, and depreciation, have been deducted.

Data Envelopment Analysis (DEA) was first introduced by Charnes, Cooper, and Rhodes in 1978 (Charnes *et al*., 1978). The core idea of this method is to create a benchmark, known as the frontier production line, from the efficient DMUs (Decision Making Units), which serve as a reference for projecting inefficient DMUs. This study assumes that all DMUs operate at their ideal scale of operation, which is why the Constant Return-to-Scale (CRS) model is selected, focusing on input reduction while maintaining a given level of output (Cooper *et al*. 2007; Rabar 2017). The selection of this model is particularly relevant due to the onset of the COVID-19 pandemic in 2020, during which most companies were only permitted to carry out limited production activities by implementing the "new normal" with social distancing protocols.

Alternatively, other researchers may incorporate scale efficiency measurement to determine whether a company is operating at constant return-to-scale (scale efficiency score = 1), or whether it is under increasing (IRS) or decreasing return-to-scale (DRS), where the scale efficiency score is less than 1. Under IRS, a company can increase its production scale to maximize output, whereas DRS requires a company to downsize its operations. In DRS, any additional cost results in proportionally less revenue, leading to significant financial losses. The model that includes scale efficiency measurement is known as Variable Return-to-Scale (VRS), which was first popularized by Banker, Charnes, and Cooper in 1984 (Banker et al., 1984).

The general equation and constraints of DEA CRS input-oriented are expressed in the Equation (1). Where n represents the total number of DMUs producing m inputs. The output r is denoted as y_r, while the input i is represented as x_i. The λ_j are the weights applied across the n samples. The efficiency score is denoted by θ. To calculate the complete set of efficiency scores, each sample must satisfy the specified constraints.

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

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

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

$$\lambda_j, s_i^-, s_r^+ \geq 0, \qquad j = 1,\dots,n \tag{1}$$

The second stage of analysis uses the bias-corrected efficiency scores obtained from the bootstrap procedure in the first stage, which was performed with 2,000 iterations, and estimates the regression model using ordinary least squares (OLS). Since DEA is a non-parametric method, the results may still contain bias that could affect the accuracy of linear regression analysis. Therefore, bias correction is essential, producing a new value known as the bias-corrected efficiency score (BCES) (Simar & Wilson, 2007). This BCES is then used as the dependent variable and estimated against predictors such as company size, beta (volatility or systematic risk), and ESG rating.

Company size is calculated using the natural logarithm of total assets, while the beta coefficient measures the expected movement of a stock relative to the overall market (Wybawa *et al.*, 2023). ESG rating is treated as a dummy variable, indicating whether a company is ESG-rated or ESG-unrated, to reflect its standardization and certification in ESG practices. To date, only 9 out of the 20 listed companies in the palm oil industry have been rated for their ESG practices. These companies include AALI, ANJT, CPIN, DSNG, JPFA, LSIP, SSMS, TAPG, and TBLA. Equation (2) shows the linear relationship between the reciprocal-BCES and its various predictors. The reciprocal or inverse score is chosen over the original value to simplify calculations, as it has an unlimited range [1, ∞] and is left-truncated at 1 (Badunenko & Tauchmann, 2018; Simar & Wilson, 2007).

$$Reciprocal\_BCES_{it} = \beta_0 + \beta_1 \ln(Asset)_{it} + \beta_2 Beta_{it} + \beta_3 ESG\_Rating_i + \beta_5 Year_{t,1} + \beta_6 Year_{t,2} + \beta_7 Year_{t,3} + \beta_8 Year_{t,4} + \varepsilon_{it}$$

Where Reciprocal-BCES is the dependent variable, influenced by several predictors or explanatory variables (x_i): Ln(Asset), representing company size through the natural logarithm of total assets; Beta, which captures stock volatility relative to the market; and ESG Rating, a dummy variable (1 for ESG-rated companies and 0 for non-rated companies), reflecting the presence of standardized ESG practices. Additionally, Year (Year2019 to Year2024) is included as a set of dummy variables to account for time-specific effects, such as the impact of the COVID-19 pandemic. In Equation (2), Year2019 is chosen as the reference category for the other year variables. The intercept represents the baseline Reciprocal-BCES, and the error term accounts for unexplained variability.

RESULTS

This study includes a total of 120 observations, generated from 20 DMUs over a 6-year research period. Table 3 presents the descriptive statistics of all research variables (x_i, y_i, z_i), which are on a ratio scale, provided for each year of the study. The descriptive parameters include the maximum value, minimum value, median, and standard deviation. Normality tests for each variable were conducted using the Shapiro-Wilk test, indicating that none of the data groups follow a normal distribution, as shown by p-values less than 0.05 at a 95% confidence interval. As a non-parametric method, DEA does not require normal distribution or correlation among variables (Cooper *et al.*, 2007).

The efficiency score for each DMU in each year is calculated using DEA tools run through the R-package with R-Studio as the interface. The analysis is conducted on a yearly basis, resulting in the construction of six frontier production lines, which serve as the most efficient references (θ =1) for the other inefficient DMUs in each respective research year. Using the same statistical software, a bootstrap mechanism and OLS regression are performed. Table 4 presents both the deterministic and bias-corrected efficiency scores for all 20 DMUs, arranged randomly.

Visually, the year-to-year changes in both the average deterministic efficiency scores, obtained from the conventional DEA measurement, and the bias-corrected efficiency scores, derived from the bootstrap technique, are displayed in Figure 3. Since 2019, the average efficiency scores of palm oil listed companies have shown an overall upward trend, despite the global COVID-19 pandemic in 2020. The graph roughly indicates that the increase in efficiency scores in 2022 and 2023 was faster compared to 2020 and 2021, a period marked by the global adaptation to the new normal (Mena et al., 2022; Hayakawa & Mukunoki, 2021). Although the average efficiency scores moderated slightly in 2024 compared to 2023, both deterministic and bias-corrected scores remained above their levels in 2019–2021. Over the 6-year research period, the highest average efficiency score was achieved in 2023, demonstrating the sector's resilience in facing uncertain global market conditions.

Table 3. Descriptive Statistics of Research Variables
Tabel 3. Statistik Deskriptif Variabel Penelitian

Year	Parameter	Input Variables (million IDR)				Output Variables (million IDR)			Explanatory Variables	
		COGS	OpCost	FinCost	PPE	OpRev	FinInc	NetInc	Ln(Ast)	β
2019	Max	32,285,538	2,838,008	911,984	20,342,294	36,198,102	239,147	898,698	31.18	0.98
	Min	161,538	23,318	597	151,488	229,249	174	-4,893,138	26.91	-0.12
	Median	2,163,294	400,338	237,737	2,502,215	2,315,763	6,730	12,287	29.84	0.27
	Std.Dev.	7,367,684	638,873	281,807	4,873,307	8,324,234	60,213	1,143,337	1.13	0.36
2020	Max	34,557,130	3,554,189	907,156	20,397,323	40,434,346	324,855	1,539,798	31.20	1.69
	Min	217,871	38,557	585	214,581	260,214	105	-1,108,389	26.90	0.00
	Median	2,217,988	332,776	254,936	2,621,728	3,059,782	8,934	28,842	29.87	0.47
	Std.Dev.	7,825,079	764,360	291,038	4,840,425	9,211,336	81,027	611,706	1.14	0.56
2021	Max	46,047,334	7,074,950	1,110,570	19,613,531	57,004,234	576,156	2,829,418	31.33	1.42
	Min	308,195	35,015	441	212,282	346,365	73	-1,417,294	26.90	-0.07
	Median	2,852,464	409,801	217,456	2,589,492	4,248,294	5,771	464,788	29.88	0.69
	Std.Dev.	10,354,353	1,497,300	300,731	4,692,728	12,799,941	130,929	884,456	1.13	0.45
2022	Max	61,733,885	6,710,789	1,341,133	19,435,518	75,045,559	119,439	5,504,956	31.38	1.38
	Min	295,077	27,344	676	231,039	317,856	50	-301,813	26.82	-0.30
	Median	3,473,058	375,097	210,938	2,700,132	4,706,991	7,531	775,375	29.92	0.47
	Std.Dev.	13,224,918	1,433,031	360,020	4,681,227	16,039,561	35,710	1,309,159	1.13	0.39
2023	Max	59,769,661	5,277,816	1,270,476	18,912,273	66,530,549	174,277	1,661,258	31.31	1.31
	Min	219,719	57,298	566	107,881	219,942	30	-303,853	26.66	0.00
	Median	3,726,721	376,040	197,204	2,698,391	4,633,428	13,439	301,229	29.92	0.44
	Std.Dev.	12,815,879	1,138,374	357,737	4,754,508	14,297,296	51,296	486,780	1.14	0.37
2024	Max	70,821,390	5,988,902	1,198,518	17,794,236	78,835,443	234,936	3,240,599	31.45	1.77
	Min	208,703	22,746	653	207,652	196,742	53	-193,730	26.58	-0.71
	Median	3,570,929	361,704	203,380	2,965,187	4,624,126	16,399	461,051	29.88	0.36
	Std.Dev.	12,815,879	1,138,374	357,737	4,754,508	14,297,296	51,296	486,780	1.14	0.37

Notes: COGS refers to Cost of Goods Sold (x_1); OpCost refers to Operating Cost (x_2); FinCost refers to Finance Cost (x_3); PPE refers to Plant, Property, and Equipment (x_4); OpRev refers to Operating Revenue (y_1); FinInc refers to Finance Income (y_2); NetInc refers to Net Income (y_3); Ln(Ast) refers to Ln(Total Asset) (z_1); and β refers to Beta (z_2). To eliminate the effect of exchange rate fluctuations in the efficiency analysis, all monetary values are presented in Indonesian Rupiah (IDR).

Catatan: COGS mengacu pada Harga Pokok Penjualan (x_1); OpCost mengacu pada Biaya Operasional (x_2); FinCost mengacu pada Biaya keuangan (x_3); PPE mengacu pada Tanaman, Properti, dan Peralatan (x_4); OpRev mengacu pada Pendapatan Operasional (y_1); FinInc mengacu pada Pendapatan Keuangan (y_2); NetInc mengacu pada Laba Bersih (y_3); Ln(Ast) mengacu pada Ln(Aset Total) (z_1); dan β mengacu pada Beta (z_2) Untuk menghilangkan pengaruh fluktuasi nilai tukar dalam analisis efisiensi, semua nilai moneter disajikan dalam Rupiah Indonesia (IDR).

Table 4. Descriptive Statistics of Research Variables
Tabel 4. Statistik Deskriptif Variabel Penelitian

DMU	Deterministic Efficiency Score						Bias-Corrected Efficiency Score					
	2019	2020	2021	2022	2023	2024	2019	2020	2021	2022	2023	2024
1	1.000	1.000	1.000	1.000	1.000	0.962	0.967	0.967	0.931	0.957	0.966	0.930
2	1.000	1.000	1.000	1.000	1.000	1.000	0.920	0.931	0.930	0.946	0.965	0.940
3	1.000	0.960	1.000	1.000	0.910	0.861	0.968	0.934	0.963	0.954	0.895	0.840
4	0.704	0.696	0.747	0.843	0.970	0.925	0.694	0.687	0.735	0.835	0.962	0.907
5	1.000	1.000	1.000	1.000	1.000	0.948	0.954	0.944	0.933	0.942	0.967	0.921
6	1.000	0.947	0.835	0.884	0.949	0.862	0.971	0.934	0.819	0.871	0.939	0.839
7	0.781	0.860	0.876	1.000	0.899	0.927	0.767	0.848	0.857	0.981	0.885	0.902
8	0.566	0.703	0.859	0.916	0.964	0.798	0.552	0.680	0.834	0.897	0.949	0.775
9	0.832	0.828	1.000	0.924	1.000	0.997	0.813	0.810	0.968	0.909	0.963	0.966
10	1.000	1.000	1.000	1.000	1.000	1.000	0.924	0.927	0.928	0.947	0.966	0.941
11	1.000	1.000	1.000	1.000	1.000	1.000	0.924	0.928	0.931	0.948	0.964	0.941
12	1.000	1.000	0.928	1.000	1.000	0.990	0.928	0.930	0.910	0.983	0.965	0.958
13	0.842	0.931	0.932	0.847	1.000	1.000	0.825	0.913	0.909	0.832	0.963	0.940
14	0.980	0.979	1.000	1.000	1.000	1.000	0.968	0.963	0.944	0.950	0.969	0.959
15	0.925	0.908	0.857	0.931	0.921	0.870	0.912	0.890	0.834	0.917	0.909	0.843
16	1.000	1.000	1.000	1.000	1.000	1.000	0.926	0.952	0.970	0.957	0.967	0.939
17	1.000	1.000	1.000	1.000	1.000	1.000	0.918	0.928	0.932	0.955	0.965	0.952
18	0.988	1.000	0.962	1.000	1.000	1.000	0.962	0.976	0.941	0.950	0.965	0.939
19	1.000	1.000	0.872	0.879	0.947	1.000	0.964	0.976	0.847	0.864	0.934	0.955
20	0.782	0.739	0.756	0.752	0.813	0.814	0.775	0.723	0.738	0.735	0.802	0.796
Mean	**0.920**	**0.928**	**0.931**	**0.949**	**0.969**	**0.948**	**0.881**	**0.892**	**0.893**	**0.916**	**0.943**	**0.909**

Using the bias-corrected efficiency scores obtained from the bootstrap procedure, an ordinary least squares (OLS) regression model is estimated to examine the effects of the explanatory variables. The bias-corrected efficiency score (BCES), serving as the dependent variable, is taken from the previous measurement shown in Table 3. To extend the data range from [1, ∞] instead of [0, 1], the reciprocal version of BCES (RBCES) is generated, where values closer to one indicate greater efficiency. The OLS regression model is estimated in R, and the results are presented in Table 5.

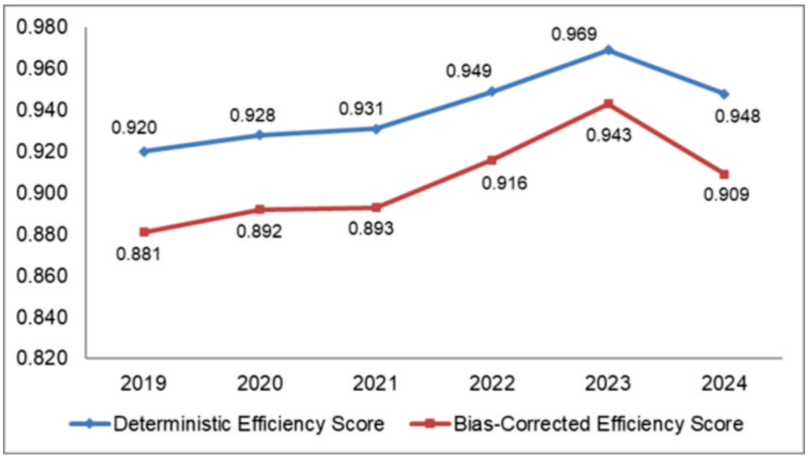

Figure 3. Year-to-Year Changes in Deterministic and Bias-Corrected Average Efficiency Scores
Gambar 3. Perubahan Tahunan Skor Efisiensi Rata-Rata Deterministik dan Terkoreksi Bias

Table 5. Estimated Coefficients and p-Values from the Linear Regression
Tabel 5. Koefisien Estimasi dan p-Value dari Regresi Linier

Predictor	Estimate	Std. Error	t-value	p-value	
(Intercept)	1.174	0.313	3.757	0.000	***
Ln(Asset)	0.000	0.011	-0.012	0.991	
Beta	0.055	0.026	2.100	0.038	*
ESG-rated	-0.072	0.025	-2.870	0.005	**
Year2020	-0.041	0.041	-0.998	0.321	
Year2021	-0.052	0.039	-1.323	0.189	
Year2022	-0.075	0.039	-1.950	0.054	.
Year2023	-0.111	0.039	-2.857	0.005	**
Year2024	-0.064	0.039	-1.662	0.100	.
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1					

Notes: The OLS regression model yields a residual standard error of 0.113 on 103 degrees of freedom, a multiple R-squared of 0.170, an adjusted R-squared of 0.105, and an F-statistic of 2.630 on 8 and 103 degrees of freedom, with an overall model p-value of 0.012. The reference categories for the dummy variables are ESG-unrated and Year2019.

Catatan: Model regresi OLS menghasilkan *residual standard error* sebesar 0,113 dengan 103 derajat kebebasan, *multiple R-squared* sebesar 0,170, *adjusted R-squared* sebesar 0,105, serta *F-statistic* sebesar 2,630 dengan 8 dan 103 derajat kebebasan, dengan *p-value* model secara keseluruhan sebesar 0,012. Kategori referensi untuk variabel *dummy* adalah *ESG-unrated* dan *Year2019*.

The predictors in this model are used to estimate the reciprocal bias-corrected efficiency scores (RBCES), where a lower RBCES value indicates greater company efficiency. The natural logarithm of assets (Ln(Asset)), representing company size, has a p-value of 0.991, indicating that company size does not significantly estimate efficiency. Beta, which measures stock volatility, is significant at the 5% level with a p-value of 0.038. The positive coefficient for Beta suggests that higher volatility makes companies less efficient, meaning as Beta increases, efficiency decreases.

The years are represented as dummy variables, with Year2019 as the reference. Both Year2020 and Year2021 show insignificant p-values, meaning efficiency in these years is not significantly different from 2019. Year2022 and Year2024 show marginal significance at the 10% level, suggesting some improvement in efficiency compared to 2019, although they are not statistically significant at the 5% level. The highest efficiency is observed in Year2023, with significance at the 1% level, showing that 2023 was significantly more efficient than 2019. ESG ratings, represented as a dummy variable with ESG-unrated as the reference, are significant at the 1% level. The negative coefficient for ESG-rated companies indicates that those with standardized ESG certifications are more efficient than their unrated counterparts.

DISCUSSION

Indonesia's palm oil industry plays a critical role in the Indonesian economy through exports, foreign exchange earnings, employment, and rural development. From 2018 to 2024, exports accounted for approximately 48% to 65% of total national production annually, showing the industry's strong dependence on international markets (BPS, 2025b). This export orientation helps explain why firm efficiency was closely linked to external demand and global commodity-price dynamics. When prices and demand were favorable, listed palm oil firms were better able to translate relatively stable input use into stronger revenue and profit outcomes. This pattern is important for interpreting the efficiency scores in this study, because the performance of listed palm oil companies cannot be separated from the sector's role as an export-driven commodity industry.

The resilience of the industry became especially visible during the COVID-19 pandemic in 2020 and 2021 (Annas & Izaati, 2022). Although national production declined slightly in 2020, the sector still generated higher revenues than in 2019 because global crude palm oil prices increased sharply. In 2020, CPO prices rose by 28.7% compared with the previous year, and in 2021 they increased again by about 56%, surpassing USD 1,000 per metric ton (BPS, 2025b, Wibowo *et al*., 2023). High prices were also maintained through 2022, supporting the industry while production gradually recovered toward pre-pandemic levels (Annas & Izaati, 2022; Kiyota, 2022). Because operating revenue is one of the DEA output variables, this price effect helps explain why efficiency improved during the pandemic and recovery years despite broader macroeconomic disruption.

The efficiency pattern across years is therefore economically intuitive. Higher export revenues increased output relative to inputs, especially when production and operating costs did not rise proportionately. This helps explain why efficiency scores strengthened in 2020 and 2021 and improved further in 2022 and 2023. Although the average score moderated slightly in 2024 compared with the 2023 peak, it still remained above the levels observed in 2019–2021. Another supporting factor was the global shortage of sunflower oil following the Russia–Ukraine war. Because sunflower oil is an important substitute for palm oil, the disruption shifted part of global vegetable-oil demand toward palm oil and strengthened export opportunities for producers in Indonesia (Ben Hassen & El Bilali, 2022; Wibowo *et al*., 2023).

The negative coefficient of Beta is another important result. In this study, higher stock-market volatility was associated with lower efficiency, implying that firms facing greater systematic risk were less able to convert inputs into favorable operating outcomes. This relationship is plausible during crisis conditions. Higher Beta reflects greater exposure to market uncertainty, financing pressure, and unstable investor expectations, all of which can complicate operating decisions and resource allocation (Shankar *et al*., 2021). During the pandemic, firms with more volatile market profiles were likely to preserve liquidity, postpone commitments, and adopt more defensive strategies. Such responses may be rational under uncertainty, but they can also reduce operational flexibility and weaken efficiency when revenue growth does not fully offset the cost of caution (Ortmann *et al*., 2020).

This interpretation is broadly supported by earlier empirical findings. Arora *et al.* (2019) provide partial support by showing that asset turnover, as a proxy for operating efficiency, can have a negative link with systematic risk under pooled estimation. More directly, Hadianto *et al.* (2023) found that efficiency and profitability ratios negatively influenced systematic risk in Indonesian listed firms. Similarly, Topalo lu and Abasız (2026) reported that return on assets had a negative effect on the beta coefficient in the Turkish industrial sector. Collectively, these studies support the view that stronger internal performance and more efficient asset use are generally associated with lower market risk, while elevated Beta is more consistent with financing pressure and weaker operating discipline. In the present study, this helps explain why more stable firms were better positioned to maintain efficient operations (Ramelli & Wagner, 2020; Zhang *et al.*, 2020).

Environmental, Social, and Governance (ESG) practices also played a critical role in shaping efficiency. ESG-rated firms consistently showed higher efficiency than ESG-unrated firms, indicating that standardized sustainability practices were associated with stronger resource management, better governance, and greater resilience during both the pandemic and recovery periods. This result is consistent with the argument that ESG enhances operational stability by improving governance structures, risk management, and supply-chain practices (Callista *et al*., 2024; Prell *et al*., 2020; Suhardjo *et al*., 2024; Tey & Brindal, 2021). It also aligns with prior evidence showing that ESG can strengthen operational and financial outcomes. Chung et al. (2024) found that ESG investment improved hotels' operational efficiency, especially around crisis conditions. Lu et al. (2025) showed that ESG practices enhanced firm efficiency in the global tourism and hospitality industry. This result implies that ESG adoption may strengthen managerial discipline and operating quality, which can ultimately support better revenue generation and profitability. Chen et al. (2023) found that stronger ESG performance was associated with better corporate financial performance, especially in higher-risk settings.

The resilience of ESG-rated firms in this study can therefore be interpreted as both an operational and a strategic advantage. Companies with stronger ESG frameworks tend to be more transparent, more responsive to stakeholders, and more focused on long-term value creation rather than short-term gains (Chong & Loh, 2023). During the post-pandemic period in 2022 and 2023, ESG-rated palm oil companies continued to demonstrate superior efficiency, and this pattern remained visible in 2024 despite the slight moderation in the industry average. Their ability to attract more sustainable capital, manage risk more effectively, and maintain stakeholder confidence likely reinforced this advantage (Lins *et al*., 2017; Serafeim & Yoon, 2022). ESG practices may also provide firms with a more disciplined framework for resource use, governance, and crisis response, which helps translate sustainability commitments into stronger operational outcomes (Attanasio *et al*., 2022; Bellucci *et al*., 2019; Cubilla-Montilla *et al*., 2019; Prasetyani *et al*., 2024; Shahimi *et al*., 2023).

CONCLUSION

This study examines the effects of company size, Beta, and ESG ratings on the efficiency of palm oil companies listed on the Indonesia Stock Exchange during 2019–2024. The results show that company size does not significantly affect efficiency, while market-related and sustainability-related factors play a more important role in explaining differences in firm performance. The efficiency trend also indicates that listed palm oil companies were able to maintain relatively strong performance during and after the crisis period, with further improvement observed in the post-pandemic years.

A key finding of this study is that stock market volatility, as measured by Beta, negatively affected efficiency, indicating that companies with greater market risk tended to be less efficient during uncertain periods. This underscores the importance of risk management in maintaining operational performance. The study also shows that ESG-rated companies were more resilient and efficient than non-rated firms, suggesting that stronger sustainability and governance practices contribute to better operational outcomes. Overall, these results indicate that efficiency in the listed palm oil industry depends less on firm size than on market stability and stronger ESG integration.

These findings have important implications for practice and policy. For companies, the results highlight the importance of strengthening risk management and ESG implementation as part of long-term efficiency improvement. For investors and policymakers, the findings suggest that encouraging ESG adoption and better corporate risk management may help improve the resilience and sustainability of the palm oil sector. Nevertheless, this study has several limitations. The analysis is limited to palm oil companies listed on the Indonesia Stock Exchange, so the findings may not fully represent the broader palm oil industry in Indonesia, particularly unlisted firms and independent smallholders. In addition, the analysis mainly reflects the upstream and export-oriented segment and therefore does not yet capture efficiency dynamics across the full palm oil value chain. Future research is needed to include a wider range of industry actors and to examine how efficiency and resilience differ across upstream, downstream, and smallholder segments.

REFERENCE

Anam, M. K., & Suhartini, S. (2020). Efficiency of palm oil companies in Indonesia: A DEA approach. *HABITAT, 31*(2), 55–63. https://doi.org/10.21776/ub.habitat.2020.031.2.7

Annas, A., & Izaati, I. N. (2022). Pandemic COVID-19 impact on Indonesian palm oil trade. *Int. J. Prog. Sci. Technol., 35*(1), 81-86.

Arora, L., Kumar, S., & Goel, U. (2019). *Firm performance and systematic risk*. In *Proc. 2nd Int. Conf. Bus. Manag. Econ* (pp. 63–79). https://doi.org/10.33422/2nd.icbmeconf.2019.06.1025

Attanasio, G., Preghenella, N., De Toni, A. F., & Battistella, C. (2022). Stakeholder engagement in business models for sustainability: The stakeholder value flow model for sustainable development. *Bus. Strat. Environ., 31*, 860-874. https://doi.org/10.1002/bse.2922

Azahari, D. H., Dian, D. L., Amalia, R., & Kusumawardhana, R. (2024). Strategy for increasing exports of Indonesian palm oil. IOP Conf. *Ser.: Earth Environ. Sci., 1379*(1), 012026. https://doi.org/10.1088/1755-1315/1379/1/012026

Badunenko, O., & Tauchmann, H. (2018). Simar and Wilson two-stage efficiency analysis for Stata. *FAU Disc. Pap. Econ., No. 08/2018*, Friedrich-Alexander-Universität Erlangen-Nürnberg, Institute for Economics.

Bancin, H. D., Dolorosa, E., & Yurisintha, E. (2022). The impact of COVID-19 pandemic on palm oil companies stock in Indonesia. *Jurnal Manajemen & Agribisnis, 19*(1), 1–10. https://doi.org/10.17358/jma.19.1.108

Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Manage. Sci., 30*(9), 1078-1092. https://doi.org/10.1287/mnsc.30.9.1078

Bellucci, M., Simoni, L., Acuti, D., & Manetti, G. (2019). Stakeholder engagement and dialogic accounting: Empirical evidence in sustainability reporting. *Account. Audit. Accountability J., 32*, 1467-1499. https://doi.org/10.1108/AAAJ-09-2017-3158

Ben Hassen, T., & El Bilali, H. (2022). Impacts of the Russia-Ukraine war on global food security: Towards more sustainable and resilient food systems? *Foods, 11*(15), 2301. https://doi.org/10.3390/foods11152301

Bogheiry, A., Thaha, M., & Rahmah, L. (2023). Global dependence analysis on Indonesian palm oil production and its effect on environmental security using the Copenhagen school approach. *J. World Sci., 2*(3), 466-482. https://doi.org/10.58344/jws.v2i3.243

BPS. (2025a). *Produk domestik bruto Indonesia triwulanan 2021–2025* (Vol. 8). Badan Pusat Statistik.

BPS. (2025b). *Statistik tanaman perkebunan tahunan Indonesia 2024 (kelapa sawit, kopi, kakao, karet, teh, dan komoditas perkebunan unggulan)* (Vol. 1). Badan Pusat Statistik.

Callista, F. L., Marcello, N., & Andrian, T. (2024). Bridging ESG disclosures and corporate financial performance: A study on top-listed companies of the ASEAN-5 countries. *Int. J. Sustain. Policy Pract., 20*(2), 1-26. https://doi.org/10.18848/2325-

1166/CGP/v20i02/1-26

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *Eur. J. Oper. Res., 2*(6), 429-444. https://doi.org/10.1016/0377-2217(78)90138-8

Chen, S., Song, Y., & Gao, P. (2023). Environmental, social, and governance (ESG) performance and financial outcomes: Analyzing the impact of ESG on financial performance. *J. Environ. Manag., 345*, 118829. https://doi.org/10.1016/j.jenvman.2023.118829

Chong, T., & Loh, L. (2023). Innovating ESG integration as sustainable strategy: ESG transparency and firm valuation in the palm oil sector. *Sustainability, 15*(22), 15943. https://doi.org/10.3390/su152215943

Chung, K., Nguyen, L. T. M., & Nguyen, D. T. T. (2023). Improving hotels' operational efficiency through ESG investment: A risk management perspective. *Serv. Sci., 16*(3), 172–183. https://doi.org/10.1287/serv.2023.0080

Coelli, T. J., Rao, D. S. P., O'Donnell, C. J., & Battese, G. E. (2005). *An introduction to efficiency and productivity analysis*. Springer.

Cooper, W. W., Seiford, L. M., & Tone, K. (2007). *Data envelopment analysis: A comprehensive text with models, applications, references and DEA-solver software*. Springer. https://doi.org/10.1007/978-0-387-45283-8

Cubilla-Montilla, M., Nieto-Librero, A.-B., Galindo-Villardón, M. P., & Garcia-Sanchez, I.-M. (2019). Are cultural values sufficient to improve stakeholder engagement human and labor rights issues? *Corp. Soc. Responsibility Environ. Manage., 26*, 938-955. https://doi.org/10.1002/csr.1733

Hadianto, B., Herlina, H., & Njotoprajitno, R. S. (2023). Debt policy, efficiency ratio, profitability, and systematic risk: Evidence from Indonesia. *Owner: Riset dan Jurnal Akuntansi, 7*(3), 2683–2690. https://doi.org/10.33395/owner.v7i3.1690

Hayakawa, K., & Mukunoki, H. (2021). The impact of COVID-19 on international trade: Evidence from the first shock. *J. Jpn. Int. Econ., 60*, 101135. https://doi.org/10.1016/j.jjie.2021.101135

Kiyota, K. (2022). The COVID-19 pandemic and the world trade network. *J. Asian Econ., 78*, 101419. https://doi.org/10.1016/j.asieco.2021.101419

Lins, K. V., Servaes, H., & Tamayo, A. (2017). Social capital, trust, and firm performance: The value of corporate social responsibility during the financial crisis. *J. Finance, 72*(4), 1785–1824. https://doi.org/10.1111/jofi.12505

Lu, W.-M., Ting, I. W. K., & Huang, S.-H. (2025). Environmental, social and governance (ESG) initiatives and firm efficiency in the global tourism and hospitality industry: The role of business strategy. *Asian Acad. Manag. J. Account. Finance, 21*(1), 275–312. https://doi.org/10.21315/aamjaf2025.21.1.10

Mena, C., Karatzas, A., & Hansen, C. (2022). International trade resilience and the COVID-19 pandemic. *J. Bus. Res., 138*, 77–91. https://doi.org/10.1016/j.jbusres.2021.08.064

Ortmann, R., Pelster, M., & Wengerek, S. T. (2020). COVID-19 and investor behavior. *Finance Res. Lett., 37*, 101717. https://doi.org/10.1016/j.frl.2020.101717

Prasetyani, D., Gravitiani, E., Cahyadin, M., Juwita, A. H., & Bintariningtyas, S. (2024). Two decades of palm oil business-environmental quality nexus: A bibliometric approach. *Int. J. Energy Econ. Policy, 14*(1), 290-300. https://doi.org/10.32479/ijeep.15186

Prell, M., Zanini, M. T., Caldieraro, F., & Migueles, C. (2020). Sustainability certifications and product preference. *Mark. Intell. Plan., 38*, 893-906. https://doi.org/10.1108/MIP-12-2019-0616

Purnomo, H., Okarda, B., Dermawan, A., Ilham, Q. P., Pacheco, P., Nurfatriani, F., & Suhendang, E. (2020). Reconciling oil palm economic development and environmental conservation in Indonesia: A value chain dynamic approach. *Forest Policy Econ., 111*, 102089.

Rabar, D. (2017). An overview of data envelopment analysis application in studies on the socio-economic performance of OECD countries. *Econ. Res.-Ekon. Istraživanja, 30*(1), 1770-1784. https://doi.org/10.1080/1331677X.2017.1383178

Ramelli, S., & Wagner, A. F. (2020). Feverish stock price reactions to COVID-19. *Review of Corporate Finance Studies, 9*(3), 622–655. https://doi.org/10.2139/ssrn.3550274

Serafeim, G., & Yoon, A. (2022). Stock price reactions to ESG news: The role of ESG ratings and disagreement. *Rev. Account. Stud., 28*, 1500-1530. https://doi.org/10.1007/s11142-022-09675-3

Shahimi, S., Hafizuddin-Syah, B. A. M., & Hanisah, S. F. (2023). Sustainability practices and financial profitability: The case of the world's top 20 crude palm oil producers. *SAGE Open, 13*, 1-14. https://doi.org/10.1177/21582440231203832

Shankar, K. U., Ahmad, W., & Kareem, S. A. (2021). Beta volatility and its consequences for hedging systematic risk with reference to stock market during COVID-19. *IT Ind., 9*(3), 482-492.

Siew, L. W., Fai, L. K., & Hoe, L. W. (2018). Investigation on the efficiency of financial companies in Malaysia with data envelopment analysis model. *J. Phys.: Conf. Ser., 995*, 012021. https://doi.org/10.1088/1742-6596/995/1/012021

Simar, L., & Wilson, P. W. (2007). Estimation and inference in two-stage semi-parametric models of production processes. *J. Econom., 136*, 31-64. https://doi.org/10.1016/j.jeconom.2005.07.009

Soetanto, T. V., & Fun, L. P. (2014). Performance evaluation of property and real estate companies listed on Indonesia Stock Exchange using data envelopment analysis. *J. Manajemen Kewirausahaan, 16*(2), 121-130. https://doi.org/10.9744/jmk.16.2.121-130

Suhardjo, I., Akroyd, C., & Suparman, M. (2024). Unpacking environmental, social, and governance score disparity: A study of Indonesian palm oil companies. *J. Risk Financial Manage., 17*(7), 296. https://doi.org/10.3390/jrfm17070296

Syahza, A. (2019). The potential of environmental impact as a result of the development of palm oil plantation. *Manag. Environ. Qual.: Int. J., 30*(5), 1072-1094.

Topaloğlu, G., & Abasız, T. (2026). The relationship between systematic risk and financial ratios: A sectoral assessment within the scope of Borsa Istanbul. *J. Empir. Econ. Soc. Sci., 8*(1), 92–106. https://doi.org/10.46959/jeess.1858136

Tey, Y. S., & Brindal, M. (2021). Sustainability stewardship: Does roundtable on sustainable palm oil certification create shareholder value? *Corp. Soc. Responsibility Environ. Manage., 28*, 786-795. https://doi.org/10.1002/csr.2088

Ulfah, M., Ismono, H., & Murniati, K. (2019). The export performance of Indonesia's palm oil in international market. *J. Manaj. Agribisnis, 16*(2), 140-150. http://dx.doi.org/10.17358/jma.16.2.140

Wibowo, H., Adam, H., & Fauziah, M. (2023). Changes in global, domestic, and stock price as a response to Indonesian CPO export ban: An opening door into a worldwide financial distress. Int. *J. Sci. Soc., 5*(5), 66-84. https://doi.org/10.54783/ijsoc.v5i5.868

Wybawa, E. P., Rahmanita, M., Mumin, A. T., Nurbaeti, & Siregar, H. (2023). Efficiency measurement of tourism and recreation companies (Industry Code E51) listed on the Indonesia Stock Exchange. *Int. J. Sustain. Dev. Plan., 18*(2), 591-601. https://doi.org/10.18280/ijsdp.180229

Zhang, D., Hu, M., & Ji, Q. (2020). Financial markets under the global pandemic of COVID-19. *Finance Res. Lett., 101528*.

Zhang, J., & Zhang, J. (2018). Efficiency analysis of listed agricultural company based on DEA. Adv. *Intell. Syst. Res., 146*, 198-200. https://doi.org/10.2991/icaita-18.2018.50