

CAN MACHINE LEARNING BETTER PREDICT ACCOUNTING-BASED FIRM PERFORMANCE IN THE POST-ESG ERA?

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Abstract

This study aims to examine whether the rise of the ESG era improves the predictability of firm performance. We focus on a specific point in time when the number of firms with ESG scores reported by ASSET4ESG increases exponentially, which we define as the ESG era. This study focuses on the Malaysian context, which exhibits a clear distinction of increase number of firms with ESG scores since 2020 compared to the other countries. Accordingly, we employ machine learning (ML) models (Random Forest, Gradient Boosting Machines, and XGBoost), and compare them with linear models (OLS and LASSO) to evaluate their predictive performance for firm performance in ESG era (2020-2024) relative to the pre-ESG era period (2001–2019). Our findings show that ML models achieve 10-14% higher predictability for ROA compared to linear models during the ESG era. When ESG-related variables are incorporated into the independent variable matrix, the predictive performance of ML models further improves to 19-25%. Using SHAP analysis, we find that the Altman Z-score, sales efficiency, and industry growth exert the strongest influence on firm performance, while the ESG combined score ranks below these financial indicators. This suggests that ESG contributes less directly to firm performance, but its interaction with financial variables enhances the overall predictability of firm performance.

Keywords: ESG, Machine Learning, Performance, ROA, Predictability

INTRODUCTION

ESG engagement has become a common focus in the literature. Most studies in the finance literature examine the role of ESG in influencing financial outcomes at the firm level. However, relatively few studies explore whether ESG implementation serves as a game changer in financial management. Specifically, limited attention has been given to whether ESG adoption enhances the quality of financial management, subsequently improving the explanatory power of financial variables on firm performance. Addressing this gap is important, as it aligns with the fundamental principles of ESG, which emphasize greater transparency to foster healthy relationships with various stakeholders. Understanding whether the transition from the pre- to post-ESG era reshapes financial management practices is therefore essential to evaluating ESG's effectiveness as a transformative force.

While ESG frameworks in the Western hemisphere have not been gaining increasing attention (Wei et al., 2025), Asian countries have instead made continuous and substantial efforts

to promote higher ESG compliance among firms. For example, Malaysia is set to require the disclosure of Scope 3 emissions in sustainability reports by 2027 for publicly listed firms. Malaysia, like its neighboring countries, has also begun implementing mandatory sustainability reporting requirements in a phased manner since 2023. The ESG disclosure provides an important foundation for third-party data providers, such as Refinitiv's ASSET4 ESG database, to collect and compile comprehensive sustainability information into ESG combined scores. According to ASSET4 ESG data (2025), the number of Malaysian firms possessing ESG scores, based on individual complete sustainability disclosures, has increased sixfold since 2020, significantly outpacing other Asian countries. This development provides a valuable context for defining the post-2020 period as the ESG era in Malaysia, during which sustainability practices have become increasingly widespread among publicly listed firms in the Malaysian market.

This study aims to examine whether the ESG era provides better predictability of corporate financial information on firm performance. The rationale is that, ESG practices in alignment with sustainability principles has reduced information asymmetry (Kim & Park, 2023) and investment efficiency (Bilyay-Erdogan et al., 2023). Although ESG performance is found significantly related to market-based firm performance, we argue that the benefits of ESG is long-term, which is less immediately reflecting on accounting performance. For instance, ESG practices impact corporate risk-taking (Ooi et al., 2024), which is a strategic decisions that may affect accounting performance in the long-term, yet, its effect on current performance may be less significant.

Considering both the immediate direct effects of ESG and its immediate indirect influence on current financial management practices, this study applies machine learning models, which are more efficient in addressing the intrinsic relationship between ROA and its determinants. Machine learning algorithms can automatically identify such patterns. Moreover, machine learning estimators are capable of capturing complex, nonlinear relationships between firm decisions or outcomes and their determinants, thereby better reflecting the inherent nonlinearity of financial characteristics (see Figure 1.0).

By employing machine learning techniques, this study aims to investigate how the post-ESG era enhances the predictability of financial, industry and economic variables on return on assets (ROA). Specifically, this study seeks to address the following research questions:

1. Does the predictive power of ROA, based on the explanatory variable matrix, become significantly higher in the post-ESG era compared to the pre-ESG era?
2. How important are ESG factors in directly predicting ROA?

In the past studies, the commonly used OLS approach may not efficiently address the complexity of firm performance framework. With OLS, corporate finance literature in various area have shown inconsistent findings. For example, Louis, Sun, and Urcan (2012) show cash holdings is negatively related to future profitability while Kim, Kim, and Bettis (2014) show a positive link between cash and performance. Alnori (2020) even finds non-linearity of cash holdings on firm performance, revealing weaknesses of OLS in addressing complexity of firms' decisions to its performance outcomes. This is similarly evidenced by Vithessonthi and Tongurai (2015) for large- and small sized firms exhibit the opposite relationship between leverage and firm performance. The similar non-linearity is observed in board size (Yermack, 1996; Coles et al., 2008). Overall, the past studies may tell limitation of OLS approach to obtain consistent findings based on different sample.

While prior studies examine the determinants of ROA using in-sample tests, which is often at the expense of out-of-sample validity, this study instead implements out-of-sample testing to capture complex and high-dimensional patterns in the determinants of ROA. Specifically, the machine learning models are trained on data from 2001–2019 and subsequently evaluated on an out-of-sample period (2020–2024). By establishing well-trained models, an approach largely overlooked in the OLS-focused strand of the literature, we develop efficient algorithms capable of

exploring the full model space and mitigating redundant variation among potentially highly correlated predictors (Gu et al., 2020).

Overall, the out-of-sample results (2020–2024) demonstrate higher predictive credibility than traditional linear models (OLS and LASSO). The findings confirm that the relationship between firm fundamentals and ROA is inherently nonlinear. In particular, the 10.65% reduction in RMSE achieved by XGBoost relative to the OLS baseline. The results indicate that advanced ensemble methods are better suited to capturing the complex, threshold-based nature of corporate profitability. Furthermore, we show that predictive performance improves when ESG factors are incorporated into the explanatory variable matrix. Therefore, this study provides evidence that ESG does not merely enhance stakeholder-oriented outcomes but also influences firms' financial decision-making, potentially through increased transparency in financial reporting and improved strategic decision-making, ultimately contributing to better firm performance.

Subsequently, we examine the relative importance of the determinants within a machine learning framework by comparing changes in variable importance between the pre- and post-ESG eras. Using SHAP analysis, we find that the most influential financial fundamentals in predicting ROA are the Altman Z-score, sales efficiency, and industry asset growth. These findings suggest that, in addition to firm-level financial health and profitability, industry performance serves as an important predictor of firm performance. Overall, incorporating ESG factors into the machine learning models improves the predictability of ROA. However, ESG variables are consistently ranked lower in importance, indicating that their predictive role is not directly influential.

EVIDENCE OF NONLINEARITY IN ROA DETERMINANTS

Figure 1. illustrates that the relationships between the selected determinants and ROA are inherently nonlinear. As shown in the figure, firm size (measured as the natural logarithm of total assets) exhibits a concave relationship with ROA. Firms transitioning from small to medium size experience a notable increase in ROA, consistent with the economies of scale hypothesis. However, this relationship flattens at higher levels of firm size, reflecting diminishing returns to scale. At this stage, larger firms may face agency costs and bureaucratic inefficiencies that constrain further improvements in ROA despite continued growth.

In addition, the ratio of capital expenditure to total assets demonstrates a U-shaped (or "hook-shaped") relationship with ROA. Firms with very low capital expenditure tend to exhibit lower ROA, possibly due to stagnation, while firms with very high capital expenditure also experience reduced ROA. This may be attributed to the fact that investment costs are recognized before the associated revenues materialize. The peak of the curve highlights an optimal level of investment intensity that maximizes profitability.

Furthermore, across the three debt-related panels, the nonlinear (blue) curves display a pronounced inverted U-shaped pattern. ROA initially increases as firms take on moderate levels of debt, likely to finance growth, but declines sharply once leverage exceeds a critical threshold (approximately 30–40% of total assets). In contrast, the linear (red dashed) approximation fails to capture this dynamic, underestimating the risks associated with high leverage while overstating the benefits of low leverage. Notably, short-term debt relative to total assets exhibits a steeper decline in ROA at higher levels compared to long-term debt, suggesting that short-term liquidity pressures have a more immediate and detrimental impact on profitability.

Finally, while the relationship between asset tangibility and ROA appears less strongly nonlinear, it still deviates from linearity. The nonlinear trend indicates that beyond a certain point, increasing fixed assets imposes a drag on operational efficiency rather than contributing proportionally to returns. This finding provides empirical support for the preference toward asset-light business models in modern financial practice.

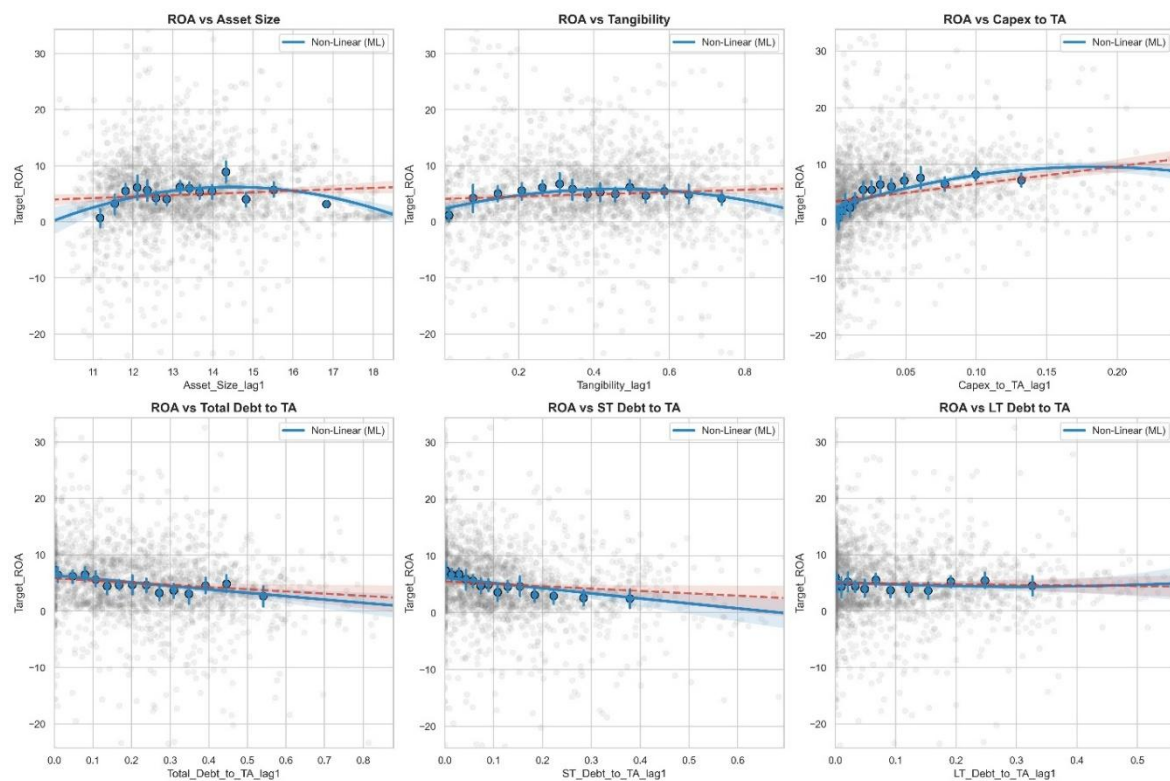


Figure 1. ROA and Firm Financial Characteristics

RESEARCH METHODS

1. *Maching Learning Modelling*

This study employs several machine learning (ML) models and compares their predictive performance with traditional linear approaches, namely the linear model (LM) and LASSO. While certain ML models, particularly XGBoost, can inherently handle missing data, linear models such as OLS and LASSO typically fail in the presence of missing values. To ensure consistency and comparability across all models, this study addresses the missing data issue by constructing an unbalanced panel dataset and removing observations with missing independent variables. This approach ensures that all models are evaluated using the same sample.

Furthermore, this study investigates the effectiveness of ML models in capturing nonlinear relationships and ranks variable importance accordingly. By employing ML algorithms, we are able to model complex nonlinear relationships between dependent and independent variables, as well as uncover hidden interactions among them. Given that these ML methods are fully nonparametric and sufficiently flexible to capture such structures without strong prior assumptions, we compare their performance against the LM benchmark using R^2 . Superior R^2 values from ML models would indicate that accounting for nonlinearity provides a more accurate representation of the relationship between the independent variables and ROA. In addition, we evaluate differences in predictive accuracy using RMSE and test the statistical significance of these differences relative to the LM benchmark.

2. *Model Tuning and Model Fitting*

Model tuning refers to the process of identifying the optimal algorithmic settings prior to the learning phase. Unlike linear models, which estimate coefficients directly from the data without adapting their structural form, ML models require the specification of hyperparameters that govern their complexity, such as tree depth or regularization strength. This step is crucial to prevent the

model from mistaking random noise for meaningful patterns, which could otherwise result in high in-sample R2 but poor out-of-sample performance.

Accordingly, ML approaches are better suited to capture nonlinear relationships than linear models, as evidenced in Figure 1.0, which illustrates the nonlinearity of ROA determinants. Moreover, tuning enables ensemble methods such as XGBoost to determine the appropriate level of interaction and model complexity required to accurately represent these relationships without overfitting.

Following the framework of Kuhn and Johnson (2013), we implement a structured tuning procedure to optimize hyperparameters that are not directly estimable from the data. For LASSO regression, we employ 5-fold cross-validation within the training sample (1991–2019) to select the optimal penalty parameter (α) that minimizes mean squared error. For ensemble ML models, including Random Forest (RF), GBM, and XGBoost, we adopt a time-series out-of-sample validation approach. Specifically, models are trained on historical data and evaluated on a forward-looking validation period (2020–2024), ensuring that the selected hyperparameters remain robust to structural changes in financial panel data, thereby eliminating look-ahead bias and ensuring the validity of the results.

EMPIRICAL MODEL

We evaluate firm performance using two empirical models. The first is the baseline model, in which ROA is modeled as a function of financial, industry, and macroeconomic determinants, as specified in Equation 1.

$$ROA_{it} = f\{Firm_Fundamental_Variables, IndustryVariables, Economic_Variables\}_{it} + \varepsilon_{it} \quad (1)$$

The second model is an enhanced specification that incorporates a set of ESG factors alongside the financial, industry, and macroeconomic determinants, as presented in Equation 2.

$$ROA_{it} = f\{Firm_Fundamental_Variables, IndustryVariables, Economic_Variables, ESGfactors\}_{it} + \varepsilon_{it} \quad (2)$$

We compare the predictive power of the explanatory variables across both models to highlight the improvement achieved by incorporating ESG factors. We expect the enhanced model to exhibit a higher R2 than the baseline model, demonstrating the effectiveness of ESG factors in “bridging the gap” caused by model decay and capturing additional variation in firm performance.

RESULTS AND DISCUSSION

Table 1. Out-of-Sample Performance of Linear Models versus Machine Learning

Model	R2	RMSE	Difference (%)
Panel A: Conventional ROA Model			
OLS (benchmark)	0.3230	8.5285	--
LASSO	0.3231	8.5281	0.00%
RF	0.4433	7.7335	-9.32%***
GBM	0.4209	7.8881	-7.51%***
XGBoost	0.4595	7.6207	-10.65%***
Panel B: ESG-Enhanced ROA Model			
OLS	0.3412	8.0837	-0.24%
LASSO	0.3424	8.0764	-0.27%
RF	0.5726	6.5113	-0.89%
GBM	0.5117	6.9598	-1.93%*
XGBoost	0.5513	6.6710	0.21%

This table reports the out-of-sample R^2 , for linear models (LM), least absolute shrinkage and selection operator (LASSO) model, RF, GBM, and XGBoost. The estimates are reported for the out-of-sample (2020-2024). The dependent variable is ROA. The last column reports the percentage difference between the corresponding model's RMSE and the LM as the benchmark. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Panel A of Table 1 presents the notable performance differences between linear models (OLS and LASSO) and tree-based ensemble models (RF, GBM, and XGBoost). According to the statistics, XGBoost is the top performer, reducing RMSE by 10.65% relative to the linear models at the 1% significance level. RF is the second-best performer, reducing RMSE by 9.32%, followed by GBM with a 7.51% reduction. These results indicate that ROA is not determined by purely linear relationships, consistent with the findings of Amini et al. (2021), who also applied ML techniques to predict firm capital structure. The observed nonlinearity aligns with threshold effects identified in prior studies, for example, high cash holdings can harm profitability, while cash levels within an optimal threshold reduce transaction costs. The lack of a significant difference between OLS and LASSO suggests that these linear approaches perform similarly and are not able to capture these complex nonlinear patterns.

Overall, the superior predictive performance of the tree-based ensembles implies that financial information and managerial decisions have become increasingly relevant to firm performance. This may reflect greater transparency prompted by sustainability practices, as well as lessons learned from past financial crises, resulting in financial decisions with reduced agency costs. Although Table 1 cannot explicitly explain the drivers behind the improved predictability of financial data in recent years, it provides two key insights: (1) firms are learning from past experience and adopting more sustainable practices, enhancing the predictive power of their financial decisions and reporting; and (2) financial information exhibits nonlinear patterns, which are effectively captured by tree-based ensembles but not by linear models.

Panel B of Table 1 examines out-of-sample performance after incorporating ESG-related variables into the explanatory matrix, including the combined ESG score, individual ESG pillar scores, equality measures of ESG pillars, and the number of ESG-scored firms by year. Across all models, R^2 improves after adding ESG variables, demonstrating that the enhanced model captures a larger portion of the variance in corporate profitability. Notably, RF shows a substantial increase in R^2 , from 0.4433 to 0.5726. Among the tree-based models, GBM appears particularly sensitive to ESG factors, showing a statistically significant improvement in predictive performance at the 10% significance level.

IMPORTANCE OF VARIABLE: SHAP ANALYSIS

SHAP analysis provides a clear hierarchy of factors driving ROA. We conduct SHAP analysis for both the baseline model and enhanced model to compare changes in variable importance. The results, visualized in bar charts (Figure 2.), indicate that ROA in the baseline model is primarily influenced by risk metrics (*Zscore*) and sales efficiency (*Sales_ratio*). The Altman Z-score emerges as the most powerful predictor, consistent with the intuition that financially stable firms exhibit superior performance. This is followed by the sales-to-assets ratio, a proxy for operational efficiency, and industry performance, which suggests that industry-level dynamics, such as the business cycle, significantly affect firm-specific outcomes. In contrast, macroeconomic factors such as inflation and term spread are ranked lowest, indicating that firm-specific determinants outweigh general economic conditions in predicting ROA.

The SHAP results for the enhanced model provide additional insights. While the top three predictors remain the same, the inclusion of ESG variables reshuffles the feature hierarchy. Among ESG factors, the combined ESG performance score (*ESG*) is the most influential, though it ranks below key financial variables in overall importance. Environmental scores (*Env*) and the equality of

ESG pillar scores (*StdevESG*) are more important than governance (*Gov*) and social (*Soc*) scores, suggesting that environmental performance plays the strongest role in driving ROA. Moreover, firms with uneven ESG pillar performance appear to be flagged by the model, indicating that the distribution of ESG efforts across pillars carries predictive weight.

Comparing the two models, the SGA ratio, ranked sixth in the baseline model, rises above stock return volatility (*Volatility*) in the enhanced model. This indicates that ESG factors may interact with operational efficiency, amplifying the predictive importance of certain firm-level indicators. Furthermore, ESG disclosures likely signal sustainability and resilience to the market, dampening the effect of market noise and improving the model's overall predictive accuracy.

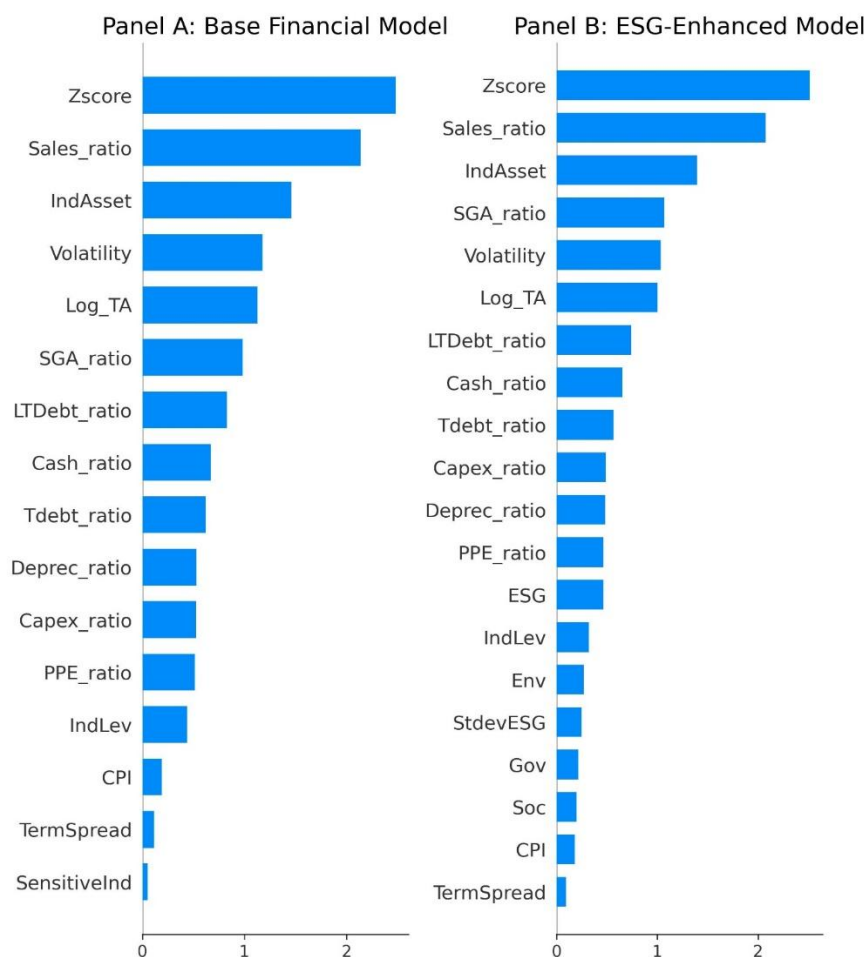


Figure 2. Ranking of Importance of Variable

BEESWARM PLOT

This study further employs the Beeswarm plot to illustrate the directional effects of the determinants on ROA, highlighting the nature of the relationship between each independent variable and the dependent variable. As shown in Figure 3.0, the Altman Z-score (*Zscore*) and sales efficiency (*Sales_ratio*) display a clear pattern, with blue points on the left and red points on the right, indicating a strong positive relationship with ROA. A similar pattern is observed for the industry performance indicator (*IndAsset*), reinforcing the notion that overall industry performance is a strong predictor of firm-level outcomes. In contrast, operating efficiency (*SGA_ratio*) exhibits the opposite pattern, suggesting a negative relationship with ROA. This implies that higher SGA expenses relative to sales reduce profitability, as overhead costs significantly erode returns. A

comparable pattern is observed for *Volatility*, indicating that negative market responses to stock prices signal lower firm performance, consistent with the “market is always right” hypothesis and the risk-averse behavior of investors.

Regarding ESG factors, the Beeswarm plot shows that the combined ESG performance score exhibits a distinct red cluster on the right, confirming a positive relationship with ROA. This aligns with existing literature suggesting that strong ESG performance enhances multiple aspects of firm operations, ultimately boosting financial outcomes. Among the ESG pillars, environmental performance (*Env*) shows a similar positive pattern, reflecting market emphasis on green initiatives such as environmentally friendly technologies and pro-environmental strategies. In contrast, governance (*Gov*) and social (*Soc*) scores exert weaker directional influence on ROA.

Notably, the standard deviation of ESG pillar scores (*StdevESG*) shows red points concentrated on the left for high dispersion and blue points on the right for low dispersion. This suggests that unequal development across ESG pillars undermines ROA predictability. The ML model interprets ESG inequality as a sign of strategic misalignment, indicating lower sustainability and reduced potential for supporting firm performance improvements.

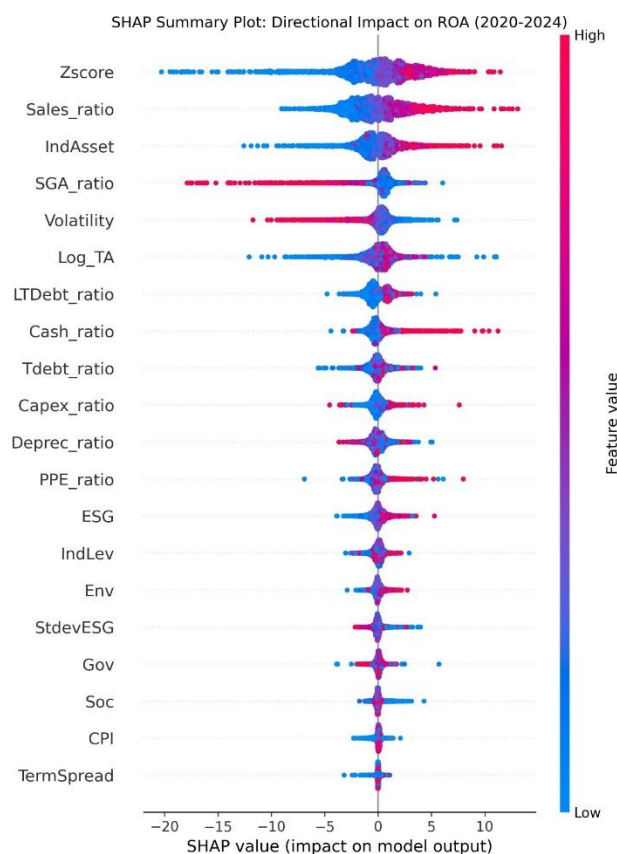


Figure 3. Results of SHAP Analysis

CONCLUSION

This study is among the few that demonstrate the effectiveness of machine learning (ML) algorithms in predicting firm performance, measured by ROA, within a highly nonlinear and discrete environment. We anticipate that these algorithms will be particularly valuable in areas of finance where frictions, such as high transaction costs and investment irreversibilities, prevent firms from

continuously and dynamically adjusting their actions. This paper contributes to the literature on firm performance by showing that ML can identify a broader set of ROA determinants and rank their relative importance, rather than merely evaluating variable significance. Overall, ML models should be considered essential tools for scholars and practitioners studying financial management and firm performance. The superior performance of all ML models tested, RF, GBM and XGBoost, highlights their ability to handle unknown nonlinearities and complex interactions among variables.

This study suggests that the post-ESG era enhances the predictability of financial variables on ROA. As ESG compliance improves among Malaysian publicly listed firms, it provides a substantial boost to sustainability practices across the corporate sector. While ESG factors may not exert a direct influence on ROA, they appear to shape financial management strategies in ways that indirectly benefit firm performance. For example, sustainability practices, such as maintaining transparency for stakeholders, limiting excessively risky investments, and engaging with communities to build customer loyalty, can strengthen financial characteristics like stock price informativeness, financial stability, and sales consistency, thereby improving accounting-based measures of firm performance through their indirect effects.

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