Research Article

A COMPARATIVE ANALYSIS OF RETURN VOLATILITY AND ITS EFFECT ON STOCK RETURNS OF BLUE-CHIP AND NON-BLUE-CHIP

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ABSTRACT

Background: Stock return volatility is a key measure of the investment risk that indicates the extent of fluctuation and uncertainty of the stock returns. Investors need to understand volatility when making investment decisions, particularly when assessing the potential risks and returns of different stocks. These considerations are more relevant when considering blue-chip and non-blue-chip stocks, which have different characteristics in terms of market capitalization, liquidity and company fundamentals. These differences may result in differences in return volatility of the two groups and thus their comparative analysis is important to understand the risk characteristics in the capital market.
Purpose: This study is to analyze the differences of return volatility between blue chip stocks represented by LQ45 Index and non-blue chip stocks represented by IDX-SMC Liquid Index, and to examine the effect of volatility on the return in both groups.
Design/methodology/approach: The data used consists of daily closing prices for the period 2020–2025, which are transformed into returns and then modeled using the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) approach to obtain conditional variance (σ^2_t) as a measure of volatility. The volatility comparison between the two indices is tested using the Mann–Whitney U Test. The analysis of the effect of volatility on returns is conducted through regression by including σ^2_t as an independent variable.
Findings/Results: The results indicate that the IDX-SMC liquid index exhibits a statistically significant higher level of return volatility compared to the LQ45 index. Furthermore, the regression results show that return volatility has a negative and statistically significant effect on the LQ45 index T+1 period returns at the 10% significance level, but has a positive but statistically insignificant effect on the IDX-SMC Liquid index T+1 period returns.
Conclusion: The results suggest that stock return volatility is a measure of market risk and uncertainty, but not a consistent determinant of daily stock returns. The positive effect of volatility on IDX-SMC Liquid returns is not significant, while the effect of volatility on LQ45 returns is negative and significant at the 10% significance level.The results show the difference of volatility characteristics and the relationship between risk and returns of the two stock indices.
Originality/value (State of the Art): This study adds to the empirical literature by presenting a comparative analysis of return volatility between blue-chip and non-blue-chip stocks in the Indonesian capital market. The LQ45 and IDX-SMC Liquid indices are examined to provide insight into the difference in volatility levels and the relationship between volatility and stock returns in the following period. The results provide a deeper understanding of how volatility characteristics differ across stock categories and the implications for investment risk assessment.

ARTICLE INFO

Keywords:
Volatility, stock returns, GARCH, blue chip, non-blue chip, LQ45, IDX-SMC Liquid

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INTRODUCTION

Investors need to understand various pieces of information important in the capital market, one of which is the up-and-down movement of stock returns, known as volatility (Nastiti & Suharsono, 2012). Understanding volatility is crucial. This is because it determines the investor's ability to take advantage of profit opportunities.

Good returns can be achieved through capital gains or dividends (Mukmin & Firmansyah, 2015). In general, return volatility is an indicator of a very fundamental risk in modern finance. Volatility shows price fluctuations and reflects uncertainty in price formation. High and low return volatility becomes a signal for investors regarding size risks that must be faced when holding some assets. Therefore, understanding deep characteristics and volatility becomes a key element in making rational and data-driven decisions (Ponziani, 2022).

The relevance of stock return volatility to the broader economy is significant. Because stock return volatility reflects the level of uncertainty faced by the economy, it is relevant at both the micro and macro levels. Investment can be defined as the placement of funds in assets for finance or the real hope of getting future profits, while investors are individuals or institutions that carry out investment activities with consideration of the expected level of risk and return (Arnaya & Purbawangsa, 2020). At the micro level, return volatility plays a role as a signal of risks that affect investor preferences in making decisions on investment and portfolio allocation (Markowitz, 1952). In macroeconomics, stock market volatility is often used as an indicator of financial market stability and general economic sentiment, especially in developing countries. Empirically there are many studies that prove the existence of relatedness of stock market volatility and macroeconomic variables such as inflation and interest rates (Sitanggang & Hidayat, 2013). Likewise, Rahayu (2025) found that stock market volatility is associated with GDP and the value of the rupiah exchange rate, which confirms that these factors affect the changes in stock market volatility. Volatility does not occur in isolation; it happens within the context of a dynamic economy.

In the framework theory of modern portfolios, volatility is not only viewed as fluctuations in statistics but also as size risk, the main determining factor in investor preferences for portfolios. Markowitz (1952) emphasized that investors are rational and optimize portfolios based on the trade-off between expected return and variance as a representation of risk, so decisions on investment always consider the connection between potential reward results and uncertainty. This line of reasoning was carried further by Bollerslev (1986) who developed the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model which extends the ARCH model by allowing for the effect of past errors on the current conditional variance. GARCH provides a more realistic and simple framework to capture the characteristic dynamic market volatility, rather than the classical approach, which assumes a constant variance of returns. The model is widely used in time series stock market research to analyze volatility dynamics at the level of the market index and sectoral, because of its ability to accurately capture the empirical characteristics of financial returns (Manurung et al., 2022).

Discussion about risk and return was then expanded by Fama and French (1993), who argue that, beyond market factors, the size of the company and the book-to-market equity ratio are factors that significantly affect risk.

In his research they find that in a way historical share with capitalization small caps have a higher average return than share with capitalization big (big cap), in this matter Fama & French (1993) used the median market equity in the NYSE index as the cutoff. As a consequence, the return volatility is also higher for shares with small capitalization. Research: A similar study was also carried out by Oraon (2020), who conducted a 5-year return comparison between the Nifty 50 Index as big-cap stocks with a capitalization criterion of ₹20,000 cr or more and the Nifty Small-Cap 100 Index as small-cap stocks with a capitalization criterion between ₹4,000 and ₹5,000 cr. Oraon (2020) concluded that, over a five-year period, the two categories had similar average returns. However, small-cap stocks are associated with significantly higher volatility and extreme outliers. The research conducted by Alioui et al. (2015) shows that the returns from significant big-cap stocks are more volatile compared to those from small-cap stocks on the Russell 3000 index during the period of 2010-2012.

The empirical evidence suggests that there is disagreement or controversy in the literature regarding the relationship between company size and stock return performance. Therefore, it is important to empirically test whether the basic implications of Fama and French (1993) that small-cap stocks have significantly higher risk and return volatility than large-cap stocks are still relevant in the current context of the Indonesian capital market.

Testing this no. 1 aim to compare the level volatility of returns between index blue chip and non-blue chip stocks, but also to analyze how the volatility of the return affects the returns obtained by each group of index shares. This analysis has become crucial considering that the Indonesian capital market has dynamic characteristics, where the relationship between risk and return can be influenced by factors such as macroeconomics, policy regulations, and different domestic microeconomics with capital markets in developed countries. Therefore, the analysis of comparative return volatility and its influence on the required return is more empirical, contextual, and relevant to the conditions of the Indonesian capital market.

METHODS

This study uses the type of secondary data obtained from the economic and financial data provider platform, CEIC Data. This research uses time series data to analyze and compare the return volatility between the shares of two groups over a specific period. The writer used series data time in the study: This is data recorded in the Indonesian Stock Exchange (BEI) which is an LQ45 and IDX-SMC liquid index. Specifically, the data consist of daily closing prices of both indices, for the period January 2020 to October 2025.

In this study, shares are divided into blue chip and non-blue chip at individual stock level, by using the index share approach officially published by Indonesia Stock Exchange (IDX). The LQ45 index can be a good proxy for blue chip stocks because it contains stocks with large market caps, high liquidity and strong fundamentals. These stocks are selected and evaluated periodically by the IDX. The LQ45 index represents stocks with large market capitalizations, high liquidity, and strong fundamentals, which are periodically selected and evaluated by the IDX. Meanwhile, the IDX-SMC Liquid index is used as a proxy for non-blue-chip stocks because it reflects stocks capitalized from small to medium with an adequate level of liquidity, which is also selected based on the criteria of market capitalization and liquidity. Selection of the second index is based on the official classification of BEI and the general practice of studying the empirical Indonesian capital market.

Method of analysis in study The analysis uses the symmetric Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model approach on time series data to compare daily return volatility blue chip stocks (LQ45) and non-blue chip stocks (IDX-SMC Liquid).

Stock return volatility is an important indicator. This is because it reflects the inherent uncertainty in the process of forming asset prices in finance. Increasingly high volatility of returns indicates greater investment risk, which investors must consider when making investment decisions. In time-series econometric analysis, stock price volatility cannot be observed directly. Stock return variation is used as a proxy for the most common risks in financial literature (Sari et al. 2017).

Temporarily, the volatility of returns is calculated using the closing price index. Because the index aggregates market prices and reflects the impact of actions on all constituents, it serves as a marker for the economy. Actually, they are changing share prices. In addition, financial data in general have high and volatile characteristics with no stationarity at the level, which can potentially cause problems during the estimation of series models. To overcome the problem said, stock returns counted use natural logarithms to reduce data fluctuations and increase the possibility of fulfillment assumptions and stationarity (Widodo & Faizi, 2023). Thus, stock returns are counted using the continuously compounded return formula as follows (Wooldridge, 2013):

$$r_t = \ln P_t/P_{t-1}$$

where r_t is the stock's return on time t; continuously compounded return; P_t is opening stock price on day t; and P_{t-1} is closing price share on day t -1.

If the data has effect heteroscedasticity, then model estimation continues with the use of generalized autoregressive conditional Hershedasticity (GARCH) method. Selection of the GARCH model in study This is because stock returns generally show characteristics of heteroscedasticity conditional, where the period volatility tends to be high and the period volatility low and vice versa. The phenomenon is known as volatility clustering and cannot be arrested in a way adequate by the model with the assumption of constant variance. Compared to the approach of static volatility, the GARCH model is capable of modeling volatility in a dynamic and time-varying way, making it more in accordance with the analysis of stock market risk (Bollerslev, 1986). The GARCH model itself is an improvement from the ARCH model introduced by Robert Engle in 1982, where the model is employed to address time-series data exhibiting heteroskedasticity in the residuals, also known as heteroscedasticity (Prasetyo et al. 2024). In general, the ARCH model can be written as the following:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \epsilon^2_{t-1} + \alpha_2 \epsilon^2_{t-2} + \alpha_3 \epsilon^2_{t-3} + \alpha_p \epsilon^2_t$$

However, if the variance of the error term from previous periods is also included in the model structure, the model is known as Generalized Autoregressive Conditional Heteroskedasticity (GARCH). The GARCH model can be estimated using the Maximum Likelihood Estimation (MLE) method. The simplest GARCH specification, known as GARCH(1,1), can be expressed as follows:

$$\sigma^2_t = \alpha_0 + \alpha_1 \epsilon^2_{t-1} + \lambda_1 \sigma^2_{t-1}$$

In general, a GARCH model of order (p, q) can be expressed as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \cdots + \alpha_p \epsilon_{t-p}^2 + \lambda_0 \sigma_{t-p}^2 + \cdots + \lambda_1 \sigma_{t-q}^2$$

This refinement was introduced by Bollerslev (1986), who emphasized that the variance of the error term is influenced not only by past error terms but also by the variances of error terms from previous periods. Thus, the GARCH model is capable of capturing more complex volatility dynamics than the pure ARCH model.

Information: σ^2 (Variance Conditional (volatility) at the time to -t); α (ARCH Coefficient); λ (GARCH coefficient); p (ARCH Order (sum of squared error lags); q (GARCH order (number of lags of past variance)); ε^2 (Squared Error Term at time to

Based on empirical findings regarding diversity, a gap exists in fundamental research (referred to as the research gap). Although there are studies that tested the LQ45, some focus on comparing it with thematic indices (such as ESG and JII) or use historical risk analysis methods (like standard deviation). Problem main thing you want overcome study This is not yet an existence analysis or comparative analysis using the generalized autoregressive conditional

The GARCH model explicitly compares the dynamic volatility of returns between two contrasting market capitalizations on the IDX: the LQ45 Index (blue chip) and the IDX-SMC Liquid Index (non-blue chip). The use of GARCH is required because this model is capable of catching frequent volatility clustering effects that occur in a dynamic market (Bollerslev, 1986). Therefore, this study aims to analyze and compare the volatility of blue-chip and non-blue-chip stock returns using the GARCH model in the Indonesian capital market.

The hypotheses of this study are formulated as follows:
H1: There is a significant difference in return volatility between blue-chip and non-blue-chip stocks
H2: Return volatility significantly affects blue-chip and non-blue-chip stock returns on the IDX (2020–2025)

RESULTS

Analysis Descriptive Data Return

The average return of non-blue-chip stocks was positive, whereas that of blue-chip stocks was negative (Table 1). However, the average returns of both stock groups were relatively small and close to zero. Non-blue-chip stock returns had a standard deviation of 0.0140682, compared with 0.0136517 for blue-chip stocks. The minimum return of non-blue-chip stocks was -0.101370 which was lower than the minimum return of blue chip stocks (-0.095261). The blue-chip stocks had a higher maximum return of 0.139075 against 0.100286 for the non-blue-chip stocks. These descriptive statistics indicate differences in return distribution characteristics between blue-chip and non-blue-chip stocks during the observation period.

Stationarity Test of Return Data

Figure 1 shows the return patterns of blue-chip and non-blue-chip stocks. Based on the plots, the return series appear to fluctuate around their respective mean values, suggesting that the data may be stationary. However, to confirm the stationarity of the return series, a formal stationarity test is conducted. This study employs the Augmented Dickey-Fuller (ADF) test to examine the stationarity of the data.

Heteroscedasticity Test (ARCH Effect)

We examined the ARCH-LM test by looking at the p-value (Prob > chi2) for each of the variables. If the p-value is less than the significance level ($\alpha = 0.05$), the null hypothesis (H0) is rejected and this implies the presence of ARCH effect. The two variables have the ARCH effect based on the ARCH-LM test result as the p-value is less than the 5% significance level ($0.000 < 0.05$). Hence, H0 is rejected for both variables which confirms the presence of ARCH effects. These findings indicate that volatility modeling using ARCH or GARCH models is appropriate for further analysis. Lagrange multiplier test results in Table 2.

Test White Noise

The p-values (Prob > chi2) for both variables are substantially higher than the 5% significance level ($\alpha = 0.05$); therefore, H_0 cannot be rejected. This indicates that the residuals of the blue-chip AR(4, 5, 7) model and the non-blue-chip AR(5, 7, 10) model exhibit no significant autocorrelation and behave as white noise. These results suggest that the selected mean equation models adequately capture the autocorrelation patterns in stock returns, leaving no significant autocorrelation in the residuals. Therefore, the analysis can proceed to the specification and estimation of the GARCH models. White noise test results in Table 3.

A Comparative Analysis of Return Volatility

To formally compare the differences in daily return volatility between blue-chip and non-blue-chip stocks, this study employs the Mann–Whitney U test (two-sample Wilcoxon rank-sum test). The non-parametric test is chosen because it does not require the assumption of normally distributed data and is considered more appropriate when volatility data are not normally distributed as is often the case in financial data. This test is to see if there is a statistically significant difference in the median volatility between the two groups of stocks. The null hypothesis (H_0) states that the median volatility of blue-chip and non-blue-chip stocks is equal, whereas the alternative hypothesis (H_1) states that there is a difference in median volatility between the two groups.

The results of the Mann–Whitney U test are presented in Table 4. Based on the table, the number of observations in each stock group is 1,407. The rank sum for blue-chip stocks is 1,841,011, while that for non-blue-chip stocks is 2,119,694, with an expected rank sum of 1,980,352.5 for each group. The test statistic (Z) is 6.476, with a p-value of 0.000. Since the p-value is lower than the significance level ($\alpha = 0.05$), the null hypothesis (H_0) is rejected. Therefore, there is a statistically significant difference in the median daily return volatility between blue-chip and non-blue-chip stocks on the Indonesia Stock Exchange during the observation period.

Table 1. Descriptive statistics

Variable	Obs	Mean	Std Dev	Min	Max
Blue Chip	1407	-0.000139	0.0136517	-0.095261	0.139075
Non Blue Chip	1406	0.000064	0.0140682	-0.101370	0.100286

Table 2. Lagrange multiplier test results

Variables	lags (p)	chi2	df	Prob > chi2
Blue Chip	1	34.367	1	0.000
Non Blue Chip	1	19.432	1	0.000

Table 3. White noise test results

Variable	Portmanteau (Q) statistic	Prob > chi2
Blue Chip	28.8220	0.9055
Non Blue Chip	24.8351	0.9711

Table 4. Mann–Whitney U Test Results

Variable	Obs	Rank Sum	Expected
Blue Chip	1407	1841011	1980352.5
Non Blue Chip	1407	2119694	1980352.5
	Z = 6.476		
	Prob > |z| = 0.000		

Influence Volatility against Return

This analysis is supposed to check whether the conditional variance (σ^2), computed from the selected GARCH models, plays an important role in the daily returns of each index in terms of the concept of risk-return trade-off. Modern portfolio theory suggests that the risk-return relationship is such that higher risk usually implies higher expected returns (Markowitz, 1952). To test this relation empirically, the present study uses a simple linear regression approach. The dependent variable is the daily return at period t+1 (r_{t+1}) and the independent variable is the conditional variance at period t. The basic model used in this study is the following:

$$r_{t+1} = \alpha + \beta\sigma^2 + \varepsilon_{t+1}$$

The interpretation of this model boils down to the coefficient β, which shows the direction and strength of the association between volatility and returns. A positive and statistically significant β implies that higher volatility is associated with higher subsequent returns, consistent with the risk-return trade-off theory. By contrast, a negative and statistically significant β suggests an inverse relationship, in which higher volatility is associated with lower future returns. If β is not statistically significant, we cannot say that volatility has a significant effect on subsequent returns. Therefore, the sign and statistical significance of β serve as the primary basis for interpreting the empirical relationship between volatility and return.

Based on the simple linear regression results, the model examining the effect of volatility on blue-chip stock returns is statistically insignificant at the 5% significance level (α = 0.05) but significant at the 10% significance level (α = 0.10). This is indicated by the p-value of the volatility variable (0.064), which is greater than 0.05 but less than 0.10 (Table 5). Therefore, volatility, measured using GARCH conditional variance, has a statistically significant effect on daily blue-chip stock returns at the 10% significance level during the study period. However, the volatility coefficient is negative (−11.46489), indicating an inverse relationship between volatility and stock returns. In other words, higher volatility is associated with lower subsequent returns.

Based on the simple linear regression results, the model examining the effect of volatility on non-blue-chip stock returns is insignificant. This is supported by the p-value of the volatility variable (0.850) which is much higher than 0.05 (Table 6). Therefore, the effect of volatility measured by GARCH conditional variance is statistically insignificant on daily non-blue-chip stock returns during the study period. The value of the Volatility coefficient is positive (1.753058) which indicates that volatility and returns have a positive relationship. However, since this relationship is statistically insignificant, there is insufficient evidence to conclude that changes in volatility have a significant effect on non-blue-chip stock returns within the simple linear regression model employed in this study.

Difference Volatility Return Share Blue Chip & Non Blue Chip

The empirical results show that the return volatility of non-blue-chip stocks (proxied by the IDX-SMC Liquid Index) is significantly higher than the return volatility of blue-chip stocks (proxied by the LQ45 Index) over the period from January 2020 to October 2025. These findings indicate distinct risk characteristics between large-cap stocks and medium- and small-cap stocks listed on the Indonesia Stock Exchange (IDX).

Table 5. Regression results volatility against blue chip returns

Blue Chip	Coefficient	Std.Error	t	P>|t|
Volatilitas	-11.46489	6.172405	-1.86	0.064
Cons	0.0016101	0.0010768	1.50	0.135

***),* *), and *), Significant at the level real 1%, 5%, and 10%

Table 6. Regression results volatility against non- blue chip returns

Non Blue Chip	Coefficient	Std.Error	t	P>|t|
Volatilitas	1.753058	9.25851	0.19	0.850
Cons	-0.0006532	0.0016185	-0.40	0.687

***),* *), and *), Significant at the level real 1%, 5%, and 10%

These differences in risk characteristics are also mirrored in the descriptive statistics of the two stock groups. The minimum return for non-blue-chip stocks is −0.101370 and for blue-chip stocks is −0.095261 indicating that there is a more extreme negative return during the observation period. Meanwhile, the blue-chip stocks has a higher maximum return of 0.139075 compared to non-blue-chip stocks of 0.100286. This pattern indicates that although non-blue-chip stocks have higher volatility and more extreme negative returns, blue-chip stocks reach higher maximum returns during the observation period. These findings highlight the differences in return distribution characteristics between the two stock groups.

These results are in line with the size effect discussed by Fama and French (1993) in theory, who highlighted that returns on small-cap stocks are more volatile than returns on large-cap stocks. Medium and small firms are more uncertain in their business, they have lower access to finance and lower stock liquidity. These characteristics may make the stock prices of non-blue-chip companies more sensitive to market information and investor sentiment, resulting in higher return volatility.

Meanwhile, the blue chip stocks in the LQ45 Index are usually companies with large market capitalization, relatively solid fundamentals and high trading liquidity. These characteristics could make blue-chip stocks more able to weather market shocks, leading to relatively more stable price action. The participation of institutional investors in blue-chip stocks may also contribute to market liquidity and help moderate excessive price fluctuations, particularly during periods of economic uncertainty.

These findings are also consistent with the empirical evidence reported by Alioui et al. (2015), who found that small-cap stocks exhibited higher volatility than large-cap stocks, reflecting their greater sensitivity to market shocks and changes in macroeconomic conditions.

From a practical point of view, these findings suggest that investors in the Indonesian capital market need to consider the differences in the characteristics of volatility and return patterns between blue-chip and non-blue-chip stocks in building their investment portfolios. Non-blue-chip stocks are more volatile in returns, and have more extreme negative returns, reflecting higher risk exposure. Modern portfolio theory (Markowitz, 1952) posits that higher risk investments are generally expected to have higher returns, reflecting the risk-return trade-off. However, the empirical findings of this study do not offer sufficient evidence that higher volatility in non-blue-chip stocks leads to higher subsequent returns. Blue-chip stocks also tend to have relatively lower return volatility and achieved a higher maximum daily return during the study period. These characteristics may provide investors with alternative considerations when balancing risk and potential returns in their investment portfolios.

Influence Return Volatility on Stock Returns

The results of the estimation using the Ordinary Least Square method (OLS) with robust standard errors show that the previous period return volatility has no significant effect on the next stock returns in the nonblue-chip group. For the blue-chip stocks (indicated by LQ45 Index), the volatility coefficient is negative (−11.46489) and statistically significant at the 10% significance level, but not at the 5% level. The negative coefficient means that higher volatility is usually

associated with lower subsequent returns. In contrast, for non-blue-chip stocks indicated by IDX-SMC Liquid Index, the coefficient of volatility is positive (1.753058) but statistically insignificant. This positive coefficient indicates a positive relationship between volatility and subsequent returns. However, there is not enough statistical evidence to establish this relationship. These findings indicate that, although non-blue-chip stocks exhibit higher return volatility, this higher risk is not necessarily accompanied by higher subsequent returns.
The difference in the direction of the coefficients of volatility between the blue-chip stocks and the non-blue-chip stocks captures the potential differences in market characteristics and investor behaviors in the two groups of stocks. The finding for blue-chip stocks with a negative volatility coefficient that is statistically significant at the 10% significance level is consistent with the findings of Alioui et al. (2015) who reported that large-cap stocks tend to generate higher returns under a relatively low volatility. However, the statistically insignificant relationship between volatility and returns in non-blue-chip stocks suggests that volatility may function primarily as an indicator of market risk and uncertainty rather than as a significant predictor of subsequent returns.

These results also support the results of French et al. (1987) who found that the relationship between volatility and stock returns may be relatively weak and may vary across market conditions. They stressed the importance of volatility in reflecting changes in expected market risk and its relationship to expected returns. Furthermore, Campbell and Hentschel (1992) found that the impact of volatility on stock returns depends on prevailing market conditions and the level of volatility itself, suggesting that the relationship may vary over time.

To summarize, the results of this study suggest that although there is a statistically significant difference in return volatility between blue-chip and non-blue-chip stocks, volatility does not have a statistically significant effect on subsequent returns for non-blue-chip stocks. In contrast, the relation between volatility and subsequent returns is negative and statistically significant at the 10% level for blue chip stocks. These findings reinforce the view that volatility is primarily an indicator of investment risk and market uncertainty, rather than a reliable predictor of subsequent returns, particularly in the context of the Indonesian capital market during the period from January 2020 to October 2025.

CONCLUSIONS AND RECOMMENDATIONS

Conclusions

This study aims to analyze the difference in stock return volatility between blue-chip stocks and non-blue-chip stocks on the Indonesia Stock Exchange (IDX) and to analyze the effect of return volatility measured by conditional variance on daily returns of each stock group. The analysis of data for the period January 2020 to October 2025 using the ARCH/GARCH framework shows that both groups of stocks have volatility clustering as evidenced by the presence of significant ARCH effects. These findings support the application of GARCH models to capture the volatility dynamics of both stock groups.

Furthermore, Mann–Whitney U test shows that the return volatility is statistically different between the two groups of stocks. Blue-chip stocks are less volatile than non-blue-chip stocks by a huge margin. This finding is consistent with the size-related evidence presented by Fama and French (1993), which indicates that small-cap stocks tend to exhibit greater return variability than large-cap stocks.

As for the relationship between volatility and future returns, the regression results show that conditional volatility has a negative and statistically significant effect on blue-chip stock returns at the 10% significance level but not at the 5% significance level. Conversely, volatility has a positive relationship with non-blue-chip stock returns, although it is statistically insignificant. These findings suggest that the relationship between volatility and subsequent returns differs across the two stock groups and that higher volatility does not necessarily translate into higher subsequent returns.

Recommendations

To summarize, the present study points to the return volatility as a significant measure of investment risk and market uncertainty, but it is not a consistent predictor of the next day returns in the two stock groups.These findings explain the differences in the risk characteristics and the risk-return relationships between the blue-chip stocks and the non-blue-chip stocks in the Indonesian capital market during the observation period.

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CONFLICT OF INTEREST: The authors declare

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