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Determinants of Profitability in Non-Financial Sectors: a Panel Data and Machine Learning Analysis of Indonesian Firms from 2012 to 2023

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Abstract
Profitability is a crucial measure of financial stability and operational success for firms. In Indonesia, the capital market has grown significantly, with the Indonesia Stock Exchange (IDX) reaching a market capitalization of IDR 11.67 quadrillion by 2023. However, there remains a gap in studies that comprehensively analyze the determinants of profitability across all non-financial sectors in Indonesia. This research aims to identify and analyze the determinants of profitability in Indonesian non-financial companies using both traditional panel data regression and machine learning techniques. Using quarterly data from 816 non-financial companies listed on the IDX from 2012 to 2023, this study employs panel regression with a fixed effects model and Driscoll-Kraay standard errors. Return on assets (ROA) and earnings per share (EPS) are employed as profitability measures, while firm size (LSIZE), company efficiency (CE), liquidity (LIQ), market power (MP), sales growth (SG), and sustainable growth rate (LSGR) are investigated as explanatory variables. Results from the panel regression analysis reveal that, except for LIQ, all variables have a positive and significant impact on profitability. The analysis is further refined using machine learning techniques, specifically Random Forest, XGBoost, and a deep learning neural network, which conclude that the most important variable influencing ROA is company efficiency, while the most important variable influencing EPS is firm size.

Keywords: Profitability, Return on Assets, Earnings per Share, Panel Data, Machine Learning, Random Forest, XGBoost, Deep Learning

INTRODUCTION

The Indonesia Stock Exchange (IDX) is the cornerstone of Indonesia's capital market, housing companies from various sectors that play a critical role in national economic growth. By December 2023, the IDX had 906 listed companies with combined market capitalization reaching IDR 11.67 quadrillion, reflecting a 22.97% increase from the previous year (Idnfinancials, 2024). This expansion presents numerous opportunities for investors, making sectoral analysis crucial for understanding profitability dynamics across different industries (Korauš, 2022; Manullang & Hutabarat, 2020).

Profitability plays a crucial role for all businesses, serving as a core measure of financial stability and operational success (Croissant & Millo, 2018; Hudson, 2024; Ivanova, 2023). For various stakeholders, profitability carries distinct meanings. Investors view it as a key driver of return on investment, creditors see it as an indicator of debt repayment capability, and for employees, it translates into job security and performance-based rewards (Abeyrathna & Priyadarshana, 2019; Asokan, 2022).

Despite the availability of research on sector-specific profitability, there is a noticeable gap in studies that comprehensively compare profitability across all non-financial sectors listed on the IDX (Jayathilaka, 2020; Karlina & Ramadhan, 2020; Yuanita, 2019). To address this gap, this study utilizes both statistical methods and machine learning techniques to understand complex patterns and interactions among variables that are not easily detected through traditional analysis (Budhidharma et al., 2023; Munawar, 2019; Pervan et al., 2019; Qin, 2022).

This study aims to answer six key research questions: (1) Does firm size affect profitability? (2) Does efficiency affect profitability? (3) Does liquidity affect profitability? (4) Does market power affect profitability? (5) Does sales growth affect profitability? (6) Does sustainable growth rate affect profitability?

Return on Assets (ROA) is widely recognized as a key profitability measure. According to Marshall et al. (2023), ROA captures a company's ability to generate earnings from its total assets. Earnings per share (EPS) represents profitability from the shareholders' perspective and is calculated by dividing net income by outstanding shares (Lim & Rokhim, 2020).

Research by Yadav et al. (2022) demonstrates that firm size significantly impacts profitability through economies of scale and operational efficiencies. Company efficiency, measured through turnover ratios, reflects how effectively firms utilize their assets (Mcclure & Kindness, 2024). Market power enables firms to control pricing and sustain higher profit margins (Chang et al., 2019). Sales growth and sustainable growth rate have been shown to positively influence profitability in various studies (Fuertes-Callén & Cuellar-Fernández, 2019; Wijaya & Atahau, 2021).

This research aims to analyze the determinants of profitability for non-financial companies listed on the Indonesia Stock Exchange by combining a panel regression approach and machine learning techniques, to identify the variables that have the greatest influence on return on assets (ROA) and earnings per share (EPS). Theoretically, this research contributes to the corporate finance literature in the context of developing countries by integrating conventional analytical methods and artificial intelligence. Practically, the results of this research are expected to serve as a reference for company management in formulating operational and sustainable growth strategies, as well as to provide useful information for investors in conducting fundamental assessments and making more informed investment decisions.

RESEARCH METHOD

This research is quantitative research with a descriptive and explanatory approach that uses secondary data from the company's financial statements. The research design applied is a panel data study, which combines the time-series dimension and the unit of analysis (cross-sectional), thus allowing a more comprehensive and dynamic analysis of the factors affecting profitability.

This study uses quarterly data from 2012 to 2023 for all non-financial companies listed on the IDX. The financial sector is excluded due to its fundamentally different business model and regulatory environment. The final dataset includes 816 companies with complete data for all variables. All variables are obtained from Capital IQ and Capital IQ Pro. The data is winsorized at the 1% level to avoid the influence of outliers (Alexander, 2016).

The empirical model follows the methodology outlined in Lim and Rokhim (2020) research and uses two equations:

$$LROA_{it} = \alpha + \beta_1 LSIZE_{it} + \beta_2 CE_{it} + \beta_3 LIQ_{it} + \beta_4 MP_{it} + \beta_5 LSG_{it} + \beta_6 LSGR_{it} + \varepsilon_{it}$$

$$LEPS_{it} = \alpha + \beta_1 LSIZE_{it} + \beta_2 CE_{it} + \beta_3 LIQ_{it} + \beta_4 MP_{it} + \beta_5 LSG_{it} + \beta_6 LSGR_{it} + \varepsilon_{it}$$

Table 1. Variable Definitions and Measurements

Variable	Definition	Formula
LROA	Log of return on assets	LROA = log(Net Income / Total Assets)
LEPS	Log of earnings per share	LEPS = log(Net Income - Pref. Div. / Avg. Shares)
LSIZE	Log of total assets	LSIZE = log(Total Assets)
CE	Company efficiency (Asset Turnover)	CE = Revenue / Total Assets
LIQ	Liquidity (Current Ratio)	LIQ = Current Assets / Current Liabilities

Variable	Definition	Formula
MP	Market power (Lerner Index)	MP = (Revenue - COGS) / Revenue
LSG	Log of sales growth	LSG = Log((Current Sales - Prev. Sales) / Prev. Sales)
LSGR	Log of sustainable growth rate	LSGR = Log(ROE × (1 - Div. Payout Ratio))

Source: Adapted from Lim & Rokhim (2020); Variable formulas are based on standard financial ratio definitions (Marshall et al., 2023; Mcclure & Kindness, 2024)

Panel data models integrate both cross-sectional and time-series dimensions. This study employs Common Effect Model (CEM), Fixed Effects Model (FEM), and Random Effects Model (REM). Model selection is conducted using Chow Test, Hausman Test, and Lagrange Multiplier Test (Hill et al., 2018; Wooldridge, 2010).

To complement panel regression analysis, this study employs Random Forest (Breiman, 2001), XGBoost (Chen & Guestrin, 2016), and Deep Learning Neural Networks (Nisbet et al., 2018). These methods help identify variable importance and capture complex non-linear relationships between independent and dependent variables.

RESULTS AND DISCUSSION

Descriptive Statistics

This section outlines the descriptive statistics of the variables used in the study, offering a general summary of the dataset. It includes key statistical measures such as the number of observations, mean, standard deviation, median, as well as the minimum and maximum values for all variables under investigation.

Table 2. Descriptive Statistics

Variable	Obs	Mean	Median	Std. Dev.	Min	Max
LROA	22,403	0.5264	0.6149	0.5371	-1.2518	1.5794
LEPS	24,790	0.8101	0.8534	0.8309	-1.4913	2.7894
LSIZE	24,809	5.3550	5.4409	0.9211	2.8382	7.2241
CE	22,255	0.8361	0.6100	0.8244	0.0030	4.5928
LIQ	23,537	2.7709	1.5410	4.2539	0.0730	31.4248
MP	23,198	0.3214	0.2700	0.2164	0.0123	0.9751
LSG	22,174	1.2253	1.2838	0.5413	-0.5070	2.2951
LSGR	22,532	0.4930	0.0000	1.0261	0.0000	3.8069

Source: Authors' calculations based on processed data from Capital IQ and Capital IQ Pro (2012-2023)

The mean value of LROA is 0.5264, with a median of 0.6149, indicating that the distribution is slightly left-skewed. The standard deviation of 0.5371 suggests moderate variability in profitability across firms. The minimum value of -1.2518 and the maximum of 1.5794 highlight a broad range of profitability levels, with some firms experiencing negative returns while others achieve significantly higher profitability.

LEPS has an average value of 0.8101 and a median of 0.8534, showing that most firms tend to have positive earnings per share. The standard deviation of 0.8309 reflects considerable variation in profitability across firms. The minimum value of -1.4913 suggests that some firms report negative earnings per share, while the maximum of 2.7894 indicates that certain firms achieve exceptionally high profitability.

The mean LSIZE is 5.3550, with a median of 5.4409, indicating that firm size is relatively symmetrically distributed. The standard deviation of 0.9211 suggests a moderate level of dispersion among firms. The minimum value of 2.8382 and maximum of 7.2241 reflect substantial differences in firm size, where some companies operate on a smaller scale while others generate significantly higher sales revenue.

The average CE is 0.8361, with a median of 0.6100, indicating that most firms generate less than one unit of revenue for each unit of assets held. The standard deviation of 0.8244 suggests substantial variation in efficiency across firms. The minimum value of 0.0030 reflects firms with minimal asset utilization, while the maximum value of 4.5928 shows that some firms efficiently convert their assets into revenue at a much higher rate.

The mean LIQ is 2.7709, with a median of 1.5410, indicating that while most firms have sufficient current assets to cover short-term liabilities, some maintain significantly higher liquidity levels. The high standard deviation of 4.2539 suggests substantial variation, with firms at the lower end having a minimum ratio of 0.0730, indicating potential liquidity risk, while others have a maximum of 31.4248, suggesting highly conservative liquidity management.

Panel Model Selection

Chow Test

The Chow test is utilized to assess whether the fixed effects model provides a better fit for the data compared to the common pool effect model. The test was applied to two dependent variables, ROA and EPS.

Table 3. Chow Test Results

Test	LROA	LEPS
Chow Test P-Value	0.0000	0.0000

Source: Authors' calculation based on panel data analysis (Wooldridge, 2010)

For both LROA and LEPS models, the p-values are significantly below the 5% significance level ($\alpha = 0.05$), resulting in the rejection of the null hypothesis. This confirms that the fixed effects model is suitable for all models. The significant effects indicate that the impact of the independent variables on ROA and EPS differs across entities, reinforcing the preference for the fixed effects model over the common pool effect model.

Hausman Test

The Hausman Test is used to compare the fixed effects model and the random effects model to determine which better fits the data. The test was performed on two dependent variables, ROA and EPS.

Table 4. Hausman Test Results

Test	LROA	LEPS
Hausman Test P-Value	0.0000	0.0000

Source: Authors' calculation based on panel data analysis (Wooldridge, 2010)

For both LROA and LEPS models, the p-values are significantly below the 5% significance level, resulting in the rejection of the null hypothesis. This confirms that the fixed effects model is suitable for all models, reinforcing the preference for the fixed effects model over the random effect model.

Diagnostic Tests

Before performing panel regression, diagnostic tests were conducted to check for potential violations of classical assumptions. The Wooldridge test for autocorrelation, Breusch-Pagan test for heteroskedasticity, and Pesaran test for cross-sectional dependence were all conducted.

Table 5. Diagnostic Test Results

Test	LROA	LEPS
Wooldridge (Autocorrelation)	0.0000	0.0000
Breusch-Pagan (Heteroskedasticity)	0.0000	0.0000
Pesaran (Cross-Sectional Dep.)	0.0000	0.0000

Source: Authors' calculation using diagnostic tests for panel data models (Wooldridge, 2010)

The diagnostic tests reveal the presence of autocorrelation, heteroskedasticity, and cross-sectional dependence in both models. To address these issues, the study applies Driscoll-Kraay Standard Errors regression, which provides robust standard errors that are consistent in the presence of these violations.

Panel Regression Results and Interpretation

Table 6 presents the panel data regression results using the Fixed Effects Model with Driscoll-Kraay standard errors. This approach addresses the violations of classical assumptions identified in the diagnostic tests and provides robust estimates of the relationships between independent variables and profitability measures.

Table 6. Panel Data Regression Results

Variable	ROA Coef.	ROA P-value	EPS Coef.	EPS P-value
LSIZE	0.1960	0.0000***	0.4643	0.0000***
CE	0.3194	0.0000***	0.0476	0.0019***
LIQ	-0.0026	0.0669	0.0004	0.8616
MP	1.1036	0.0000***	0.6237	0.0000***
LSG	0.0502	0.0000***	0.0828	0.0000***
LSGR	0.0377	0.0000***	0.0551	0.0000***
F-Statistics	160.89		287.29	
Adj. R-Squared	0.1414		0.0506	
Prob > F	0.0000		0.0000	

Source: Authors' estimation using Fixed Effects Model with Driscoll-Kraay standard errors

The Prob F values for both models are below 0.05, indicating that they are statistically significant at the 95% confidence level. This confirms the validity of the models and provides evidence that at least one independent variable significantly influences the dependent variable. The Adjusted R-Squared for ROA is 0.1414, meaning that approximately 14.1% of the variation in ROA is explained by the independent variables. Meanwhile, the Adjusted R-Squared for EPS is 0.0506, suggesting that only 5.0% of the variation in EPS is captured by the same set of variables.

Firm Size (LSIZE)

LSIZE has a significant positive relationship with both ROA (coefficient = 0.1960, p-value = 0.0000) and EPS (coefficient = 0.4643, p-value = 0.0000), indicating that larger firms tend to be more profitable. Therefore, hypotheses H_{1a} and $H_{1\beta}$ are supported. This result could be due to economies of scale, where larger firms benefit from cost efficiencies, higher market reach, and greater bargaining power, leading to increased earnings. Additionally, bigger firms often have more access to capital markets, allowing them to invest in profitable opportunities that further boost EPS. However, the lower effect on ROA suggests that while size contributes to profitability, it does not necessarily translate into higher efficiency in utilizing assets.

Company Efficiency (CE)

Company Efficiency has a significant positive relationship with both ROA (coefficient = 0.3194, p-value = 0.0000) and EPS (coefficient = 0.0476, p-value = 0.0019), indicating that firms that utilize their assets more efficiently tend to be more profitable. Therefore, hypotheses H_{2a} and $H_{2\beta}$ are supported. This result shows that ROA is a profitability measure that directly considers how well a company generates earnings from its assets, making efficiency a critical factor. The relatively lower coefficient for EPS implies that while asset efficiency contributes to overall firm profitability, its influence on shareholder returns is more limited. This finding highlights the importance of asset management in improving operational profitability.

Liquidity (LIQ)

Liquidity has an insignificant relationship with both ROA (coefficient = -0.0026, p-value = 0.0669) and EPS (coefficient = 0.0004, p-value = 0.8616), suggesting that liquidity does not play a major role in determining profitability in this context. Therefore, hypotheses H_{3a} and $H_{3\beta}$ are rejected. These results imply that while liquidity is important for operational stability and risk management, firms do not necessarily need excessive liquidity to improve profitability. Instead, companies may benefit from optimizing their liquidity position to balance financial flexibility with investment in productive assets.

Market Power (MP)

Market Power has a strong positive and significant relationship with both ROA (coefficient = 1.1036, p-value = 0.0000) and EPS (coefficient = 0.6237, p-value = 0.0000), indicating that firms with higher pricing power tend to achieve greater profitability. Therefore, hypotheses H_{4a} and $H_{4\beta}$ are supported. The stronger coefficient for ROA suggests that market power plays a crucial role in improving a firm's ability to generate returns on its assets, likely due to higher profit margins and cost advantages. Firms with strong market power can charge premium prices, reduce competitive pressures, and achieve better cost control, leading to higher operational efficiency and improved financial performance.

Sales Growth (LSG)

LSG has a positive and significant relationship with both ROA (coefficient = 0.0502, p-value = 0.0000) and EPS (coefficient = 0.0828, p-value = 0.0000), indicating that firms with higher sales growth tend to be more profitable. Therefore, hypotheses H_{5a} and $H_{5\beta}$ are supported. This result shows that firms with strong sales performance generate higher revenues, which directly boosts net income and, consequently, EPS. The lower effect on ROA implies that while increased sales improve profitability, firms must also manage their assets efficiently to translate sales growth into higher returns on assets.

Sustainable Growth Rate (LSGR)

LSGR has a positive and significant relationship with both ROA (coefficient = 0.0377, p-value = 0.0000) and EPS (coefficient = 0.0551, p-value = 0.0000). Therefore, hypotheses H_{6a} and $H_{6\beta}$ are supported. This result shows that sustainable growth reflects a firm's ability to expand its earnings capacity while maintaining financial stability, which directly enhances EPS by increasing net income over time. This highlights the importance of balancing growth and profitability to ensure long-term financial success.

Machine Learning Variable Importance Analysis

Besides regression methods, this study applies machine learning techniques to provide more advanced approaches for assessing variable importance. Three methods are employed: Random Forest, XGBoost, and Deep Learning Neural Network.

Random Forest Results

The Random Forest method involves imputing missing values using random forest imputation technique with 6 iterations and 500 trees. The initial mtry value for both ROA and EPS models is set at 2. After tuning, the optimal mtry is 3 for the ROA model and 4 for the EPS model. The Root Mean Squared Error (RMSE) decreases from 0.3864 to 0.3859 for ROA and from 0.6315 to 0.6311 for EPS after tuning, indicating improved accuracy and predictive performance.

Table 7. Random Forest Variable Importance (IncNodePurity)

Rank	ROA Variable	IncNodePurity	EPS Variable	IncNodePurity
1	CE	1723.78	LSIZE	5402.50
2	MP	1400.70	MP	2542.82
3	LSIZE	963.15	CE	2470.24
4	LIQ	819.21	LIQ	2468.77
5	LSG	700.42	LSG	1882.33
6	LSGR	453.77	LSGR	1294.60

Source: Authors' analysis using Random Forest algorithm (Breiman, 2001)

Based on Random Forest analysis, the variable importance for ROA in sequence is CE, MP, LSIZE, LIQ, LSG, and LSGR. For EPS, the sequence is LSIZE, MP, CE, LIQ, LSG, and LSGR. This analysis highlights the dominant role of CE and MP in the ROA model and LSIZE in the EPS model, suggesting that company efficiency, market power, and firm size are critical determinants of financial performance.

XGBoost Results

XGBoost is implemented by splitting the data into training and testing sets with an 80:20 ratio. The models are initially fitted using a maximum depth of 3 and 200 boosting rounds. After tuning, the optimal RMSE for the ROA model is reached at round 139 (RMSE = 0.4089), while for the EPS model it is achieved at round 132 (RMSE = 0.6702).

Table 8. XGBoost Variable Importance (Gain)

Rank	ROA Variable	Gain	EPS Variable	Gain
1	CE	0.4186	LSIZE	0.6217
2	MP	0.2762	MP	0.1258
3	LSGR	0.1088	LIQ	0.0925
4	LSIZE	0.0865	CE	0.0748
5	LIQ	0.0668	LSGR	0.0531
6	LSG	0.0428	LSG	0.0318

Source: Authors' analysis using XGBoost algorithm (Chen & Guestrin, 2016)

Based on XGBoost analysis, the variable importance for ROA in sequence is CE, MP, LSGR, LSIZE, LIQ, and LSG. For EPS, the sequence is LSIZE, MP, LIQ, CE, LSGR, and

LSG. These results indicate that company efficiency and market power are crucial for ROA, while firm size plays a major role in EPS performance.

Deep Learning Neural Network Results

Deep learning neural network architecture was adapted to handle tabular input and regress ROA and EPS values, enabling the extraction of variable importance scores based on learned feature weights. This approach provides insights into the hierarchical significance of financial ratios.

Table 9. Deep Learning Neural Network Variable Importance

Rank	ROA Variable	Importance	EPS Variable	Importance
1	CE	0.4390	LSIZE	0.5430
2	MP	0.3350	LIQ	0.1200
3	LSIZE	0.1430	CE	0.1130
4	LSGR	0.0450	MP	0.1010
5	LSG	0.0280	LSGR	0.0740
6	LIQ	0.0110	LSG	0.0480

Source: Authors' analysis using Deep Learning Neural Network (Nisbet et al., 2018)

Based on Deep Learning analysis, the variable importance for ROA in sequence is CE, MP, LSIZE, LSGR, LSG, and LIQ. For EPS, the sequence is LSIZE, LIQ, CE, MP, LSGR, and LSG. These results reinforce that company efficiency and market power are crucial for ROA, while firm size plays a major role in EPS performance.

Model Improvement Results

Based on the variable importance analysis from machine learning, several scenario tests were carried out to obtain an improved model. For the ROA model, the highest adjusted R-squared value (0.1423) was obtained from a scenario excluding LSG as an independent variable, suggesting that sales growth is better not included when determining profitability using ROA as measurement. For the EPS model, the highest adjusted R-squared value (0.0506) was obtained from the original model, indicating that all independent variables should be included.

Table 10. Model Improvement Scenarios

No	Scenario	Adj. R^2
1	LROA Original Model (All 6 variables)	0.1414
2	4 Variables (CE + MP + LSIZE + LIQ)	0.1362
3	5 Variables (CE + MP + LSIZE + LIQ + LSG)	0.1347
4	4 Variables (CE + MP + LSGR + LSIZE)	0.1407
5	5 Variables (CE + MP + LSGR + LSIZE + LIQ)	**0.1423***
6	LEPS Original Model (All 6 variables)	**0.0506***

Source: Authors' calculation based on regression model refinement

Comprehensive Discussion

This study provides strategic insights into the key drivers of profitability in Indonesia's non-financial firms. The results consistently show that firm size, operational efficiency, market power, sales growth, and sustainable growth are the most influential factors across both profitability measures. These variables are not only statistically significant in the panel regression model but also repeatedly emerge as top priorities in the machine learning variable importance analysis (Rajagukguk & Siagian, 2021; Tissen & Sneidere, 2019).

A key finding is that growth is not optional—it is a necessity for survival. Companies that do not grow will eventually lose relevance in an increasingly dynamic and competitive market. However, growth must be managed wisely. A larger organization without efficiency becomes rigid, slow, and resistant to change. Efficiency must be institutionalized to maintain agility, especially for firms experiencing rapid expansion.

The machine learning analysis provides crucial insights that complement the regression results. For ROA, company efficiency consistently emerges as the most important predictor across Random Forest, XGBoost, and Deep Learning methods. This reinforces the finding that operational efficiency is the decisive factor for driving returns on assets. For EPS, firm size dominates across all machine learning models, highlighting the advantages of scale in driving market-based profitability.

The insignificant effect of liquidity on profitability deserves special attention. While liquidity is important for operational stability and risk management, excessive liquidity may indicate idle resources that could be better invested in productive assets. This finding suggests that firms should optimize their liquidity position rather than maintaining unnecessarily high liquid asset levels.

Profitability is not purely financial—it is strategic. Sustainable growth must be built on solid operational foundations, supported by pricing power, efficient asset utilization, and forward-looking strategies. To stay profitable in the long run, companies must foster innovation, allocate resources smartly, and embrace adaptability. Growth, efficiency, and sustainability must not compete but move in harmony. Only companies that can grow with focus, stay lean while scaling, and evolve with purpose will consistently outperform and endure.

CONCLUSION

This study provides strategic insights into the key drivers of profitability in Indonesia's non-financial firms by integrating conventional regression methods with advanced machine learning analysis. The results clearly demonstrate that operational efficiency emerges as the most decisive factor for driving ROA, while firm size plays a dominant role in enhancing EPS, both underscoring the need for internal optimization and strategic scaling. Liquidity shows no meaningful impact, reaffirming that excess cash does not equate to stronger performance. Market power and sustainable growth rate also significantly contribute to profitability. The machine learning analysis validates these findings through variable importance rankings, with company efficiency and firm size consistently emerging as top predictors. For firms to thrive in a highly competitive landscape, the focus must shift toward improving productivity, maximizing asset utilization, and ensuring growth is sustainable. However, the study has contextual limitations as the observation period includes the COVID-19 pandemic years (2020-2022), during which various government interventions may have caused temporary distortions in corporate financial performance. Future research should explore a broader range of industries, investigate the role of digital transformation and innovation, examine long-term effects of sustainability practices, apply more advanced machine learning techniques, and conduct cross-country comparisons to understand how regulatory and economic differences influence profitability determinants in emerging markets.

REFERENCE

Abeyrathna, S. P. G. M., & Priyadarshana, A. J. M. (2019). Impact of firm size on profitability (special reference to listed manufacturing companies in Sri Lanka). *International Journal of Scientific and Research Publications, 9*(6), 561–564.

Alexander, C. (2016). *Market risk analysis: Practical financial econometrics* (Vol. II). John Wiley & Sons.

Asokan, S. (2022). *Financial ratio analysis for business decisions*. Prentice Hall.

Budhidharma, V., Puspita, D. A., & Wijaya, R. (2023). Financial distress prediction using machine learning approaches in Indonesia. *Journal of Financial Management, 15*(2), 145–162.

Chang, Y., Wang, Y., & Liu, Y. (2019). Market power and firm performance in emerging markets. *Asian Economic Journal, 33*(2), 189–210.

Croissant, Y., & Millo, G. (2018). *Panel data econometrics with R*. John Wiley & Sons.

Fuertes-Callén, Y., & Cuellar-Fernández, B. (2019). Inter-relationship between firm growth and profitability in a context of economic crisis. *Journal of Business Economics and Management, 20*(1), 86–106.

Hill, R. C., Griffiths, W. E., & Lim, G. C. (2018). *Principles of econometrics* (5th ed.). John Wiley & Sons.

Hudson, J. (2024). Financial sector regulations and their impact on comparative analysis. *Journal of Financial Regulation, 12*(3), 234–251.

Idnfinancials. (2024). *Indonesia Stock Exchange 2023 annual report*. https://www.idnfinancials.com

Ivanova, M. (2023). Company efficiency and performance measurement. *Business Economics Review, 18*(2), 112–128.

Jayathilaka, R. (2020). Efficiency ratios and profitability: A comprehensive review. *Financial Management Quarterly, 12*(4), 289–305.

Karlina, D., & Ramadhan, A. Y. (2020). The effect of firm size on earnings per share in manufacturing firms. *Indonesian Journal of Economics and Business, 8*(1), 67–82.

Korauš, A. (2022). Efficiency measurement in financial institutions. *Economics and Finance Letters, 9*(2), 156–171.

Lim, M., & Rokhim, R. (2020). Factors affecting profitability of pharmaceutical companies in Indonesia. *International Journal of Scientific & Technology Research, 9*(1), 2568–2573.

Manullang, S., & Hutabarat, F. (2020). Analysis of sustainable growth rate on mining companies profitability. *Journal of Business and Management Review, 1*(5), 346–355.

Marshall, D. C., McManus, W. W., & Viele, D. F. (2023). *Accounting: What the numbers mean* (13th ed.). McGraw-Hill Education.

McClure, B., & Kindness, D. (2024). *Understanding efficiency ratios*. Investopedia. https://www.investopedia.com

Munawar, A. (2019). Working capital management and firm profitability in Indonesia. *Asian Journal of Business and Accounting, 12*(1), 127–151.

Nisbet, R., Elder, J., & Miner, G. D. (2018). *Handbook of statistical analysis and data mining applications* (2nd ed.). Academic Press.

Pervan, M., Pervan, I., & Ćurak, M. (2019). Determinants of firm profitability in emerging markets: Evidence from South-Eastern European countries. *Economic Research, 32*(1), 968–981.

Qin, Y. (2022). Machine learning in financial analysis: Applications and challenges. *Journal of Financial Technology, 8*(3), 234–256.

Rajagukguk, Y. M., & Siagian, V. (2021). The impact of liquidity on firm profitability: Evidence from Indonesia. *Advances in Economics, Business and Management Research, 169*, 231–236.

Tissen, B., & Sneidere, R. (2019). Return on assets and firm performance. *Business and Economic Horizons, 15*(3), 459–473.

Wijaya, L. I., & Atahau, A. D. R. (2021). Sustainable growth rate and profitability: Cross-country evidence from ASEAN. *Journal of International Financial Management & Accounting, 32*(2), 178–195.

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data* (2nd ed.). MIT Press.

Yadav, I. S., Pahi, D., & Gangakhedkar, R. (2022). The nexus between firm size, growth and profitability: New panel data evidence from Asia-Pacific markets. *European Journal of Management and Business Economics, 31*(1), 115–140.

Yuanita, N. (2019). Competition, diversification, and bank profitability: Evidence from Indonesia. *Bulletin of Monetary Economics and Banking, 22*(4), 521–542.