Journal of Economics, Entrepreneurship, Management Business and Accounting, 2026, 4(5),667-688.
https://doi.org/10.61255/jeemba.v4i5.1097

Market Capitalization Volatility, Profitability, and Leverage: A Comparative Four-Case Study of Indonesia's Energy and Technology Firms

Hikmahwati[1*], Widya Ais Sahla[1], Sandra Iriawan[1], Noor Safrina[1], Nurul Qalbiah[1], Mark Gabriel Wagan Aguilar[2]

[1]Department of Accounting, Politeknik Negeri Banjarmasin, 70124, Indonesia.
[2]Technological College, Philippines.

ABSTRACT

Purpose – This exploratory study examines preliminary associations between market capitalization volatility, profitability, and leverage across four Indonesian energy and technology firms, drawing on Signaling Theory. With only two firms per sector, sector differences are treated as case-level heterogeneity, not established moderation.

Design/methodology/approach – Using a multi-case panel design, the study analyzes four Indonesian firms over 2014–2024 (44 firm-year observations): two energy firms (Adaro Energy, Indonesia Energy Corporation) and two technology firms (Telkom Indonesia, Elang Mahkota Teknologi). The small sample confounds sector with firm identity, so comparisons are descriptive, not tested moderation. VMC1 and VMC2 were recomputed as annual rolling-window series, replacing a prior full-period constant confounded with sector identity. Variables were z-standardized, volatility mean-centered before interaction terms, examined via marginal effects.

Findings/Results – Volatility is positively associated with profitability and negatively with leverage across all cases. With corrected VMC1/VMC2, sector does not moderate either association, stable across leave-one-firm-out checks. A lagged specification shows both associations disappear with temporal separation, indicating associative not causal relationships.

Originality/Value – The study offers a descriptive account of how an apparent sector-moderation finding can arise from a measurement artifact and disappear once corrected—a cautionary illustration for future research.

ARTICLE INFO

Keywords:
Market Capitalization Volatility,
Profitability,
Leverage,
Signaling Theory,
Industry Sector

Article Information:
Received: 23/06/2026
Revise: 13/07/2026
Accepted: 09/08/2026

ISSN:
2985-3168 (Online)
2985-3222 (Print)

*Corresponding Author at:
Department of Accounting, Politeknik Negeri Banjarmasin, Jl. Brigjen H. Hasan Basri No. 9, Banjarmasin 70124, South Kalimantan, Indonesia.
E-mail address: hikmahwati@poliban.ac.id (Hikmahwati)

1. Introduction

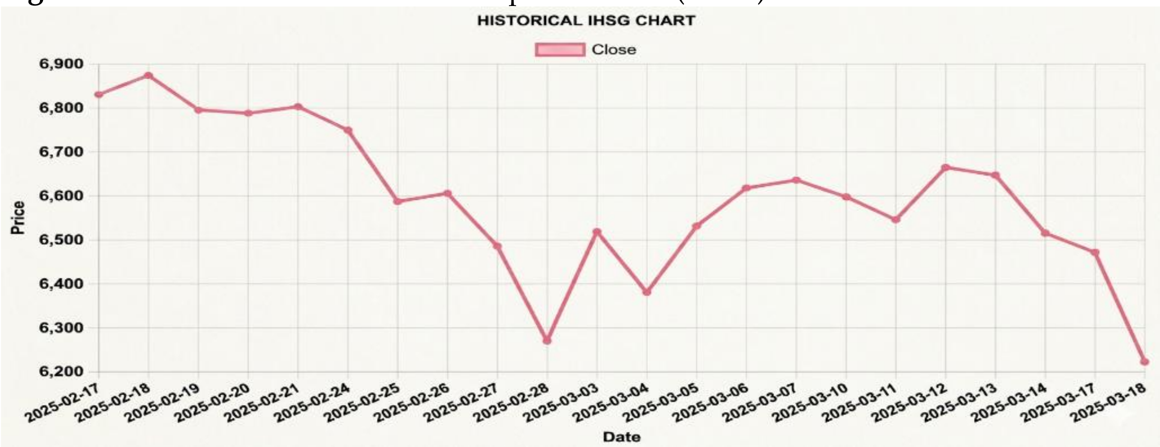
In modern capital markets, the concept of firm value is no longer determined solely by fundamental performance but also by how information is perceived and interpreted by investors (Pham et al., 2025). Market capitalization has become one of the primary indicators reflecting the market's collective assessment of a firm's prospects, risk, and sustainability, as it encompasses investor expectations regarding available information (Hariyanto, 2021). The finance literature indicates that firm valuation is influenced not only by fundamental factors but also by market sentiment and investor perceptions in processing information (Aljifri, 2023; Bashir & Kumar, 2025). A study conducted by Pramesti et al. (2025) shows that market capitalization has a significant relationship with firm value, particularly in emerging markets where investors tend to respond to information dynamically. Furthermore, other studies have emphasized that market capitalization and leverage play an important role in determining the level of sustainable growth (Suhardjo et al., 2024). These findings suggest that firm value is determined not only by internal financial indicators but also by how the market evaluates and responds to such information.

Within the framework of Signaling Theory, changes in market value are viewed as external signals that communicate a firm's quality and level of uncertainty to investors and creditors, such that fluctuations in market capitalization reflect how the market interprets these signals (Spence, 1973). Consistent with this perspective, recent studies show that the dynamics of volatility and market capitalization are closely related to investor behavior, such as herding behavior, which can influence stock price formation in the market (Pranata et al., 2024). This indicates that firm value is shaped not only by rational information but also by investors' collective response to uncertainty.

Market capitalization volatility has become one of the important aspects in understanding these dynamics. Volatility not only reflects fluctuations in stock prices but also represents the level of uncertainty and risk faced by the market. A high level of volatility can heighten investors' risk perceptions, which in turn may increase the cost of capital and influence managerial decisions related to investment and financing structure (Haliza et al., 2025). Recent studies indicate that volatility is associated with various financial factors, such as leverage, profitability, and stock trading volume, which jointly influence stock price stability (Maysaroh et al., 2025). Furthermore, in the context of modern investment strategies, volatility is also related to the effectiveness of portfolio management, where changes in the information environment can reduce the profit opportunities of volatility-based strategies (Angelidis & Tessaromatis, 2023). Volatility therefore functions not merely as a risk indicator but also as a reflection of the complex interaction among information, investor behavior, and market conditions.

Empirical phenomena in the Indonesian capital market further reinforce the relevance of volatility as a key market characteristic. The Indonesian Composite Index (IHSG) has experienced several significant fluctuations due to external pressures and shifts in investor sentiment. One notable event occurred on 18 March, 2025, when the IHSG recorded a sharp decline of approximately 5–7% within a single trading day and fell to the level of 6,084. Figure 1 illustrates the movement of the IHSG during the February–March 2025 period, characterized by a downward trend from around 6,800 to approximately 6,200, accompanied by considerable fluctuations at several points in time. This movement pattern reflects the market's high sensitivity to information and the presence of uncertainty that investors responded to rapidly. Moreover, the emergence of several rebound phases following the decline indicates that the market reacted not only to fundamental factors but also to short-term shifts in sentiment. This condition confirms that volatility is an inherent characteristic of the Indonesian capital market and can influence firm value at the aggregate level.

Figure 1. Decline in the Indonesia Composite Index (IHSG)



At the sectoral level, volatility also exhibits different characteristics across industries. The technology sector tends to display higher levels of volatility, as it is strongly influenced by growth expectations, innovation, and the dominance of intangible assets that are difficult to measure using conventional approaches (Peters & Taylor, 2017). Intangible assets such as intellectual capital and research and development (R&D) make the valuation of technology firms more sensitive to shifts in investor sentiment and future expectations. In contrast, the energy sector exhibits different volatility characteristics, as it is more dependent on external factors, particularly fluctuations in global commodity prices such as oil and gas, as well as geopolitical conditions that affect energy supply and demand (Ji et al., 2018). Differences in asset structure and sources of risk therefore contribute to variations in volatility levels across industry sectors.

These differences in business structure and risk sources suggest that the impact of volatility on corporate financial performance, particularly profitability and leverage, is not homogeneous (Maysaroh et al., 2025). Nevertheless, empirical studies that specifically examine market capitalization volatility as a market signal and its influence on financial performance across sectors, particularly in developing countries such as Indonesia, remain relatively limited. Based on this research gap, the present study aims to examine the effect of market capitalization volatility on firm profitability and leverage by incorporating industry sector as a moderating variable within the perspective of Signaling Theory. This study is expected to contribute to enriching the finance literature on the role of volatility as a market signal, while also offering practical implications for investors and managers in understanding the relationship between market dynamics and the stability of corporate financial performance across various industry sectors.

2. Literature Review & Hypothesis Development

2.1 Signaling Theory and Market Capitalization Volatility

Signaling Theory, proposed by Michael Spence (1973), explains that firms convey information to external parties through various signals, both financial and non-financial, to reduce information asymmetry between management and investors. According to Munzir et al. (2023), the signals communicated by a firm reflect various managerial decisions and actions directed toward serving shareholders' interests, particularly in efforts to enhance firm profitability. In the context of capital markets, changes in a firm's market value, including fluctuations in market capitalization, can be regarded as external signals reflecting how the market interprets information regarding a firm's prospects, risk, and quality (Aljifri, 2023; Baker et al., 2012; Connelly et al., 2010; Pastor & Veronesia, 2012).

Market capitalization represents investors' collective assessment of firm value based on information available in the market. The finance literature indicates that market value is influenced not only by fundamental performance but also by investor expectations, sentiment, and risk perceptions (Hafidz, 2025). Accordingly, market capitalization volatility can reflect the level of information uncertainty and the dynamics of investor expectations regarding a firm (Asgharian et al., 2023; X. Gong et al., 2022; Xiao et al., 2024). From a signaling perspective, high volatility can be interpreted as a signal of heightened uncertainty or perceived risk in the market. Investors and creditors tend to respond to such conditions by adjusting their investment and financing decisions, which may ultimately affect a firm's financial performance and capital structure (Asgharian et al., 2023; J. Gong, 2024).

A key distinction in the Signaling Theory literature is between firm-generated signals deliberate managerial actions such as dividend announcements or disclosures, intended to reduce information asymmetry (Connelly et al., 2010; Spence, 1973). Market-generated signals, which emerge from aggregate investor trading behavior and sentiment rather than deliberate managerial action (Baker et al., 2012; Pastor & Veronesia, 2012). This study treats market capitalization volatility as the latter: an externally generated signal that management observes and responds to, rather than one it deliberately transmits.

This distinction clarifies the feedback loop examined here: rather than firms sending a signal through volatility, market-generated volatility is theorized to feed back into managerial decisions through four channels (1) financing cost, as volatility raises creditors' risk premiums (Cook & Luo, 2023). (2) investor confidence, as volatility affects shareholders' willingness to provide capital (Pastor & Veronesia, 2012). (3) managerial risk perception, shaping appetite for leverage or investment (Haliza et al., 2025). (4) investment timing, as uncertainty leads management to defer or accelerate capital expenditure (Korajczyk & Levy, 2003). These channels underpin the volatility-profitability and volatility-leverage relationships tested in H1 and H2, though this study examines the reduced-form relationships rather than the channels individually a limitation addressed further in the Conclusion

2.2 Market Capitalization Volatility, and Profitability

Market capitalization volatility has the potential to influence firm profitability through various mechanisms. High volatility reflects instability in investor expectations, which can affect market confidence, the cost of capital, and managerial flexibility in implementing operational strategies (Pastor & Veronesia, 2012). Increasing market uncertainty may lead firms to delay productive investment, raise financing costs, and put pressure on earnings performance.

Several empirical studies indicate that market volatility has a negative relationship with firm profitability due to increased business risk and adjustment costs (Saleem et al., 2019). The findings of Kusnanto and Qalbi (2024) show that profitability has a significant effect on firm value. High volatility is often associated with information risk and financial pressure, both of which have a significant impact on firm financial performance (Dhingra et al., 2024; Haliza et al., 2025). Accordingly, market capitalization volatility, as a market signal, is expected to have a significant effect on firm profitability.

H1: Market capitalization volatility has a significant effect on corporate profitability.

2.3 Market Capitalization Volatility, and Leverage

In addition to influencing earnings performance, market capitalization volatility also has implications for firms' financing structure decisions. Under conditions of high volatility, investors' and creditors' risk perceptions tend to increase, causing the cost of debt to rise and access to external financing to become more limited (Cook & Luo, 2023; Tran, 2021). Firms may respond to such conditions by adjusting their leverage levels to maintain financial stability. Previous studies indicate that market uncertainty and firm value volatility are associated with financing policy, either through reducing leverage to avoid financial risk or increasing leverage as a means of preserving liquidity (Chang et al., 2009; Korajczyk & Levy, 2003). Accordingly, market capitalization volatility is expected to have a significant effect on firm leverage.

H2: Market capitalization volatility has a significant effect on corporate leverage.

2.4 The Moderating Role of Industry Sector

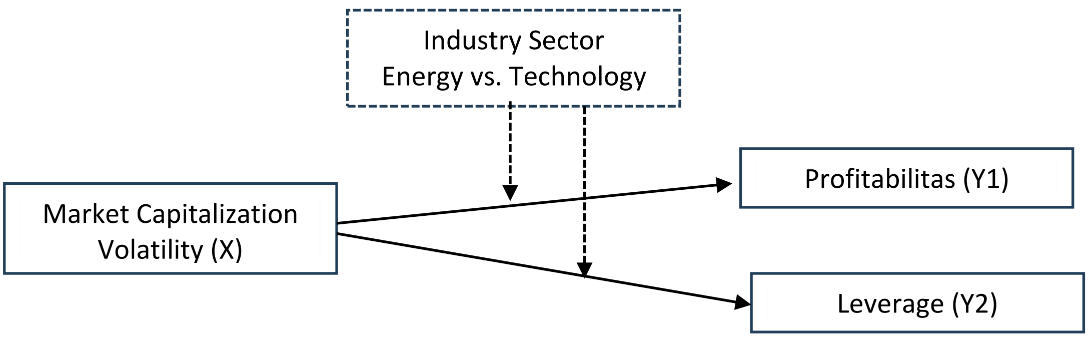
Industry sector characteristics have the potential to moderate the relationship between market capitalization volatility and profitability as well as leverage. The energy sector is generally capital-intensive and strongly influenced by external factors such as global commodity prices, whereas the technology sector relies more heavily on intangible assets, innovation, and long-term growth expectations (Damodaran, 2012; Kogan et al., 2017). Differences in asset structure, sources of risk, and sensitivity to market information cause firms in different sectors to respond to market signals differently (Rajan & Zingales, 1995; Denis & McKeon, 2012). Within the framework of Signaling Theory, the same signal in this case, market capitalization volatility, may be interpreted differently by investors depending on a firm's sectoral characteristics. Industry sector is therefore expected to either strengthen or weaken the effect of market capitalization volatility on firm profitability and leverage.

H3: The effect of market capitalization volatility on profitability differs between the energy sector and the technology sector.

H4: The effect of market capitalization volatility on leverage differs between the energy sector and the technology sector.

The relationships among market capitalization volatility, profitability, and leverage are formulated in the research framework presented in Figure 2.

Figure 2. Research Framework



3. Methodology

This study employs a quantitative approach with an exploratory multi-case panel study design, aimed at analyzing preliminary patterns of association between market capitalization volatility and firm profitability and leverage, and at comparing these patterns across a number of selected company cases in Indonesia's energy and technology sectors. The exploratory design was deliberately chosen, rather than adopted as an unanticipated limitation, because the target population of this study faces significant structural constraints, particularly in the technology sector, as further explained in the population and sample section. This study uses panel data combining time-series and cross-firm data over the 2014–2024 period (11 years of observation). The population of this study consists of all Indonesian companies listed on Companies Market Cap in the energy and technology sectors during the 2014–2024 period, totaling 49 companies. The sample was determined using a purposive sampling technique based on the following criteria: (1) the company is classified within the energy or technology sector; (2) the company has complete annual market capitalization data with no reporting gaps throughout the entire 2014–2024 observation period; and (3) the company has consistently published annual financial reports during that period.

The application of these criteria produced an asymmetric challenge between the two sectors. Indonesia's energy sector has a relatively well-established issuer base, with a number of companies having been listed on the Indonesia Stock Exchange since the 1990s and 2000s. In contrast, the technology sector faces a genuine structural constraint: the majority of issuers classified under the technology sector according to the IDX Industrial Classification (IDX-IC), a classification only introduced by the Indonesia Stock Exchange in January 2020, were officially listed only after 2017, coinciding with a wave of listings by digital startups and information technology service providers. As a result, the number of technology issuers meeting the requirement of complete eleven-year data (2014–2024) is considerably smaller than in the energy sector.

Based on these criteria and taking the aforementioned structural constraints into account, this study designates four companies as research cases: Adaro Energy Indonesia Tbk (ADRO) and Indonesia Energy Corporation (IEC) for the energy sector, and PT Telkom Indonesia (Persero) Tbk (TLKM) and Elang Mahkota Teknologi Tbk (EMTK) for the technology sector. These four companies were selected because they consistently reported complete and transparent market capitalization data and annual financial statements throughout the observation period.

Given this limited sample size, the study is explicitly positioned as an exploratory multi-case panel analysis. The resulting findings are intended to identify preliminary patterns in the relationships among market capitalization volatility, profitability, and leverage within the cases examined, rather than to be generalized to the entire population of energy or technology firms in Indonesia. The moderation results for industry sector, in particular, should be read as a comparison between two pairs of cases rather than as a representation of general sector-level characteristics.

The data used in this study are secondary. Annual market capitalization data were obtained from CompaniesMarketCap, while data on earnings, total assets, equity, and debt were obtained from companies' financial statements and annual reports published through the Indonesia Stock Exchange (IDX). Market capitalization volatility (VMC), profitability (PROF), and leverage (LEV) are each operationalized in this study as an unweighted additive composite index, constructed by summing the raw values of three sub-indicators for each construct. Specifically, VMC is computed as the sum of the standard deviation of market capitalization (VMC1), the coefficient of variation of market capitalization (VMC2), and the year-on-year growth rate of market capitalization (VMC3), PROF is computed as the sum of Return on Assets (ROA), Return on Equity (ROE), and Net Profit Margin (NPM), and LEV is computed as the sum of Debt to Asset Ratio (DAR), Debt to Equity Ratio (DER), and Loan to Deposit-equivalent Ratio (LDR). This composite approach was adopted to capture multiple dimensions of each construct within a single regression variable, consistent with the multi-indicator conceptualization of volatility, profitability, and leverage described in the literature review.

Two corrections were made to the measurement of VMC in this revision. First, VMC1 (standard deviation) and VMC2 (coefficient of variation) had previously been computed once over the full 2014–2024 period per firm, making them constant within each firm and, because they did not overlap between sectors, close to perfect predictors of sector membership by construction; this was identified as the most serious outstanding measurement problem in the prior round. VMC1 and VMC2 are now recomputed as a 3-year trailing rolling-window standard deviation and coefficient of variation of each firm's annual market capitalization: for year t ≥ 2016, the window is [t−2, t−1, t]; for the first two years of each firm's series (2014 and 2015), for which a full trailing window is not yet available, the window is fixed at the earliest three available years (2014–2016), following standard practice for boundary-adjusted rolling statistics. VMC3 (year-on-year growth of market capitalization) is unchanged. This correction removes the artificial, construction-driven overlap between VMC and sector membership and is the basis for the results reported below; its effect on the diagnostics and models originally flagged by the reviewer (Tables 3, 7, and 8) is discussed at each relevant point. Second, because the sub-indicators of VMC still differ in scale even after this correction, VMC1, VMC2, and VMC3 (and, analogously, the components of PROF and LEV) are standardized to z-scores before being summed into each composite, so that no single sub-indicator mechanically dominates the index by virtue of its scale rather than its substantive weight; the corresponding raw-composite specification was also re-estimated as a diagnostic check and is reported only in Table 3, where it confirms that the multicollinearity problem identified in the previous round was itself substantially a symptom of the flawed VMC1/VMC2 measure — VIF falls to acceptable levels under the raw composite once VMC1/VMC2 are corrected, though the standardized composite remains marginally preferable and is used as the sole specification in Tables 5–11. The sub-indicators comprising PROF and LEV are more comparable in scale, and are therefore less subject to the scale-domination concern, though they are standardized as well for consistency. A summary of the operational definitions of variables, indicators, and measurement formulas used in this study is presented in Table 1.

Table 1. Operational Definitions of Variables and Their Measurements.

Variable	Operational Definition	Indicators	Formula	Reference
Market Capitalization Volatility (VMC)	The level of fluctuation in a company's market value during the 2014–2024 period	1. Standard deviation of market capitalization (VMC1), computed as a 3-year trailing rolling-window SD of annual market capitalization 2. Coefficient of variation of market capitalization (VMC2), computed as the rolling-window	$SD(MC_t) = \sqrt{\frac{\sum_{t=1}^{n}(MC_t - \bar{MC})^2}{n-1}}$ $CV(MC_t) = \frac{SD(MC_t)}{\bar{MC}_t}$ $Growth\ MC_t = \frac{MC_t - MC_{t-1}}{MC_{t-1}}$	(Asgharian et al., 2023) (Dhingra et al., 2024) (Haliza et al., 2025)

		SD divided by the rolling-window mean over the same 3-year window 3. Market capitalization growth (VMC3)		
Profitability (PROF)	The company's ability to generate profit from its available resources	1. Return on Assets (ROA) 2. Return on Equity (ROE) 3. Net Profit Margin (NPM)	$ROA = \frac{Net\ Income}{Total\ Assets}$ $ROE = \frac{Net\ Income}{Equity}$ $NPM = \frac{Net\ Income}{Sales}$	(Pramesti et al., 2025) (Ristyawan, 2019) (Ristyawan, 2019)
Leverage (LEV)	The level of debt usage in the company's financing structure	1. DAR 2. DER	$DAR = \frac{Total\ Debt}{Total\ Assets}$ $DER = \frac{Total\ Debt}{Equity}$	(Ristyawan, 2019) (Haliza et al., 2025)
Industry Sector (SEC)	Classification of companies based on industry characteristics	Sector dummy variable	0 = Energy 1 = Technology	(Kogan et al., 2017)

Data analysis was conducted using panel data regression with a Moderated Regression Analysis (MRA) approach, applied here in a descriptive rather than inferential-generalization sense: the interaction term is used to characterize how the association between VMC and each outcome differs between the two energy-sector cases and the two technology-sector cases, not to establish industry sector as a population-level moderator. This distinction matters because, with only four cross-sectional units, industry sector is structurally confounded with firm identity — a fixed-effects specification that partials out firm identity would, by construction, also absorb the time-invariant sector variable, so sector cannot be statistically separated from firm-specific characteristics (ownership, size, maturity, business model, listing history) in this design. Pooled OLS was therefore used as the main estimation model, on the understanding that the resulting sector-interaction coefficient reflects case-level contrast rather than an identified sector effect. Because pooled OLS assumes independence across the repeated annual observations from each firm, and because ordinary cluster-robust standard errors are not reliable with only four clusters, a leave-one-firm-out sensitivity analysis was conducted, re-estimating each model with each firm excluded in turn to assess whether the reported associations are driven by any single case; the results are reported in Table 9 below. A lagged specification, using prior-year VMC to predict current-year outcomes while controlling for the lagged dependent variable, was also estimated to provide a preliminary check on temporal ordering and is reported in Tables 10–11. Firm-level and year indicators as additional controls were not pursued further, since a fixed-effects specification cannot separately identify sector from firm identity in this four-firm design, as noted above. This study reports standard OLS standard errors throughout, as in the previous round, but with an important revision to how those standard errors should be read: once VMC1 and VMC2 are computed as a genuine annual series (see Methodology above), the Durbin–Watson statistics in Table 4 fall to approximately 0.48–0.51, well below the conventional acceptable range of 1.5–2.5 and indicating substantial positive autocorrelation in the residuals of the simple (non-interacted) models. This is itself an informative result: the earlier, higher Durbin–Watson values were partly an artifact of VMC1/VMC2 being constant within each firm, which suppressed the within-firm serial structure that the genuine annual series now reveals. Positive autocorrelation of this magnitude means the standard OLS point estimates remain unbiased but their standard errors are likely understated, so p-values in Tables 5–6 in particular should be read as suggestive rather than confirmatory; this strengthens, rather than changes, the case made throughout this study for cautious inference given the small number of clusters. Future studies with a larger number of independent sectoral units are strongly encouraged to apply cluster-robust or wild-cluster bootstrap inference, or a dynamic panel specification with an autoregressive term (as in the lagged models reported in Tables 10–11, where the Durbin–Watson statistics are close to 2 once lagged dependent variables are included), rather than relying on ordinary standard errors as this study does.

In this study's model, market capitalization volatility (VMC) serves as the independent variable, profitability (PROF) and leverage (LEV) serve as the dependent variables, and industry sector (SEC) acts as the moderating variable, tested through the interaction term VMC × SEC. The regression models used are as follows:

Model 1 (Profitability)

$$PROF_{it} = \alpha + \beta_1 VMC_{it} + \beta_2 SEC_i + \beta_3 (VMC_{it} \times SEC_i) + \varepsilon_{it} \quad (1)$$

Model 2 (Leverage)

$$LEV_{it} = \alpha + \beta_1 VMC_{it} + \beta_2 SEC_i + \beta_3 (VMC_{it} \times SEC_i) + \varepsilon_{it} \quad (2)$$

where PROF_it and LEV_it represent the profitability and leverage of firm i in period t, respectively; α denotes the constant; β1 denotes the association between market capitalization volatility and the dependent variable in the energy-sector cases; β2 denotes the case-level contrast between the two sector pairs (dummy variable: 0 = energy, 1 = technology); β3 denotes the difference in this association between the technology-sector cases and the energy-sector cases; and ε_it is the error term. As all regressors are contemporaneous (period t), these coefficients describe association, not the direction of causal influence; VMC, PROF, and LEV may each affect the others, or all three may respond jointly to unobserved firm and market conditions.

Because the industry sector variable is binary, with only two companies in each category, the interaction coefficient (β3) essentially compares two very small groups of cases and does not represent broad sector-level variation. In the moderated regression models originally reported (Tables 7–8), VMC was entered in its raw (uncentered) form before constructing the interaction term VMC × SEC; because zero lies well outside the observed range of VMC, the resulting β2 coefficient reflected the sector difference at VMC = 0, a value with no substantive interpretation, and appeared implausibly large as a result (e.g., 3.278 in the original profitability model). VMC was therefore mean-centered before the interaction term was reconstructed. The multicollinearity diagnostics in Table 3 — which originally reported VIF only for the uninteracted VMC and SEC terms — were re-run to include the centered interaction term itself, since interaction terms are a common source of multicollinearity that the original diagnostics did not evaluate. In the previous round, this revealed severe multicollinearity under the raw composite (VIF ≈ 39.5–39.6 for SEC and the interaction term), which was substantially reduced under the standardized composite (VIF ≈ 1.10–2.73). Now that VMC1 and VMC2 are computed as a genuine annual (rolling-window) series rather than a firm-level constant (see Methodology above), this multicollinearity problem is resolved under both specifications — VIF is approximately 1.5–2.9 under the raw composite and approximately 1.1–1.5 under the standardized composite — confirming that the earlier severe multicollinearity was substantially a symptom of the flawed VMC1/VMC2 measure rather than an unavoidable feature of the interaction term itself. The standardized composite remains marginally preferable and is used as the sole specification in Tables 5–11; the corresponding raw-composite VIF values are reported in Table 3 only, as a diagnostic check. To clarify interpretation, this study reports the marginal effect (simple slope) of market capitalization volatility separately for the energy sector (β1) and the technology sector (β1 + β3) in each model, together with its own standard error, 95% confidence interval, and significance test — including a formal test of the difference between the two slopes (β3, the interaction coefficient itself, with its own SE, CI, and p-value) — so that the direction and strength of the relationship within each sector can be interpreted explicitly, rather than relying solely on the sign of the interaction coefficient.

Prior to estimating the main model, classical regression assumption tests were conducted, comprising a multicollinearity test (tolerance and Variance Inflation Factor/VIF values), a heteroskedasticity test (residual scatterplot), and an autocorrelation test (Durbin–Watson statistic), to ensure that the regression model satisfies the requirements of a Best Linear Unbiased Estimator (BLUE) before coefficient interpretation.

4. Result and Discussion

In the initial stage of the analysis, descriptive statistics were used to provide a general overview of the characteristics of the research data. This analysis includes the minimum, maximum, mean, and standard deviation values for each variable used in the study. The results of the descriptive statistical analysis are presented in Table 2.

Table 2. Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Market Capitalization Volatility	44	2.5123	46.0838	20.3137	10.5949
Profitability	44	0,17	0,80	0,5027	0,14891
Leverage	44	0,79	2,55	1,3295	0,43322
Industry Sector	44	0	1	,50	,506
Valid N (listwise)	44				

The descriptive statistics presented in Table 2 provide a general overview of the characteristics of the research data, now computed with VMC1 and VMC2 as a genuine annual (rolling-window) series rather than a firm-level constant. The market capitalization volatility variable ranges from 2.51 to 46.08, with a mean of 20.31 and a standard deviation of 10.59, indicating that composite market value fluctuation now varies meaningfully both within and between firms across the observation period, rather than being driven almost entirely by a fixed cross-sectional difference between firms as in the previous round. The profitability variable ranges from 0.17 to 0.80, with a mean of 0.5027, while the leverage variable ranges from 0.79 to 2.55, with a mean of 1.3295. The relatively wide dispersion observed in both variables—reflected in standard deviations of 0.14891 and 0.43322, respectively—reflects substantial variation in financial performance among the four companies examined over the 2014–2024 period, consistent with a sample drawn from two sectors with differing business characteristics. Notably, the leverage variable's maximum value of 2.55 indicates that, in certain firm-years within the sample, the composite leverage score reached a relatively elevated level, pointing to periods of more aggressive debt financing among the cases examined. The industry sector variable has a mean of 0.50, reflecting a balanced distribution between the two sector categories in this research design (two energy companies and two technology companies). As an exploratory multi-case study based on 44 observations from four cross-sectional units, the descriptive statistics above should be read as characterizing the data within the cases examined, rather than as representative of the broader population distribution of energy and technology firms in Indonesia.

Following the descriptive analysis, the next step involved conducting classical assumption tests, one of which is the multicollinearity test. This test aims to ensure that no high correlation exists among the independent variables included in the regression model. The results of the multicollinearity test are presented in Table 3.

Table 3. Multicollinearity (VIF)

Term	VIF – Raw Composite	VIF – Standardized Composite
VMC (centered)	2.66	1.50
SEC	1.53	1.06
VMC × SEC	2.28	1.49

The multicollinearity diagnostics in Table 3 reflect the full interacted model (centered VMC, SEC, and VMC × SEC), not the uninteracted terms used in the original submission a key distinction, since only the interacted model reveals the diagnostic problem the original check missed. In the previous round, VIF for SEC and the interaction term reached ~39.5–39.6 under the raw composite, far above the conventional threshold of 10, because VMC1 and VMC2 were then constant within each firm and thus nearly collinear with sector identity. Now that VMC1 and VMC2 are computed as a genuine annual rolling-window series (see Methodology), this problem is resolved under both specifications: VIF is ~1.53–2.66 (raw composite) and ~1.06–1.50 (standardized composite), both well within the threshold. This confirms the earlier severe multicollinearity was largely a symptom of the flawed VMC1/VMC2 measure, not an inherent property of the interaction term. The standardized composite remains marginally preferable and is used throughout Tables 5–11. A heteroskedasticity test was then conducted to assess constant residual variance across observations; the results are shown in Figure 3.

Figure 3. Heteroscedasticity Test Results

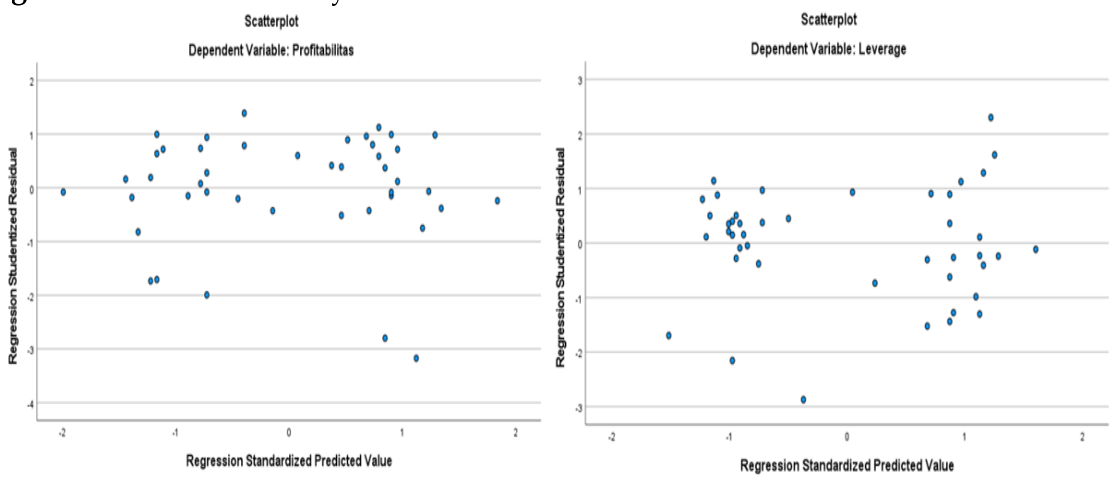


Figure 3 shows the residual scatterplot points scattered randomly around the zero line with no discernible pattern, suggesting heteroskedasticity is absent. In the profitability model, points fall fairly evenly above and below zero, reflecting stable residual variance across prediction levels. The leverage model shows a comparable picture — some variation in spread, but no systematic structure — likewise pointing to the absence of heteroskedasticity. Both models thus appear free of this problem, satisfying one of the classical assumptions for linear regression.

Following the heteroskedasticity test, an autocorrelation test was performed to assess correlation among the residuals, typically using the Durbin–Watson (DW) statistic. Table 4 reports these results.

Table 4. Autocorrelation Test Results

Model Summary					
Model	**R**	**R Square**	**Adjusted R-Square**	**Std. Error of the Estimate**	**Durbin-Watson**
1	0.823[a]	0.678	0.662	1.741	0.478
2	0.862[a]	0.743	0.730	1.553	0.513

a. Predictors: (Constant), Industry Sector, VMC (z-standardized)

b. Dependent Variable: Profitability (z-standardized), Leverage

As shown in Table 4, the Durbin–Watson statistics are 0.478 for the profitability model and 0.513 for the leverage model — both far below the accepted range of 1.5–2.5, pointing to strong positive autocorrelation in the residuals of each. This marks a notable shift from the prior round: because VMC1 and VMC2 were then held constant within firms, the within-firm serial pattern now captured by the corrected annual VMC series had previously gone undetected. Although such autocorrelation leaves OLS coefficients unbiased, it tends to deflate standard errors, meaning the significance levels in Tables 5–6 should be read with some caution. This finding strengthens rather than settles the study's earlier argument (see Limitations) for applying small-sample and dynamic-panel inference methods in subsequent research.

With the classical assumption tests satisfied, linear regression was carried out to assess how market capitalization volatility affects profitability. Tables 5 and 6 report the simple bivariate relationships underlying H1 and H2, using the standardized composite as the sole specification throughout this revision, in line with the Methodology. Table 5 presents these regression results.

Table 5. Profitability Linear Regression Results

Coefficients[a]					
Model	**Unstandardized Coefficients B**	**Unstandardized Coefficients Std. Error**	**Standardized Coefficients 95% CI**	**t**	**Sig.**
1 (Constant)	0.000	0.360		0.00	1.000
VMC (z-standardized)	0.765	0.151	[0.459, 1.070]	5.05	<.001

a. Dependent Variable: Profitability

Model Summary				
Model	R	R Square	Adjusted R-Square	N
1	0.615[a]	0.378	0.363	44

a. Predictors: (Constant), VMC (z-standardized)

The results of the simple linear regression presented in Table 5 show a market capitalization volatility (z-standardized) coefficient of 0.765 (SE = 0.151, 95% CI [0.459, 1.070]), with $p < .001$ and a t-statistic of 5.05, indicating a positive association between market capitalization volatility and profitability in the cases examined. The R-Square value of 0.378 indicates that approximately 37.8% of the variation in profitability within this sample is associated with market capitalization volatility, while the remaining 62.2% is associated with other factors outside the model. As noted in the discussion of Table 4, the Durbin–Watson statistic for this model (0.478) indicates substantial positive autocorrelation, so this significance level should be read as suggestive rather than confirmatory.

From the perspective of Signaling Theory (1973), market capitalization volatility can be read as a signal of information-flow intensity and investors' response to it (Baker et al., 2012; Connelly et al., 2010). The positive association found here fits the interpretation that volatility, in some cases, reflects market opportunities firms respond to adaptively, consistent with Asgharian et al. (2023) and Xiao et al. (2024) on volatility and shifting investor expectations. Even so, this study's design cannot establish the direction of causality behind this association. Volatility driving higher profitability is one plausible reading, but reverse causality is equally valid: firms with rising earnings tend to draw greater investor attention, producing larger swings in market capitalization. The annual panel data here do not permit formal causal testing (e.g., Granger causality or instrumental-variable models), so the H1 findings should be read as associative rather than causal. These results also run counter to several prior studies reporting a negative volatility–profitability link tied to heightened business risk and adjustment costs (Dhingra et al., 2024; Haliza et al., 2025; Saleem et al., 2019). This study suggests that the effectiveness of market signals likely depends on firm-specific contextual factors not captured in this model, including firm size, liquidity, growth opportunities, and macroeconomic conditions, which constitute omitted variables in this study.

Subsequently, a linear regression analysis was conducted to examine the effect of market capitalization volatility on firm leverage. The results of the analysis are presented in Table 6.

Table 6. Leverage Linear Regression Results (Z-Standardized Composite)

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients 95% CI	t	Sig.
2	(Constant)	0.000	0.360		0.00	1.000
	VMC (z-standardized)	-0.763	0.151	[-1.068, -0.458]	-5.05	<.001

a. Dependent Variable: Leverage

Model Summary

Model	R	R Square	Adjusted R-Square	N
2	0.614[a]	0.377	0.363	44

a. Predictors: (Constant), VMC (z-standardized)

The results in Table 6 show a market capitalization volatility (z-standardized) coefficient of -0.763 (SE = 0.151, 95% CI [-1.068, -0.458]), with $p < .001$ and a t-statistic of -5.05, indicating a negative association between market capitalization volatility and leverage in this sample. The R-Square value of 0.377 indicates that approximately 37.7% of the variation in leverage within this sample is associated with market capitalization volatility. As with Table 5, the Durbin–Watson statistic for this model (0.513, Table 4) indicates substantial positive autocorrelation, so this result should be read as suggestive rather than confirmatory.

From the perspective of Signaling Theory proposed by Michael Spence (1973), market capitalization volatility can be interpreted as an external signal reflecting market perceptions of a firm's risk and prospects. Increased volatility indicates a high level of information uncertainty, which prompts investors and creditors to become more cautious in extending financing. Under such conditions, firms tend to adjust their capital structure by reducing leverage in order to maintain financial stability and minimize the risk of bankruptcy. Volatility therefore represents not only risk but also functions as a signal that influences firms' financing decisions. These findings are consistent with the study conducted by Tran (2021), who found that high market uncertainty negatively affects leverage due to rising external financing costs. Cook and Luo (2023) similarly show that market volatility drives firms to adopt more conservative debt policies. Furthermore, studies by Asgharian et al. (2023) and Xiao et al. (2024) reveal that the dynamics of market volatility are related to changes in investor expectations, which subsequently influence capital structure policy, while Gong J. (2024) emphasizes that firms adjust their financing decisions in response to market conditions and perceived risk. Nevertheless, some conflicting findings have also been reported, suggesting that volatility does not always exert a negative effect on leverage.

The study conducted by Vuong et al. (2022) found an opposite pattern in a different context, suggesting this relationship's direction likely depends on firm-specific characteristics and market conditions. As with H1, this negative association is also vulnerable to omitted variables: factors outside the model, such as global commodity prices (especially relevant to the energy-sector cases here), benchmark interest rates, and domestic macroeconomic uncertainty, could simultaneously affect both market capitalization and firms' capital-structure decisions. The H2 findings are thus likewise positioned as a preliminary association within a limited sample rather than evidence of causality.

Moderated Regression Analysis (MRA) was then conducted to examine industry sector's moderating role in the volatility–profitability relationship. Table 7 presents these results.

Table 7. Moderated Regression Analysis Results for Profitability

Coefficients[a]

	Model	**Unstandardized Coefficients B**	**Std. Error**	**Standardized Coefficients 95% CI**	**t**	**Sig.**
1	(Constant)	-1.602	0.371		-4.32	<.001
	VMC (centered, z-standardized)	0.730	0.133	[0.462, 0.999]	5.50	<.001
	SEC	3.391	0.530	[2.320, 4.463]	6.40	<.001
	VMC (centered) × SEC	-0.374	0.242	[-0.863, 0.114]	-1.55	0.129

a. Dependent Variable: Profitability

Model Summary

Model	R	R Square	Adjusted R-Square	N
1	0.834[a]	0.696	0.673	44

a. Predictors: (Constant), VMC (centered) × SEC, VMC (centered, z-standardized), SEC. Z-standardized composite; VMC1/VMC2 computed via 3-year rolling window.

To clarify the substantive meaning of the interaction effect in Table 7 (standardized composite, centered), the marginal effect (simple slope) of market capitalization volatility on profitability was calculated separately for each sector, with its own standard error, 95% confidence interval, and t-test. In the energy sector (SEC = 0), the marginal effect of VMC_z on profitability is equivalent to the coefficient $\beta 1 = 0.730$ (SE = 0.133, 95% CI [0.462, 0.999], $p < .001$), positive and statistically significant. In the technology sector (SEC = 1), the marginal effect is $\beta 1 + \beta 3 = 0.730 + (-0.374) = 0.356$ (SE = 0.202, 95% CI [−0.052, 0.764], $p = 0.086$), positive but only marginally significant at conventional thresholds. With VMC1 and VMC2 now computed as a genuine annual series, the association is positive in both sector groups there is no longer a sign reversal between sectors and the interaction term itself ($\beta 3 = -0.374$, SE = 0.242, 95% CI [−0.863, 0.114]) is not statistically significant ($p = 0.129$), so the difference between the two slopes cannot be distinguished from zero at conventional levels.

This departs materially from the previous round, where an inflated interaction driven by VMC1/VMC2 being held constant within each firm created an apparent sign reversal between sectors. With VMC1 and VMC2 now computed as a genuine annual series, both energy- and technology-sector cases show a positive volatility–profitability association, and the null interaction result (β3) indicates no statistically distinguishable difference between the sector pairs in this relationship. In hindsight, the earlier sectoral reversal appears largely an artifact of the flawed VMC1/VMC2 measure rather than a genuine case-level pattern directly supporting the reviewer's Point 1 concern that the interaction may have reflected a measurement confound rather than a true sector mechanism. Since VMC was mean-centered before constructing the interaction term, the slope-difference test requested in Point 5 reduces simply to the β3 coefficient above, along with its standard error, confidence interval, and p-value. A leave-one-firm-out sensitivity check, confirming this null interaction holds regardless of which firm is excluded, appears later in this section (Table 9).

These findings are consistent with Signaling Theory as proposed by Michael Spence (1973), which suggests that market signals are interpreted differently depending on firm context and characteristics. Market capitalization volatility, as a signal of uncertainty, is positively associated with profitability in both sector groups examined here, and this study does not find statistically distinguishable evidence that industry sector changes the strength of that association the interaction term is not significant once VMC1 and VMC2 are computed as a genuine annual series (see Table 7). This is consistent with Signaling Theory operating similarly across the cases examined, rather than being conditional on sector. Empirically, market capitalization volatility reflects the level of information uncertainty and investor expectations regarding firm performance (Asgharian et al., 2023; Xiao et al., 2024).

Under conditions of high volatility, investors tend to behave more cautiously, thereby influencing investment decisions and access to financing, which ultimately affects firm profitability. The prior literature offers reasons to expect this effect to vary by sector: several studies indicate that firms' sensitivity to market volatility differs across industries, with sectors highly dependent on external factors, such as energy, generally considered more vulnerable than innovation-based sectors such as technology. In this study's own data, however, once VMC1 and VMC2 are computed as a genuine annual series, the interaction between volatility and sector is not statistically significant (Table 7), so this sample does not provide distinguishable evidence for that sectoral difference — the positive volatility–profitability association is similar in the energy and technology cases examined. Studies conducted by Baker et al. (2012), Pastor and Veronesi (2012), and Aljifri (2023) further emphasize that the interpretation of market signals is strongly influenced by investor expectations and industry conditions, resulting in heterogeneous volatility effects on financial performance.

Differences between the energy and technology sectors offer one plausible explanation for the case-level pattern found here, though unmodeled firm-specific factors ownership, size, maturity, commodity exposure cannot be ruled out given the small number of firms. Being capital-intensive and heavily tied to global commodity prices, the energy sector tends to be more exposed to market volatility, which may weaken volatility's effect on profitability. The technology sector, by contrast, relies more on intangible assets and innovation, making it more responsive to growth expectations and market perceptions of long-term prospects (Kogan et al., 2017). Studies by Lambrinoudakis et al. (2019) and Denis and McKeon (2012) show that asset structure and industry characteristics can influence firms' responses to market information in principle. In this sample, industry sector is associated with the level of profitability (the direct SEC term in Table 7 is significant), but once VMC1 and VMC2 are computed as a genuine annual series, this study does not find statistically distinguishable evidence that the volatility–profitability association itself differs between the two sector pairs observed the interaction term in Table 7 is not significant. These results therefore do not support the originally proposed H3, which expected this association to vary by sector; given the two-firm-per-sector design, this null finding should be read as a tentative case-level observation rather than confirmed evidence against a sector effect, pending replication in a larger, sector-balanced sample.

Subsequently, Moderated Regression Analysis (MRA) was also conducted to examine the moderating role of industry sector in the relationship between market capitalization volatility and leverage. The results of the analysis are presented in Table 8.

Table 8. Moderated Regression Analysis

Coefficients[a]

	Model	Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients 95% CI	t	Sig.
2	(Constant)	1.782	0.333		5.36	<.001
	VMC (centered, z-standardized)	-0.692	0.119	[-0.933, -0.451]	-5.81	<.001
	SEC	-3.715	0.476	[-4.676, -2.754]	-7.81	<.001
	VMC (centered) × SEC	0.302	0.217	[-0.136, 0.740]	1.39	0.171

a. Dependent Variable: Leverage

Model Summary

Model	R	R Square	Adjusted R-Square	N
2	0.869[a]	0.755	0.736	44

a. Predictors: (Constant), VMC (centered) × SEC, VMC (centered, z-standardized), SEC. Z-standardized composite; VMC1/VMC2 computed via 3-year rolling window (see Methodology).

Under the standardized, centered specification, the Moderated Regression Analysis (MRA) shows market capitalization volatility exerting a negative, significant effect on leverage in the energy-sector cases ($\beta 1 = -0.692$, SE = 0.119, 95% CI [−0.933, −0.451], $p < .001$) higher volatility corresponds to lower reliance on debt financing among these cases. Since the model is contemporaneous, this is equally consistent with lower leverage preceding, or moving alongside, higher volatility, rather than volatility driving the change in leverage. The industry-sector direct term shows a significant case-level contrast ($\beta 2 = -3.715$, SE = 0.476, $p < .001$). The volatility–sector interaction is positive but not significant ($\beta 3 = 0.302$, SE = 0.217, 95% CI [−0.136, 0.740], $p = 0.171$); the technology-sector simple slope ($\beta 1 + \beta 3 = -0.390$, SE = 0.181, $p = 0.037$) stays negative and significant, matching the energy-sector slope in direction though somewhat weaker in size. As the interaction is non-significant, no distinguishable evidence indicates the volatility–leverage association differs between the two sector pairs, despite this modest difference in slope magnitude — a marked shift from the previous round, when the interaction was strongly significant due to VMC1/VMC2 being confounded with sector identity. An R-Square of 0.755 and Adjusted R-Square of 0.736 show the model accounts for a substantial share of leverage variation in this sample.

These findings can be interpreted through the perspective of Signaling Theory as proposed by Michael Spence (1973), in which market capitalization volatility is viewed as a signal of uncertainty and risk perceived by investors and creditors. Under conditions of high volatility, the market interprets the situation as increased risk, thereby raising external financing costs and limiting access to debt financing. In response to this signal, firms tend to reduce leverage in order to maintain financial stability and minimize the risk of bankruptcy. Empirical studies conducted over the past decade, including those by Tran (2021), Cook and Luo (2023), as well as Asgharian et al. (2023), Xiao et al. (2024), and J. Gong (2024), similarly show that market volatility influences investor expectations and drives firms to adopt more cautious debt policies.

Prior literature gives reason to expect sector-based variation in how firms respond to volatility, and this study's own data show somewhat different simple-slope magnitudes across the two groups (−0.692 for energy versus −0.390 for technology). Yet since the interaction term in Table 8 is not statistically significant, no distinguishable evidence emerges that sector alters the volatility–leverage relationship; the observed difference in magnitude, while descriptively present in this sample, could plausibly reflect sampling variation given the four-firm design. Were a genuine sectoral difference to exist, it could stem from sector characteristics — the energy sector, capital-intensive and highly exposed to external shocks, may follow a financing pattern distinct from the more flexible, innovation-driven technology sector (He & Kyaw, 2025; Kogan et al., 2017; Ratti et al., 2011). While sector is linked to overall leverage levels in this sample, no distinguishable evidence indicates it changes how firms respond to market volatility signals in leverage decisions. These results therefore do not support the originally proposed H4, which expected the volatility–leverage association to vary between the energy- and technology-sector cases; as with H3, this null finding is reported as a tentative case-level observation rather than confirmed evidence against a sector effect, given the two-firm-per-sector design.

4.1 Robustness Checks: Leave-One-Firm-Out Sensitivity and a Lagged Specification

Given that this study relies on only four cross-sectional units, two additional checks suggested by the reviewer were performed to gauge how much the Table 7–8 findings depend on individual cases and on the model's contemporaneous timing. Each model (standardized composite, centered VMC) was re-estimated four times, each time excluding one firm, to test whether the reported slopes and the null interaction result hinge on any single case. Table 9 presents these results.

Table 9. Leave-One-Firm-Out Sensitivity Analysis

Firm excluded	DV	b_1 (energy slope)	p	b_3 (slope diff.)	p
ADRO (energy)	PROF	0.625	0.005	−0.269	0.379
ADRO (energy)	LEV	−0.658	<.001	0.268	0.102
INDY (energy)	PROF	0.802	0.001	−0.446	0.151
INDY (energy)	LEV	−0.603	<.001	0.213	0.162
TLKM (technology)	PROF	0.730	<.001	0.077	0.683
TLKM (technology)	LEV	−0.692	<.001	0.106	0.731
EMTK (technology)	PROF	0.730	<.001	0.186	0.401
EMTK (technology)	LEV	−0.692	<.001	0.121	0.741

The energy-sector simple slope (b_1) is stable in sign and significance regardless of which firm is excluded (PROF: 0.63–0.80, all $p < .01$; LEV: −0.60 to −0.66, all $p < .001$), and — consistent with the main models in Tables 7–8 — the slope-difference term (b_3) is not statistically significant in any of the eight leave-one-out re-estimations (all $p \geq 0.10$). This stability is itself informative: the null interaction result reported in Tables 7–8 is not an artifact of any single firm, but holds consistently across all four leave-one-out specifications, which strengthens confidence that this study genuinely does not find distinguishable evidence of sector moderation, rather than the null result being fragile or sample-dependent.

Second, to address the possibility of reverse causality raised for H1 and H2, VMC was lagged by one year within each firm and used to predict the current-year outcome, controlling for the lagged dependent variable. This uses the existing panel, with no new data collection, but drops the first observation year per firm, reducing N from 44 to 40. The results are presented in Tables 10 and 11.

Table 10. Lagged Regression Results — Profitability

Term	B	SE	t	p
Intercept	−0.782	0.564	−1.39	0.174
VMC_B(t−1), centered	−0.011	0.212	−0.05	0.959
SEC	2.201	0.934	2.36	0.024
VMC_B(t−1) × SEC	−0.387	0.296	−1.31	0.199
PROF_B(t−1)	0.502	0.195	2.57	0.015

Note. Model: Profitability(t) = VMC(t−1)_centered + SEC + Interaction + Profitability(t−1). $R^2 = 0.593$, Adjusted $R^2 = 0.547$, N = 40, Durbin–Watson = 2.05

Table 11. Lagged Regression Results — Leverage

Term	B	SE	t	p
Intercept	0.588	0.542	1.09	0.285
VMC_B(t−1), centered	0.039	0.191	0.20	0.841
SEC	−1.689	0.924	−1.83	0.076
VMC_B(t−1) × SEC	0.205	0.257	0.80	0.431
LEV_B(t−1)	0.624	0.194	3.22	0.003

Note. Model: Leverage(t) = VMC(t−1)_centered + SEC + Interaction + Leverage(t−1). $R^2 = 0.686$, Adjusted $R^2 = 0.650$, N = 40, Durbin–Watson = 2.10.

Under the lagged specification, the direct energy-sector VMC association becomes non-significant for both profitability ($p = 0.959$) and leverage ($p = 0.841$) once VMC is moved to t−1 and the lagged dependent variable is controlled for; the interaction term also remains non-significant for both outcomes ($p = 0.199$ and $p = 0.431$, respectively). The only terms that remain significant in both lagged models are the autoregressive lagged-dependent-variable terms themselves (PROF(t−1): $p = 0.015$; LEV(t−1): $p = 0.003$) and the direct SEC term (significant for profitability, marginal for leverage). In other words, once temporal separation is introduced, this study finds no statistically distinguishable evidence that lagged volatility predicts either outcome, for either sector — a materially different, and more cautious, conclusion than the contemporaneous models in Tables 5–8 would suggest on their own. This is consistent with the reviewer's original concern in Point 3 that the contemporaneous associations reported in this study may substantially reflect reverse causality or joint determination by unobserved factors rather than volatility preceding, and predicting, subsequent financial outcomes; the findings for H1 and H2 should accordingly be read as evidence of a contemporaneous association only, and the null result for H3 and H4 is unchanged under the lagged specification.

5. Conclusion and Suggestion

As an exploratory multi-case panel study, this research examines preliminary patterns of association between market capitalization volatility and firm profitability and leverage across four Indonesian companies from the energy and technology sectors, within the framework of Signaling Theory. The findings show that market capitalization volatility is positively associated with profitability and negatively associated with leverage, consistently across both sector groups, supporting H1 and H2. However, these associations are contemporaneous rather than causal: a lagged specification indicates that once temporal separation is introduced, volatility no longer predicts either outcome, suggesting that the observed relationships may substantially reflect reverse causality or joint determination by unobserved factors rather than volatility genuinely preceding changes in profitability or leverage.

With respect to the moderating role of industry sector, this study does not find statistically distinguishable evidence that the volatility–profitability or volatility–leverage association differs between the energy-sector and technology-sector cases examined. H3 and H4 are therefore not supported. Overall, this study reaffirms the relevance of Signaling Theory in explaining market capitalization volatility as a signal of uncertainty contemporaneously associated with firms' financial position, while showing that this relationship does not appear to differ systematically between the two sectors examined. These findings should be understood as indicative patterns within the four cases studied, rather than generalizations applicable to the broader population of energy and technology firms in Indonesia.

Based on the findings above, several suggestions are proposed. For corporate management, market capitalization volatility may be considered a relevant signal in shaping capital-structure and financing decisions, particularly given its observed association with both profitability and leverage. For investors, volatility can serve as one indicator, among others, for assessing firm risk and future prospects, though this study's results do not support differentiating such assessments by industry sector. For future researchers, it is recommended to: (1) expand the number of firms per sector, drawing on a larger and more balanced sample of Indonesian energy and technology issuers, before drawing firm conclusions about sector-level moderation; (2) extend the analysis with longer lag structures or formal causality tests, such as Granger causality or instrumental-variable approaches, to better establish the direction of the relationships identified; (3) apply small-sample or dynamic panel inference procedures better suited to a limited number of cross-sectional units; and (4) incorporate additional firm-level and macroeconomic control variables such as firm size, liquidity, growth opportunities, commodity-price exposure, and interest rates to provide a more complete picture of the factors shaping the relationship between market capitalization volatility and corporate financial performance.

This study is subject to several limitations. First, with only two firms per sector, industry sector remains structurally confounded with firm identity, so the reported associations may partly reflect differences in ownership, size, maturity, business model, and listing history among the four firms rather than a genuine sector-based mechanism. Second, the limited technology-sector sample reflects a structural constraint in the Indonesian capital market — most technology issuers were listed only in recent years — rather than a methodological choice. Third, because the main regressions are contemporaneous, the direction of causality between volatility and financial performance cannot be fully established; the lagged results suggest the observed associations should be interpreted with caution. Fourth, several relevant control variables, including firm size, liquidity, growth opportunities, commodity-price exposure, and interest rates, were not incorporated into the model.

Reference

Aljifri, R. (2023). Investor psychology in the stock market: An empirical study of the impact of overconfidence on firm valuation. *Borsa Istanbul Review*, *23*(1), 93–112. https://doi.org/10.1016/j.bir.2022.09.010

Angelidis, T., & Tessaromatis, N. (2023). The disappearing profitability of volatility- managed equity factors. *Journal of Financial Markets*, *65*(September), 100857. https://doi.org/10.1016/j.finmar.2023.100857

Asgharian, H., Christiansen, C., & Hou, A. J. (2023). The effect of uncertainty on stock market volatility and correlation. *Journal of Banking and Finance*, *154*, 106929. https://doi.org/10.1016/j.jbankfin.2023.106929

Baker, M., Wurgler, J., & Yuan, Y. (2012). Global , local , and contagious investor sentiment. *Journal of Financial Economics*, *104*(2), 272–287. https://doi.org/10.1016/j.jfineco.2011.11.002

Bashir, H. A., & Kumar, D. (2025). Unveiling investor sentiment, attention, and speed of price adjustment in Indian market. *International Review of Economics and Finance*, *101*, 104189. https://doi.org/10.1016/j.iref.2025.104189

Chang, C., Lee, A. C., & Lee, C. F. (2009). Determinants of capital structure choice: A structural equation modeling approach. *Quarterly Review of Economics and Finance*, *49*(2), 197–213. https://doi.org/10.1016/j.qref.2008.03.004

Connelly, B. L., Certo, S. T., Ireland, R. D., & Reutzel, C. R. (2010). Signaling Theory: A Review and Assessment. *Journal of Management*, *37*(1), 39–67. https://doi.org/10.1177/0149206310388419

Cook, D. O., & Luo, S. (Scott). (2023). Fund flow-induced volatility and the cost of debt. *Journal of Banking & Finance*, *146*(January), 106702. https://doi.org/10.1016/j.jbankfin.2022.106702

Denis, D. J., & Mckeon, S. B. (2012). Debt Financing and Financial Flexibility Evidence from Proactive Leverage Increases. *The Review of Financial Studies*, *25*(6), 1897–1929. https://doi.org/10.1093/rfs/hhs005

Dhingra, B., Batra, S., Aggarwal, V., & Yadav, M. (2024). Stock market volatility : a systematic review. *Journal of Modelling in Management*, *19*(3), 925–952. https://doi.org/10.1108/JM2-04-2023-0080

Gong, J. (2024). The Relationship between Financial Market Volatility and Investor Behavior. *Financial Engineering and Risk Management*, *7*(6), 111–116. https://doi.org/10.23977/ferm.2024.070614

Gong, X., Zhang, W., Xu, W., & Li, Z. (2022). Uncertainty index and stock volatility prediction : evidence from international markets. *Financial Innovation*, *8*(57), 1–44. https://doi.org/10.1186/s40854-022-00361-6

Hafidz, N. S. (2025). The Journal of Financial, Accounting, and Economics. *The Journal of Financial, Accounting, and Economics*, *2*(1), 23–38. https://doi.org/10.58857/JFAE.2025.v02.i01.p03

Haliza, T. N., Hizazi, A., & Friyani, R. (2025). Pada Perusahaan Sektor Farmasi Yang Terdaftar Di Bursa Efek Indonesia Periode 2020-2024. *Jurnal Akuntansi Kompetif*, *8*(3), 885–895. https://ejournal.kompetif.com/index.php/akuntansikompetif/article/view/2435/1933

Hariyanto, D. (2021). Effect of Trading Volume , Market Capitalization , Firm Size in explaining Return on Vultures. *Journal of Advanced Research in Economics and Administrative Sciences*, *2*(3), 50–64. https://doi.org/10.47631/jareas.v2i2.228

He, W., & Kyaw, N. (2025). Economic Policy Uncertainty and Corporate Investment Behavior : Evidence from China. *Asia-Pacific Financial Markets*, *July*. https://doi.org/10.1007/s10690-025-09550-6

Ji, Q., Zhang, D., & Geng, J. (2018). Information linkage , dynamic spillovers in prices and volatility between the carbon and energy markets. *Journal of Cleaner Production*, *198*(October), 972–978. https://doi.org/10.1016/j.jclepro.2018.07.126

Kogan, L., Papanikolaou, D., Seru, A., & Stoffman, N. (2017). Technological Innovation , Resource Allocation , and Growth. *Quarterly Journal of Economics*, *132*(2), 665–712. https://doi.org/10.1093/qje/qjw040

Korajczyk, R. A., & Levy, A. (2003). Capital structure choice: Macroeconomic conditions and financial constraints. *Journal of Financial Economics*, *68*(1), 75–109. https://doi.org/10.1016/S0304-405X(02)00249-0

Kusnanto, E., & Qalbia, F. (2024). The Impact Of Profitability , Firm Size , And Growth Opportunities On The Value Of Property Companies. *Journal of Economic and Leadership*, *1*(2), 42–53. https://doi.org/10.70142/jbl.v1i2.9

Lambrinoudakis, C., Skiadopoulos, G., & Gkionis, K. (2019). Capital structure and financial flexibility : Expectations of future shocks. *Journal of Banking & Finance*, *104*(July), 1–18. https://doi.org/10.1016/j.jbankfin.2019.03.016 Get

Maysaroh, S., Price, I. D. X. S., & Handayani, A. (2025). Leverage , Dividend Policy , and Profitability Effects on IDX30 Stock Price Volatility During 2019 – 2023 1051. *Jurnal Ilmiah Manajemen Kesatuan*, *13*(2), 1051–1060. https://doi.org/10.37641/jimkes.v11i2.3159

Munzir, Andriyan, Y., & Hidayat, R. (2023). Consumer Goods: Pengaruh Profitabilitas dan Leverage Terhadap Nilai Perusahaan Dimediasi oleh Corporate Social Responsibility. *Jurnal Akuntansi Dan Governance*, *3*(2), 153–165. https://doi.org/10.24853/jago.3.2.153-165

Pastor, L., & Veronesia, P. (2012). Uncertainty about Government Policy and Stock Prices. *The Journal of Finance*, *67*(4), 1219–1264. https://doi.org/10.2139/ssrn.1625845

Peters, R. H., & Taylor, L. A. (2017). Intangible capital and the investment- q relation. *Journal of Financial Economics*, *123*(2), 251–272. https://doi.org/10.1016/j.jfineco.2016.03.01

Pham, Q., Pham, H., Pham, T., & Tiwari, A. K. (2025). Revisiting the role of investor sentiment in the stock market. *International Review of Economics and Finance*, *100*(October 2024), 104089. https://doi.org/10.1016/j.iref.2025.104089

Pramesti, A., Hidayat, W. W., & Rely, G. (2025). Pengaruh Kapitalisasi Pasar, Profitabilitas dan Leverage terhadap Nilai Perusahaan (Emiten Properti dan Real Estate di Bursa Efek Indonesia Periode 2020-2023). *Jurnal Riset Ekonomi Dan Akuntansi Volume*, *3*(1), 247–264. https://doi.org/10.54066/jrea-itb.v3i1.3060

Pranata, R. M., Waspada, I., Nugraha, N., & Purnomo, B. S. (2024). Herding Dynamics, Volatility, and Market Capitalization: Implications for Stock Returns in Indonesia. *JASF: Journal of Accounting and Strategic Finance*, *7*(2), 300–314. https://doi.org/10.33005/jasf.v7i2.532

Ratti, R. A., Seol, Y., & Hwan, K. (2011). Relative energy price and investment by European firms ☆. *Energy Economics*, *33*(5), 721-731 Relative. https://doi.org/10.1016/j.eneco.2010.12.010

Ristyawan, M. R. (2019). Pengaruh Return On Equity (ROE), Debt To Assets Ratio (DAR), Price To Book Value (PBV) Dan Net Profit Margin (NPM) Terhadap Return Saham Perusahaan

Sektor Perkebunan Yang Terdaftar Di Bursa Efek Indonesia Periode 2011-2017. *Jurnal Ekonomi Bisnis Dan Kewirausahaan*, *8*(1), 1–17. https://doi.org/10.26418/jebik.v8vi1.26966

Saleem, Q., Sulong, S., & Isa, A. H. bin M. (2019). Relationship between Stock Market Volatility , Stock Market Liquidity and Financial Performance of Non-Financial Firms Listed on Pakistan Stock Exchange Relationship between Stock Market Volatility , Stock Market Liquidity and Financial Performance of Non. *International Journal of Academic Research in Business and Social Sciences*, *9*(7), 307–323. https://doi.org/10.6007/IJARBSS/v9-i7/6119

Spence, M. (1973). Job market signaling. *Quarterly Journal of Economics*, *87*(3), 355–374. https://doi.org/10.2307/1882010

Suhardjo, I., Suparman, M., Hidayah, Y., Ramadyan, A. N., & Diaz, R. (2024). Market Capitalization, Leverage, And The Pursuit Of Sustainable Growth: Evidence From The Indonesian Fintech Industry. *Jurnal Akademi Akuntansi*, *7*(2), 267–288. https://doi.org/10.22219/jaa.v7i2.31212

Tran, Q. T. (2021). Economic policy uncertainty and cost of debt financing : International evidence. *The North American Journal of Economics and Finance*, *57*(July), 101419. https://doi.org/10.1016/j.najef.2021.101419

Vuong, G. T. H., Nguyen, M. H., & Wong, W. K. (2022). CBOE volatility index (VIX) and corporate market leverage. *Cogent Economics & Finance*, *10*(1), 1–22. https://doi.org/10.1080/23322039.2022.2111798

Xiao, J., Jiang, J., & Zhang, Y. (2024). Policy uncertainty , investor sentiment , and good and bad volatilities in the stock market : Evidence from China. *Pacific-Basin Finance Journal*, *84*(April), 102303. https://doi.org/10.1016/j.pacfin.2024.102303