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Determining Financial Ratio Thresholds to Minimize ESG Risk Scores

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ABSTRACT

This study examines whether publicly listed Indonesian firms need to meet minimum financial conditions before ESG risk mitigation becomes feasible. Drawing on data from 85 companies with Sustainalytics ESG Risk Ratings listed on the Indonesia Stock Exchange (IDX) in 2024, the analysis uses Gaussian Mixture Model (GMM) clustering preceded by Principal Component Analysis (PCA). Five clusters were identified based on the lowest Bayesian Information Criterion (BIC). ANOVA and eta squared (η^2) tests show that Return on Assets (η^2=0.555), Debt-to-Asset Ratio (η^2=0.481), and Operating Margin (η^2=0.464) most strongly distinguish clusters. The 25th percentile of the lowest-ESG-risk cluster yields the following minimum thresholds: ROA ≥ 2.89%, ROE ≥ 12.6%, Operating Margin ≥ 41.25%, EBITDA Margin ≥ 50.38%, Current Ratio ≥ 0.18x, and Debt-to-Asset Ratio ≤ 35.00%. These values provide policymakers, investors, and corporate planners a concrete financial baseline for assessing ESG readiness.

Keywords: ESG risk; financial threshold; cluster analysis; gaussian mixture model; Indonesia; public companies.

INTRODUCTION

Corporate value creation has grown more complicated as sustainability moves from a peripheral concern to a central one in how investors and regulators assess firms. The Environmental, Social, and Governance (ESG) framework has gained traction precisely because it captures non-financial risk exposures that can materially affect long-run performance [15] [10].

The ESG risk perspective differs from ESG performance scores: it focuses on how well a firm has managed its exposure to environmental, social, and governance risks, rather than on outputs alone [2]. A lower ESG risk score reflects stronger managerial and financial capacity to handle sustainability-related concerns [20]. This risk-based lens is widely regarded as more relevant to investment decisions because it centers on long-term downside exposure [5] [6].

Despite the documented benefits of ESG adoption, implementation is not cost-free. Financially constrained firms tend to struggle with resource allocation for sustainability, given both the high upfront costs and pressure to maintain short-term efficiency [9] [10] [12]. Financially flexible firms, by contrast, tend to have more room to absorb ESG commitments without disrupting operations [7] [10]. This divergence suggests the relationship between financial condition and ESG risk is non-linear a point that linear studies tend to miss.

Two theoretical frameworks underpin this study. Slack Resources Theory [3] holds that firms with surplus financial resources are better placed to invest in discretionary activities, including ESG. Stakeholder Theory [8] adds that firms need sufficient financial resilience to fulfill sustainability obligations consistently. Together, they suggest a minimum financial capacity threshold is a prerequisite for meaningful ESG implementation. It should be noted, however, that this financial-slack view is not without challengers: some scholars argue that resource constraints can also spur more efficient, innovation-driven ESG practices rather than uniformly suppressing them, so the direction of the relationship remains an empirical rather than a settled theoretical question [10].

In Indonesia, this issue has grown more pressing as sustainable finance regulations take hold and stakeholder scrutiny of listed companies intensifies [18]. Yet most empirical work in Indonesia still focuses on linear ESG-financial relationships, overlooking how firms differ in their combined financial and ESG risk profiles. No study has explicitly mapped minimum financial thresholds for effective ESG implementation. The novelty of this study lies

not in the mere absence of prior investigation but in its configuration-based and threshold-oriented perspective: rather than testing a linear association between financial condition and ESG risk, it identifies discrete financial configurations (via unsupervised clustering) and translates the lowest-ESG-risk configuration into concrete, empirically derived threshold values. This study addresses that gap by pursuing two objectives: (1) identifying how Indonesian listed firms cluster based on their financial ratios and ESG risk; and (2) deriving minimum financial ratio thresholds that indicate readiness to reduce ESG risk scores.

Hypothesis Development

A firm's financial condition, as reflected in profitability, liquidity, leverage, and growth ratios, plays a critical role in supporting its capacity to manage long-term risks, including ESG risk [10] [6]. Firms with stronger profitability and greater financial flexibility tend to possess adequate resources to develop robust governance systems, risk management frameworks, and consistent sustainability investments [10] [15].

Consistent with Slack Resources Theory [3], firms possessing financial slack are more likely to invest in ESG beyond minimum regulatory compliance. Accordingly, a strong financial structure is expected to be associated with a lower ESG risk profile [10] [15]. Given that this study employs an unsupervised clustering approach, hypotheses are formulated as analytical propositions:

H_0: There are no significant differences in financial ratios across clusters distinguished by ESG risk level; therefore, no significant threshold values exist.

H_1: There are significant differences in financial ratios across clusters distinguished by ESG risk level; therefore, significant threshold values exist.

RESEARCH METHOD

This study employs a quantitative approach using machine learning-based data analysis. Secondary data were obtained from corporate financial reports and the Trading View platform. The research population comprises all companies with available ESG risk data listed on the IDX in 2024.

A census sampling method was applied, yielding 85 complete observations. Figure 1 illustrates the sector distribution of the selected sample. Because the clustering approach is unsupervised, H_0 and H_1 are tested indirectly through one-way ANOVA on each financial ratio across the resulting clusters, rather than through a conventional regression-based hypothesis test. For example, for Return on Assets (ROA), the F-statistic compares between-cluster variance to within-cluster variance in ROA; a statistically significant F-value ($p < 0.05$) is interpreted as evidence against H_0 for that variable, with η^2 quantifying the share of ROA's variance attributable to cluster membership. The same procedure is applied to each of the 18 financial ratios.

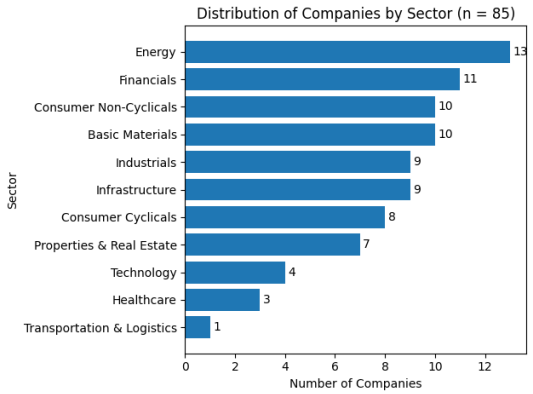


Figure 1. Sample Sector Distribution (n = 85)
Source: Authors' calculations (2026)

Table 1. Descriptive Statistics of Research Variables

Variable	N	Mean	Std. Dev.	Min.	P25	P50	Max.
ESG Risk	85	28.56	9.62	8.42	21.59	27.89	51.74
ROE	85	12.39	9.07	-7.63	6.55	12.88	48.11
ROA	85	6.59	5.77	-2.00	2.11	5.25	23.39
Operating Margin	85	21.60	16.61	-6.88	7.73	19.45	74.18
EBITDA Margin	85	29.72	22.11	-7.90	13.78	27.03	107.85
Asset Turnover	85	0.72	0.80	0.05	0.25	0.44	4.97
Operating Expense Ratio	85	17.90	15.64	0.10	6.79	11.78	66.76
Current Ratio	85	2.76	4.50	0.13	1.13	1.75	37.04
Quick Ratio	85	2.19	4.44	0.13	0.49	1.10	36.92
Debt-to-Asset Ratio	85	21.96	20.12	0.00	7.70	20.00	85.33
Interest Coverage Ratio	85	67.51	330.90	-10.89	3.21	6.91	2937.31
Revenue Growth	85	11.38	17.76	-17.51	3.12	8.50	97.49
Net Income Growth	85	20.43	57.83	-105.56	-4.81	7.28	227.48
Asset Growth	85	8.50	10.90	-17.16	2.78	7.59	47.43
PER Ratio	85	19.97	37.70	-97.58	5.89	9.99	187.19
Market-to-Book Ratio	85	2.25	2.84	0.19	0.77	1.41	18.21
Dividend Payout Ratio	85	39.31	33.52	0.00	4.01	36.66	100.00
Intangible Asset Ratio	85	4.75	9.09	0.00	0.01	0.60	50.85
CapEx-to-Asset Ratio	85	5.35	5.41	0.00	1.50	3.97	24.98

Source: Authors' calculations (2026)

Table 1 presents descriptive statistics for all research variables following data cleaning (Winsorization at the 1st and 99th percentiles).

Variable Operationalization

Table 2. Research Variable Operationalization

Category	Variable	Proxy / Measurement	Direction	Source
Profitability	Return on Assets (ROA)	Net Income / Total Assets	Benefit	Financial Report
	Return on Equity (ROE)	Net Income / Shareholders' Equity	Benefit	Financial Report
	Operating Margin	Operating Income / Revenue	Benefit	Financial Report
	EBITDA Margin	EBITDA / Revenue	Benefit	Financial Report
Efficiency	Asset Turnover	Revenue / Total Assets	Benefit	Financial Report
	Operating Expense Ratio	Operating Expenses / Revenue	Cost	Financial Report
Liquidity	Current Ratio	Current Assets / Current Liabilities	Benefit	Financial Report
	Quick Ratio	(Current Assets − Inventory) / Current Liabilities	Benefit	Financial Report
Solvency	Debt-to-Asset Ratio	Total Debt / Total Assets	Cost	Financial Report
	Interest Coverage Ratio	EBIT / Interest Expense	Benefit	Financial Report
Growth	Revenue Growth	(Revt − Revt-1) / Revt-1	Benefit	Financial Report
	Net Income Growth	(NIt − NIt-1) / NIt-1	Benefit	Financial Report
	Asset Growth	(TAt − TAt-1) / TAt-1	Benefit	Financial Report
Market	PER Ratio	Price per Share / EPS	Benefit	TradingView
	Market-to-Book Ratio	Market Capitalization / Book Value of Equity	Benefit	TradingView
	Dividend Payout Ratio	Dividends / Net Income	Benefit	Financial Report
Investment Structure	Intangible Asset Ratio	Intangible Assets / Total Assets	Benefit	Financial Report
	CapEx-to-Asset Ratio	Capital Expenditure / Total Assets	Benefit	Financial Report
ESG Risk	ESG Risk Score	ESG Risk Rating (Sustainalytics)	Cost	Sustainalytics

Source: Authors' calculations (2026)

The variables employed encompass financial ratios representing various dimensions of firm performance, as presented in Table 2. In addition to backward-looking accounting ratios, this study includes market valuation ratios, namely the Price-to-Earnings Ratio (PER) and the Market-to-Book Ratio (PBV), as forward-looking indicators that reflect investor expectations regarding a firm's capacity to sustain long-term ESG commitments [4]. Their inclusion is supported by empirical evidence demonstrating that firms with superior ESG performance tend to command higher market valuations ([1] Albuquerque; [14] [19]; [23]).

Analytical Procedure

Data analysis followed a sequential multistage procedure consistent with established practice in machine learning-based financial clustering [13] [16]. The first step was outlier treatment. Winsorization at the 1st and 99th percentiles constrained extreme values without dropping observations, a common approach in empirical finance for improving robustness while keeping the sample intact [22].

After outlier treatment, variables were adjusted for directional consistency. Financial ratios carry different interpretive orientations: some are benefit variables (higher is better) and others are cost variables (lower is better). To remove directional bias in multivariate analysis, all variables were aligned through min-max normalization. Benefit variables underwent the standard transformation, while cost variables were reverse-scaled to ensure that higher values consistently indicate better performance [15] [16].

The normalized variables were then standardized via z-score transformation, giving each variable zero mean and unit variance. This step ensures that no single variable dominates distance-based computations. Z-score standardization was chosen over min-max scaling, which is sensitive to extreme values, and robust scaling, which works better for heavily skewed distributions [13] [16].

Principal Component Analysis (PCA) addressed the high dimensionality of the financial data. PCA transforms standardized variables into principal components, capturing most of the variance in the original dataset. It is widely used in financial research to reduce multicollinearity while retaining the core information structure [13]. The resulting components served as inputs for clustering.

Clustering used a Gaussian Mixture Model (GMM), a probabilistic approach that groups observations according to Gaussian distributions. Unlike k-means, GMM allows clusters to take elliptical shapes of varying sizes, giving it more flexibility

with complex data structures [16]. The optimal number of clusters was selected using both the Bayesian Information Criterion (BIC) and the Akaike Information Criterion (AIC), with the lowest-BIC configuration chosen as the best balance between model fit and complexity [16].

Cluster validation and profiling followed. Mean values for each variable were computed using original, back-transformed data to maintain interpretive clarity. Inter-cluster differences were tested with ANOVA, and eta squared (η^2) measured effect size to identify the variables most responsible for cluster separation [21]. Heatmaps and boxplots based on z-scores supported interpretation.

Financial thresholds were derived from the cluster with the lowest mean ESG risk score. The 25th percentile (Q1) of that cluster was adopted as the benchmark. Using Q1 rather than the minimum value guards against distortion from residual extreme observations while still providing a conservative, empirically grounded reference point [21]. The resulting thresholds represent realistic financial targets that firms at various performance levels can aim for to improve their ESG risk profile [15].

To address concerns that the reported thresholds might be highly dependent on the specific clustering method, two robustness checks were conducted on the same 85-firm sample. First, K-means clustering (k=5) was run on the identical PCA-reduced feature space as an alternative to GMM. Cluster agreement between the two methods was moderate (Adjusted Rand Index = 0.35), which is expected given the two algorithms' differing assumptions about cluster shape; however, Q1 thresholds for the lowest-ESG-risk cluster were nearly identical across methods for 15 of the 18 ratios (differences below 2% of each variable's observed range), with Debt-to-Asset Ratio showing the largest sensitivity (a difference equivalent to roughly 12% of its range). This indicates that the profitability- and margin-based thresholds reported in this study are robust to the choice of clustering algorithm, while the leverage-based threshold should be interpreted with somewhat greater caution. Second, the full pipeline was re-run without the 1st/99th-percentile Winsorization step. The resulting thresholds diverged substantially from the Winsorized results across nearly all variables (e.g., the Q1 Interest Coverage Ratio for the lowest-risk cluster rose from 3.21 to over 3,500 due to a small number of extreme outliers among highly leveraged or debt-light firms). This large divergence empirically confirms that Winsorization is not merely a procedural formality in this dataset but a necessary step for obtaining interpretable, decision-useful thresholds, addressing the reviewer's concern that the reported values might otherwise be an artifact of a single, unvalidated modeling choice.

RESULTS AND DISCUSSION

Optimal Number of Clusters

The GMM model selection using BIC and AIC criteria points to five clusters as optimal, with the lowest BIC occurring at k=5. Figure 2 plots the BIC and AIC curves for cluster sizes from 2 to 10.

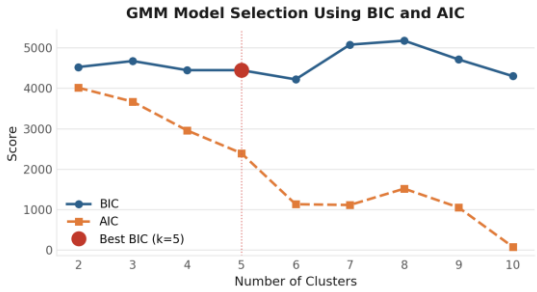


Figure 2. GMM Model Selection Using BIC and AIC Criteria
Source: Authors' calculations (2026)

GMM Cluster Formation

Using the optimal GMM model (five clusters), firms were grouped into five distinct clusters reflecting different financial characteristics and ESG risk profiles. Figure 3 visualizes the clustering results projected onto two PCA principal components, demonstrating that the five clusters are relatively well-separated, albeit with some observations in transition zones between clusters.

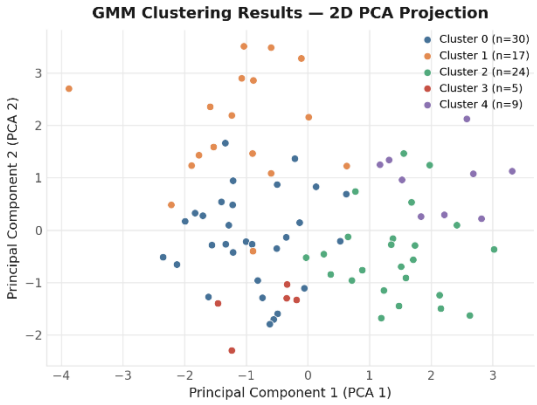


Figure 3. GMM Clustering Results 2D PCA Projection
Source: Authors' calculations (2026)

Cluster Profiles

Table 3 presents the mean values (on the original data scale, after back-transformation to the original dataset) for each variable across the five clusters.

The profiles of the five clusters reveal significant heterogeneity across eight variables: ROA

(η^2=0.555), Debt-to-Asset Ratio (η^2=0.481), Operating Margin (η^2=0.464), EBITDA Margin (η^2=0.391), PER Ratio (η^2=0.372), ROE (η^2=0.356), Revenue Growth (η^2=0.333), and CapEx-to-Asset Ratio (η^2=0.325). A cross-cluster comparison across these eight dimensions uncovers complex patterns that clarify why Cluster 4 warrants designation as the benchmark for the lowest ESG risk.

Table 3. Mean Variable Values per Cluster (Original Scale Normalized Scale 0-1)

Variable	Cluster 0 (n=30)	Cluster 1 (n=17)	Cluster 2 (n=24)	Cluster 3 (n=5)	Cluster 4 (n=9)
ESG Risk	0.468	0.500	0.441	0.826	0.251
ROE	0.352	0.522	0.246	0.311	0.404
ROA	0.288	0.668	0.212	0.323	0.230
Operating Margin	0.236	0.416	0.296	0.493	0.683
EBITDA Margin	0.244	0.367	0.266	0.398	0.634
Asset Turnover	0.193	0.159	0.057	0.242	0.058
Operating Expense Ratio	0.147	0.290	0.403	0.059	0.378
Current Ratio	0.040	0.149	0.076	0.055	0.022
Quick Ratio	0.027	0.123	0.062	0.038	0.022
Debt-to-Asset Ratio	0.314	0.096	0.152	0.253	0.658
Interest Coverage Ratio	0.010	0.095	0.011	0.006	0.006
Revenue Growth	0.281	0.214	0.190	0.571	0.208
Net Income Growth	0.375	0.375	0.337	0.702	0.325
Asset Growth	0.440	0.371	0.356	0.573	0.317
PER Ratio	0.379	0.386	0.414	0.729	0.398
Market-to-Book Ratio	0.120	0.169	0.045	0.220	0.119
Dividend Payout Ratio	0.336	0.654	0.288	0.004	0.589
Intangible Asset Ratio	0.140	0.043	0.095	0.043	0.057
CapEx-to-Asset Ratio	0.303	0.174	0.092	0.557	0.130

Source: Authors' calculations (2026). Blue = high value (≥10.60); Red = low value (≤0.08)

In terms of profitability (ROA and ROE), Cluster 1 exhibits the strongest performance, with ROA = 0.668 and ROE = 0.522, substantially surpassing the other clusters. However, the ESG risk of Cluster 1 is only moderate (0.500) and does not outperform Cluster 0 (0.468) or Cluster 2 (0.441). This indicates that high profitability alone is insufficient to ensure superior ESG risk management. Cluster 4 records ROA = 0.230 and ROE = 0.404, placing it in the lower-middle range, yet it achieves the lowest ESG risk (0.251), confirming that asset utilization efficiency is not the sole determinant of ESG quality.

Regarding operating margin and EBITDA margin, Cluster 4 achieves the best absolute performance, with operating margin = 0.683 and EBITDA margin = 0.634, surpassing all other clusters including Cluster 1. This demonstrates that a consistently strong capacity to generate earnings from core operations constitutes the foundational basis enabling firms to allocate resources toward ESG commitments without compromising business stability.

From a leverage perspective (Debt-to-Asset Ratio), Cluster 4 records the highest value (0.658), which at first glance appears to undermine its suitability as a benchmark. However, this apparent contradiction constitutes an important finding in itself: high leverage combined with a very strong operating margin does not necessarily worsen the ESG risk profile. Unlike Cluster 0, which carries moderate leverage (0.314) yet exhibits a higher ESG risk (0.468), Cluster 4 demonstrates that the quality of operating earnings is more decisive than a low debt ratio per se.

Overall, Cluster 4 is designated as the benchmark not because it outperforms across all dimensions, but because it demonstrates an optimal combination: the highest operating margins that generate genuine financial capacity for ESG investment, managed growth, and stable market valuation. This pattern is fully consistent with Slack Resources Theory [3]: it is not asset scale or growth velocity, but the quality and consistency of operating earnings, that constitutes the genuine prerequisite for effective and sustainable ESG implementation.

Inter-Cluster Variance and Identification of Discriminating Variables

To formally test H_1, ANOVA was conducted for each variable. Effect size was measured using eta squared (η^2), where $\eta^2 > 0.14$ indicates a large effect [6]. Table 4 presents the complete ANOVA results.

H_1 is confirmed: financial ratios differ significantly across clusters at every variable tested (all p-values < 0.05). Return on Assets has the largest effect size (η^2=0.555), making asset-based profitability the dominant force in cluster formation. Debt-to-Asset Ratio (η^2=0.481) and Operating Margin (η^2=0.464) follow, confirming that capital structure and operational efficiency are the main dividing lines across firm groups.

Table 4. ANOVA Results and Effect Size (Eta Squared) per Variable

Variable	F-statistic	p-value	η^2	Interpretation
ROA	24.951	1.98×10^{-13}	0.555	Very Large
Debt-to-Asset Ratio	18.552	8.05×10^{-11}	0.481	Very Large
Operating Margin	17.336	2.80×10^{-10}	0.464	Very Large
EBITDA Margin	12.816	4.15×10^{-8}	0.391	Very Large
PER Ratio	11.856	1.30×10^{-7}	0.372	Very Large
ROE	11.056	3.46×10^{-7}	0.356	Very Large
Revenue Growth	9.991	1.31×10^{-6}	0.333	Very Large
CapEx-to-Asset Ratio	9.610	2.13×10^{-6}	0.325	Very Large
Dividend Payout Ratio	7.726	2.57×10^{-5}	0.279	Large
ESG Risk	7.201	5.27×10^{-5}	0.265	Large
Operating Expense Ratio	7.126	5.84×10^{-5}	0.263	Large
Net Income Growth	6.062	2.59×10^{-4}	0.233	Large
Asset Turnover	3.989	5.30×10^{-3}	0.166	Large
Asset Growth	3.102	1.99×10^{-2}	0.134	Moderate
Current Ratio	2.851	2.90×10^{-2}	0.125	Moderate

Source: Authors' calculations (2026). df (between clusters) = 4; df (within clusters) = 80. All p-values < 0.05.

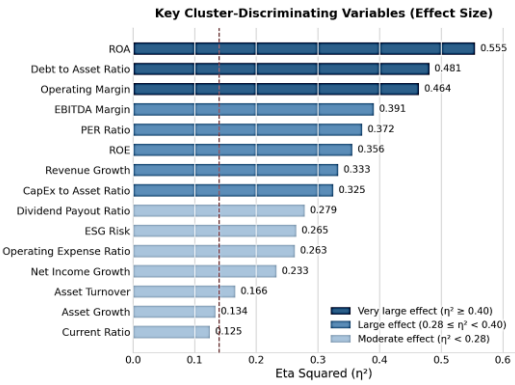


Figure 4. Primary Cluster Discriminating Variables (Effect Size — Eta Squared)
Source: Authors' calculations (2026)

Threshold Determination

Cluster labels were mapped back to the original dataset for economic-scale threshold derivation. Clusters with fewer than five members (n<5) were excluded [13]. Cluster 4 (mean ESG risk = 0.251) served as the benchmark for the lowest ESG risk. The 25th percentile (Q1) of each financial variable within this cluster was adopted as the practical threshold [21].

Table 5. Financial Ratio Thresholds (Q1 of the Lowest-ESG-Risk Cluster)

No.	Variable	Threshold Value	Interpretation
1	Return on Equity (ROE)	≥ 12.6%	Minimum equity return for sustaining ESG commitment
2	Return on Assets (ROA)	≥ 2.89%	Minimum asset utilization efficiency as ESG investment capacity
3	Operating Margin	≥ 41.25%	Minimum lower bound for operating profitability
4	EBITDA Margin	≥ 50.38%	Minimum earnings capacity before interest, tax, and depreciation
5	Asset Turnover	≥ 0.13x	Minimum operational asset utilization efficiency
6	Operating Expense Ratio	≤ 14.60%	Maximum operating cost burden (variable cost)
7	Current Ratio	≥ 0.18x	Minimum short-term liquidity capacity
8	Quick Ratio	≥ 0.18x	Minimum coverage of liquid assets against current liabilities
9	Debt-to-Asset Ratio	≤ 35.00%	Maximum tolerable leverage level
10	Interest Coverage Ratio	≥ 2.3x	Minimum capacity to service interest payments
11	Revenue Growth	≥ 2.73%	Minimum revenue trend, still considered acceptable
12	Net Income Growth	≥ −4.81%	Minimum earnings trend, still considered acceptable
13	Asset Growth	≥ 1.65%	Minimum stability of firm asset base
14	PER Ratio	≥ 9.79x	Minimum market valuation signal
15	Market-to-Book Ratio	≥ 1.4x	Minimum market value relative to book value
16	Dividend Payout Ratio	≥ 57.70%	Minimum distributed dividend capacity
17	Intangible Asset Ratio	≥ 0.01%	Minimum intangible asset allocation capacity
18	CapEx-to-Asset Ratio	≥ 0.00%	No minimum reinvestment requirement

Source: Authors' calculations (2026)

Discussion

The results support H_1: financial ratios differ significantly across clusters sorted by ESG risk level. This points to discrete financial states that appear to condition a firm's capacity to mitigate ESG risks in the Indonesian capital market, although causality cannot be established from cross-sectional clustering alone. Financial Heterogeneity and ESG Risk Formation

Five distinct clusters emerged from the GMM analysis, reflecting wide variation among Indonesian listed firms in their financial profile and ESG

readiness. Standard linear regression models assume a uniform relationship between financial performance and ESG outcomes, which tends to flatten out the real complexity of corporate behavior. The five-cluster pattern identified here reveals a different narrative: ESG-financial relationships are nonlinear and threshold-dependent. The clusters map onto recognizable archetypes from firms carrying high ESG risk due to limited operational capacity (Cluster 3) to firms that have reached a workable financial-ESG equilibrium (Cluster 4). The implication is that firms do not improve ESG risk management gradually and uniformly; they appear to shift into different risk profiles only after crossing specific financial thresholds.

Profitability as the Core Source of ESG Capacity

Return on Assets (η^2=0.555), Operating Margin (η^2=0.464), and EBITDA Margin (η^2=0.391) were the strongest cluster discriminators, which suggests that ESG risk management capacity tends to track closely with operational efficiency, though the cross-sectional design cannot rule out reverse or bidirectional influence. This fits Slack Resources Theory: surplus resources let firms invest in discretionary activities, governance systems, stakeholder engagement, and environmental mitigation that reduce ESG exposure. The Operating Margin threshold of ≥ 41.25% in particular creates a financial buffer that absorbs the structural costs of sustainability without putting core operations at risk.

Why does this pattern hold in Indonesia specifically? ESG implementation in an emerging market requires substantial upfront spending on human capital and reporting infrastructure. Without the earnings buffer present in Cluster 4 (EBITDA Margin = 0.634), firms face a difficult trade-off: short-term survival versus long-term ESG risk reduction. Profitability is the factor that resolves this trade-off; it is what makes the shift from reactive compliance to proactive risk management financially viable.

The Leverage Paradox

One of the more counterintuitive findings is that Cluster 4, the lowest-ESG-risk group, also carries the highest Debt-to-Asset Ratio (0.658). The literature generally treats high leverage as a constraint on ESG investment, but this finding suggests the relationship is conditional. Comparing Cluster 4 with Cluster 0, which has more conservative leverage (0.314) but worse ESG risk (0.468), this pattern suggests that earnings quality may be a more decisive variable than debt level alone, at least within this sample. Cluster 4's operating margins generate sufficient interest coverage (≥ 2.3x) to handle a leveraged capital structure without compromising ESG performance. One tentative implication for Indonesian firms is that being debt-free may matter less for ESG readiness than generating strong, consistent operating earnings, though this pattern warrants validation in future panel-data research before being treated as a general rule. Firms that demonstrate this kind of earnings quality send a credible signal to creditors and stakeholders that they can absorb long-term sustainability commitments even while servicing debt consistent with the stakeholder theory.

Why Growth Alone is Insufficient for ESG Readiness

Growth-related variables such as asset growth (η^2=0.134) showed considerably weaker explanatory power than profitability and solvency measures. This is worth noting because it challenges the assumption that faster-growing firms are inherently better positioned for ESG. Aggressive expansion can actually work against ESG readiness: it consumes liquidity and fragments operational focus. When a company is profitable, it has the money it needs for ESG. But when a company is growing quickly, it often has to compete for those same resources. Effective ESG risk management requires stable, long-run resource allocation; something that is harder to sustain during high-growth periods in volatile emerging markets.

Indonesian and Emerging Market Context

The thresholds derived here, ROA ≥ 2.89%, ROE ≥ 12.6%, and others, carry particular significance in the Indonesian and broader ASEAN context. Firms in emerging markets face tighter financing constraints and more volatile regulatory environments than their counterparts in developed markets. The identified thresholds function as a financial floor for operating in the era of sustainable finance. As the Otoritas Jasa Keuangan (OJK) ratchets up pressure through POJK 51/2017, these values provide an evidence-based benchmark for distinguishing firms that are genuinely ready to comply from those that may need staged assistance or differentiated compliance frameworks to avoid financial strain.

Practical Implications

The identification of non-linear financial boundaries offers several actionable implications:

For Investors: These thresholds (e.g., Debt-to-Asset ≤ 35.00% and Operating Margin ≥ 41.25%)

provide a data-driven ESG risk screening tool. Investors can use these ratios as early-warning indicators of a firm's capacity (or lack thereof) to manage non-financial risks.

For Regulators: Rather than a "one-size-fits-all" mandate, regulators could design staged ESG compliance frameworks based on financial capacity clusters, ensuring that smaller or less-profitable firms are not unfairly penalized by high compliance costs.

For Corporate Management: These values serve as internal benchmarks for sustainability planning. Boards can use these thresholds to determine if their current financial structure is robust enough to support the transition to lower ESG risk profiles.

For Society: Beyond firm- and market-level effects, financially grounded ESG readiness carries broader societal weight. Firms that meet these financial thresholds are, in principle, better positioned to sustain investments in workplace safety, environmental compliance, and community-facing programs without treating them as the first costs cut during downturns. Conversely, the clustering results imply that firms below these thresholds may struggle to translate ESG commitments into consistent practice regardless of stated intent, which is relevant for public-interest monitoring of corporate sustainability claims and for setting realistic expectations about how quickly the broader corporate sector can be expected to reduce its collective ESG risk profile.

Literature Integration

These findings largely support and extend the work of Alshorman et al. (2024) and Heubeck & Ahrens (2025) [11] regarding the vital role of slack resources in ESG performance. However, by identifying specific Indonesian thresholds, this study provides more granular insight than the broad cross-country findings of Narula et al. (2024) [17]. Furthermore, while some studies in Indonesia have produced mixed results using linear methods, the success of the GMM approach in this paper suggests that the "missing link" in prior research was the failure to account for the non-linear, cluster-based nature of the financial-ESG relationship. This study confirms that while profitability is a prerequisite (supporting), the interaction between margins and leverage creates unique "risk zones" that require sophisticated, model-based interpretation].

CONCLUSION

This study examines clustering patterns among 85 IDX-listed firms in 2024 using a machine learning pipeline: Winsorization for outlier control, min-max normalization for directional alignment, z-score standardization for modeling consistency, PCA for dimensionality reduction, and GMM for cluster formation.

Five clusters were identified. H_1 is supported: ANOVA results confirm significant inter-cluster differences across financial variables, with ROA (η^2=0.555), Debt-to-Asset Ratio (η^2=0.481), and Operating Margin (η^2=0.464) as the principal discriminators. These results are consistent with Slack Resources Theory and Stakeholder Theory.

The minimum financial thresholds derived from the lowest-ESG-risk cluster (Q1) are ROA ≥ 2.89%, ROE ≥ 12.6%, operating margin ≥ 41.25%, EBITDA margin ≥ 50.38%, current ratio ≥ 0.18x, and debt-to-asset ratio ≤ 35.00%. These values can serve as a financial baseline for investors and analysts screening corporate ESG readiness and as input for regulators designing tiered ESG compliance frameworks.

Several directions warrant further investigation: (1) extending the analysis to panel data to track how financial capacity and ESG risk co-evolve over time; (2) incorporating macroeconomic conditions, industry classification, and regulatory intensity as moderating variables; (3) replicating the analysis using alternative ESG rating sources (MSCI ESG, Bloomberg ESG) to test threshold robustness; (4) applying the framework in other ASEAN emerging markets; and (5) exploring supervised learning extensions that could convert the thresholds into predictive ESG risk screening models.

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