MEASUREMENT OF INDIVIDUAL VALUE AT RISK IN A SMALL-CAP STOCK PORTFOLIO ON THE INDONESIA STOCK EXCHANGE

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Abstract

Small-cap stocks are characterized by high volatility and relatively low liquidity, which increase market risk exposure. This study aims to estimate individual Value at Risk (VaR) and examine the effect of stock volatility, liquidity, and stock returns on VaR in small-cap stock portfolios listed on the Indonesia Stock Exchange during 2020–2023. VaR is estimated using the Monte Carlo simulation approach with a 95% confidence level and one-year holding period. The study employs panel data regression with 120 firm-year observations. The results indicate that stock volatility has a positive and significant effect on VaR, stock returns have a negative and significant effect on VaR, while stock liquidity does not significantly affect VaR. Simultaneously, volatility, liquidity, and returns significantly explain VaR variation, with an adjusted R^2 of 0.688. These findings confirm that volatility is the primary determinant of downside risk in small-cap stocks. The study contributes to risk measurement literature in emerging markets and provides implications for portfolio risk management strategies.

Keywords: Value at Risk, Volatility, Liquidity, Return, Small-Cap Stocks, Risk Management

INTRODUCTION

The capital market functions as a mechanism for capital allocation and risk management in the modern financial system. On the Indonesia Stock Exchange, small-cap stocks are known to have high growth potential, but they are accompanied by greater price volatility compared to large-cap stocks. These characteristics increase return uncertainty and heighten the risk of investment losses.

Risk measurement becomes crucial, especially in the context of emerging markets characterized by high volatility dynamics. Value at Risk (VaR) is a quantitative approach widely used to estimate the maximum potential loss at a certain confidence level. Although research on VaR has developed considerably in global markets, empirical studies specifically examining the determinants of VaR in small-cap stocks in Indonesia remain limited.

This literature gap motivates this study to empirically examine the effects of volatility, liquidity, and return on VaR in Indonesian small-cap stocks. This study contributes by integrating Monte Carlo simulation and panel regression analysis within the context of an emerging market.

REVIEW OF LITERATURE

Agency Theory

Agency Theory explains the relationship between principals (investors) and agents (investment managers), in which potential conflicts of interest arise due to information asymmetry (Jensen & Meckling, 1976). In stock investment, portfolio managers are responsible for managing portfolios according to investors' acceptable risk levels. Therefore, objective risk measurement tools such as Value at Risk (VaR) are needed to provide transparent information about potential portfolio losses. The use of VaR helps reduce information asymmetry and improve investment decision quality, especially for small-cap stocks that carry higher risk.

Signaling Theory

Signaling Theory explains that companies provide information to investors as signals regarding their condition and prospects (Brigham & Houston, 2019). This information influences investors' perceptions of stock risk and return. In small-cap stocks, information uncertainty is relatively higher, which affects stock price volatility and investment risk. Increased volatility due to information uncertainty will lead to higher Value at Risk.

Portfolio Theory

Portfolio theory states that investors can reduce risk through diversification across various assets (Markowitz, 1952). Diversification aims to optimize returns with minimum risk. In portfolio management, risk measurement is essential for controlling potential losses. Value at Risk is one method used to quantitatively measure portfolio risk, particularly for small-cap stocks with high volatility.

Stock Volatility

Stock volatility measures price fluctuations over a certain period and is a primary indicator of investment risk (Jorion, 2019). Small-cap stocks tend to have higher volatility than large-cap stocks, thereby increasing potential losses. In VaR calculations, volatility is a key factor because it determines the magnitude of potential portfolio losses.

Stock Liquidity

Stock liquidity refers to the ease with which shares can be traded without significantly affecting their price. Small-cap stocks generally have lower liquidity, which increases investment risk (Kumar & Misra, 2020). Low liquidity can increase potential losses and raise Value at Risk.

Stock Returns

Stock return is the rate of profit earned by investors from stock investments (Tandelilin, 2010). Small-cap stocks offer higher return potential but are accompanied by greater risk. Fluctuations in stock returns affect risk levels and directly influence Value at Risk.

Value at Risk (VaR)

Value at Risk (VaR) is a statistical method used to measure the maximum potential portfolio loss within a certain period at a given confidence level (Jorion, 2019). VaR is an important risk management tool because it provides quantitative estimates of investment risk. In the context of small-cap stocks, VaR is used to measure risk resulting from high volatility, low liquidity, and fluctuations in stock returns.

Relationships Among Variables

Stock volatility has a positive relationship with Value at Risk, where increased volatility raises potential losses. Stock liquidity has a negative relationship with Value at Risk, where lower liquidity increases risk. Fluctuating stock returns also increase risk and lead to higher Value at Risk. Therefore, volatility, liquidity, and stock returns are important factors in risk measurement using VaR for small-cap stocks on the Indonesia Stock Exchange.

Previous Studies

Several previous studies indicate that Value at Risk is an effective method for measuring stock investment risk. Research shows that stock volatility significantly affects VaR because volatility reflects market risk levels. In addition, stock returns also influence VaR because returns reflect investment performance and investor risk exposure. However, studies specifically examining the effects of stock volatility, stock liquidity, and stock returns on VaR in small-cap stocks listed on the Indonesia Stock Exchange remain limited, highlighting the need for further research to fill this gap.

Hypothesis Development

Based on Agency Theory, Signaling Theory, Portfolio Theory, and prior studies, stock volatility, liquidity, and returns are important factors influencing investment risk measured using Value at Risk. High volatility increases stock price uncertainty and potential loss risk. Low liquidity makes it difficult to sell shares without affecting prices, thereby increasing risk. Furthermore, fluctuations in stock returns reflect uncertainty that contributes to higher portfolio risk.

Based on the theoretical framework and previous research, the hypotheses of this study are as follows:

H1: Stock volatility has a significant effect on Value at Risk.
H2: Stock liquidity has a significant effect on Value at Risk.
H3: Stock returns have a significant effect on Value at Risk.
H4: Stock volatility, stock liquidity, and stock returns simultaneously have a significant effect on Value at Risk.

RESEARCH METHOD

Type and Research Approach

This study employs a quantitative approach aimed at analyzing the effect of stock volatility, stock liquidity, and stock returns on Value at Risk in small-cap stock portfolios on the Indonesia Stock Exchange. A quantitative approach is used because this study seeks to test relationships among variables using statistical analysis and to measure investment risk objectively based on historical data. The analytical method used is multiple linear regression to examine the effect of independent variables on the dependent variable.

Population and Sample

The population in this study consists of all small-cap stocks listed on the Indonesia Stock Exchange during the research period. The sample consists of 30 small-cap companies listed on the Indonesia Stock Exchange. The sampling technique used is purposive sampling, which selects samples based on specific criteria relevant to the research objectives. The criteria include stocks consistently listed during the study period and having complete stock price data, enabling accurate calculation of stock volatility, liquidity, returns, and Value at Risk.

The study period spans from 2020 to 2023. Using 30 companies over four years results in 120 observations (30 companies × 4 years). This number of observations is considered adequate for quantitative statistical analysis, particularly multiple linear regression testing, and is expected to provide reliable and valid estimates in examining the effects of stock volatility, liquidity, and returns on Value at Risk in small-cap stock portfolios on the Indonesia Stock Exchange.

Type and Source of Data

The study uses secondary data in the form of historical stock prices obtained from the Indonesia Stock Exchange and other official data sources. The data include closing stock prices used to calculate stock returns, volatility, liquidity, and Value at Risk. Secondary data are used because they have a high level of objectivity and allow quantitative measurement of research variables.

Operational Definition of Variables

This study uses one dependent variable and three independent variables:

1. **Value at Risk (VaR)** – the dependent variable measuring the maximum potential portfolio loss within a certain period at a specified confidence level.
2. **Stock Volatility** – an independent variable measuring the level of stock price fluctuation over a certain period, reflecting market risk.
3. **Stock Liquidity** – an independent variable measuring how easily stocks can be traded in the market.
4. **Stock Return** – an independent variable measuring the rate of return from stock investment over a certain period.

Variable Measurement

Variables are measured quantitatively based on secondary stock price and trading activity data. All variables are calculated annually to ensure consistency with the firm-year data structure and to reflect a medium-term investment horizon. The dependent variable is Value at Risk (VaR), which measures maximum loss risk at a certain confidence level. Independent variables include stock returns, volatility, and liquidity, which theoretically influence market risk. Stock returns are calculated using annual log returns. Volatility is measured by the standard deviation of returns, while liquidity is proxied by the ratio of trading volume to shares outstanding. VaR is estimated using Monte Carlo simulation with a 95% confidence level, a one-year horizon, and 10,000 simulation iterations assuming a normal distribution. VaR is determined as the 5th percentile of the simulated return distribution.

Data Analysis Technique

Data analysis uses multiple linear regression to examine the effects of stock volatility, liquidity, and returns on Value at Risk. The regression model is:

$$\text{VaR} = \beta_0 + \beta_1 \text{Volatility} + \beta_2 \text{Liquidity} + \beta_3 \text{Return} + \varepsilon$$

Where:
VaR = Value at Risk
β_0 = Constant
β_1, β_2, β_3 = Regression coefficients
ε = Error term

Classical assumption tests are conducted to ensure that the regression model satisfies normality, multicollinearity, heteroscedasticity, and autocorrelation assumptions. Hypothesis testing is performed using partial tests (t-test) to determine the effect of each independent variable on the dependent variable, simultaneous tests (F-test) to determine joint effects, and the coefficient of determination (R^2) to measure the model's explanatory power.

Analytical Software

Data processing and analysis are conducted using Microsoft Excel and SPSS. Microsoft Excel is used to calculate stock returns, volatility, and Monte Carlo simulations for estimating Value at Risk, as well as stock liquidity indicators. SPSS is used for statistical analysis, including descriptive statistics, classical assumption tests, and regression analysis to examine the effects of volatility, liquidity, and stock returns on Value at Risk.

RESULTS AND DISCUSSION

Descriptive Statistics

Descriptive statistical analysis is used to provide an overview of the characteristics of the research variables, including stock volatility, stock liquidity, stock returns, and Value at Risk (VaR). Descriptive statistics include the minimum, maximum, average (mean), and standard deviation values for all research variables.

Table 1.
Descriptive Statistics of Research Variables

Variable	Minimum	Maximum	Mean	Std. Deviation	N
Stock Volatility	0,00	0,35	0,1327	0,10194	120
Stock Liquidity	-0,74	1,93	0,2559	0,46412	120
Stock Returns	-0,06	0,29	0,0227	0,06129	120
Value at Risk	1,41	25,63	16,6808	9,36184	120

Source: Data processed 2026

Based on Table 1, all variables have 120 observations, indicating that the research data is complete and suitable for further analysis. The stock volatility variable has an average of 0.1327 with a standard deviation of 0.10194, indicating a relatively moderate level of volatility. Stock liquidity has relatively high variation with a standard deviation of 0.46412, indicating differences in liquidity among small-cap stocks. Stock returns have a positive average value of 0.0227, indicating that small-cap stocks generally provided positive returns during the study period. Meanwhile, Value at Risk has an average of 16.6808, indicating that the maximum risk of loss in a small-cap stock portfolio is relatively high and varies across stocks.

Classical Assumption Test

The classical assumption test was conducted to ensure that the multiple linear regression model meets the BLUE (Best Linear Unbiased Estimator) assumption, ensuring that the regression estimation results are valid and can be used for hypothesis testing. The classical assumption tests in this study include tests for normality, heteroscedasticity, autocorrelation, and multicollinearity.

Normality Test

The normality test aims to determine whether the residuals in the regression model are normally distributed. The test was conducted using the Kolmogorov–Smirno method.

Table 2.
Normality Test Results

Variable	N	Kolmogorov-Smirnov Z	Sig. (2-tailed)	Conclusion
Unstandardized Residual	120	0,138	0,000	Not Normal

Source: processed data 2026

The normality test results showed a significance value of 0.000 (<0.05), indicating that the residuals are not statistically normally distributed. However, the number of observations in this study was 120, which is considered a large sample size. Based on the Central Limit Theorem, with large sample sizes, the distribution of the regression estimator will approach a normal distribution, so statistical testing using the t-test and F-test remains valid (Gujarati & Porter, 2009; Wooldridge, 2016). Therefore, the regression model remains suitable for analysis and hypothesis testing.

The results of the normality test using a graphical approach using the Histogram Regression Standardized Residual are shown in Figure: Histogram of Dependent Variable: Value at Risk.

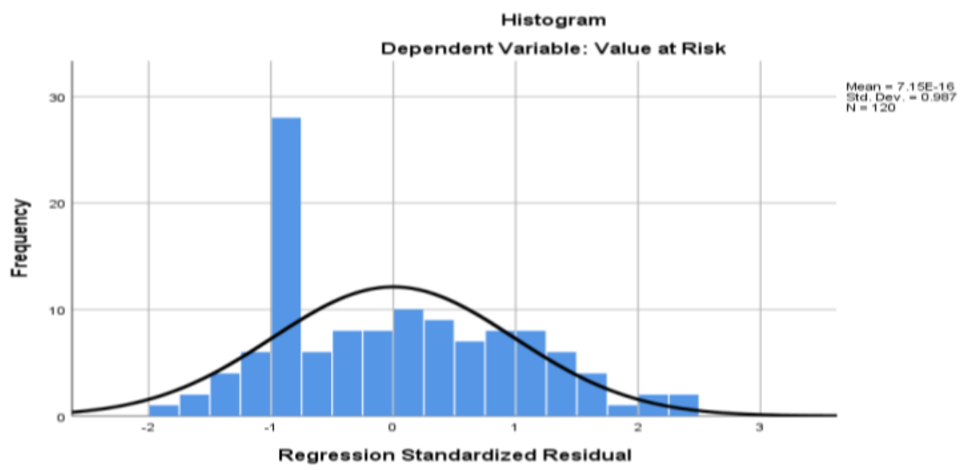

Figure 1.
Normality Test Result

Based on Figure 1, the residual distribution visually forms a pattern approaching a normal curve (bell-shaped) and is relatively symmetrical around the zero value, although there are slight deviations. Statistically, the Kolmogorov–Smirnov test shows significance, but with a large sample size, the Central Limit Theorem allows the assumption of normality to be considered adequately met.

Thus, the regression model is deemed suitable for further analysis, including partial (t) tests, simultaneous (F) tests, and coefficient of determination (R^2) tests.

Multicollinearity Test

The multicollinearity test aims to determine whether there is a high correlation between the independent variables in the regression model.

Table 2.
Multicollinearity Test Results

Variable	Tolerance	VIF	Conclusion
Stock Volatility	> 0,10	< 10	No Multicollinearity
Stock Liquidity	> 0,10	< 10	No Multicollinearity
Stock Returns	> 0,10	< 10	No Multicollinearity

Source: processed data 2026

Based on the results of the multicollinearity test, it was found that all independent variables, namely stock volatility, stock liquidity, and stock returns, had tolerance values above 0.10 and VIF values below 10. These results indicate that there is no strong correlation between the independent variables in the regression model. With no signs of multicollinearity found, the regression model meets the classical assumptions of multicollinearity, resulting in good levels of reliability and validity.

Therefore, the regression model is deemed suitable for use in regression analysis and hypothesis testing, and is able to provide accurate estimates in explaining the effect of the independent variables on the dependent variable.

Heteroscedasticity Test

The heteroscedasticity test was conducted to determine whether there is inequality of residual variance in the regression model. The test was conducted using the Glejser method.

Table 3.
Heteroscedasticity Test Results

Variable	Coeficient (B)	t count	Sig.	Conclusion
Stock Volatility	-7,114	-2,484	0,014	Heteroscedasticity occurs
Stock Liquidity	-1,119	-2,143	0,034	Heteroscedasticity occurs
Stock Returns	4,397	0,922	0,358	No Heteroscedasticity

Source: processed data 2026

Based on the results of the Glejser test, the stock volatility and stock liquidity variables showed significance values of 0.014 and 0.034, respectively ($p < 0.05$), indicating the presence of heteroscedasticity. Conversely, the stock return variable had a significance value of 0.358 ($p > 0.05$), thus indicating no heteroscedasticity. Therefore, it can be concluded that the regression model in this study does not fully meet the homoscedasticity assumption.

Because heteroscedasticity still exists in some of the independent variables, which could potentially affect the efficiency of the regression parameter estimation. Nevertheless, the regression model can still be used because heteroscedasticity does not bias the regression coefficients but only affects the efficiency of the estimator.

The results of the heteroscedasticity test using a scatterplot are shown in:

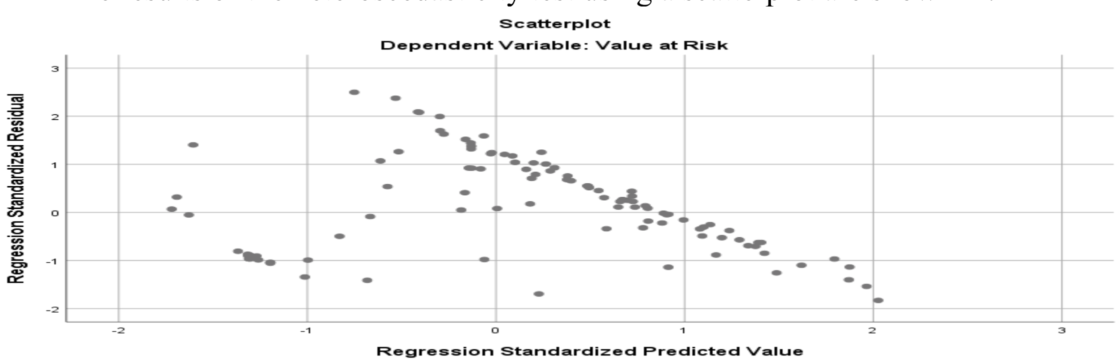

Figure 2.
Heteroscedasticity Test Result

Based on Figure 2, the residual distribution pattern is not completely random and visually indicates heteroscedasticity. This condition does not bias the regression coefficients, but it can affect the efficiency (accuracy of the standard error) of the estimator.

With a sufficient number of observations ($n = 120$), the regression model remains suitable for hypothesis testing (t-test and F-test) and coefficient of determination analysis, with caution in interpreting the residuals for possible decreased estimation efficiency.

Autocorrelation Test

The autocorrelation test aims to determine whether there is a correlation between residuals from one period to another. The test is conducted using the Durbin-Watson method.

Table 4.
Autocorrelation Test Results

Model	R	R Square	Adjusted R Square	Std Error	Durbin-Watson
1	0,834	0,696	0,688	5,22657	1,263

Source: processed data 2026

Based on the test results, the Durbin-Watson value of 1.263 indicates mild positive autocorrelation. However, with a sufficient number of observations (120 observations), the regression model can still be used for analysis and hypothesis testing because the estimator remains consistent and unbiased.

Classical Assumption Test Conclusion

Based on the results of the classical assumption test, it can be concluded that the multiple linear regression model in this study generally meets the assumptions of the feasibility of the regression model. Despite several limitations, such as residuals that are not fully normally distributed, indications of heteroscedasticity in some variables, and mild autocorrelation, the regression model remains usable due to the sufficient number of observations and the absence of multicollinearity.

Therefore, the regression model in this study is suitable for hypothesis testing and analyzing the influence of stock volatility, stock liquidity, and stock returns on Value at Risk in a portfolio of small-cap stocks on the Indonesia Stock Exchange.

Multiple Linear Regression Analysis

Multiple linear regression analysis was used to examine the effect of stock volatility, stock liquidity, and stock returns on Value at Risk, a measure of investment risk. The results of the multiple linear regression analysis are as follows:

Table 5.
Results of Multiple Linear Regression Analysis

Independent Variable	Coefficient (B)	Std. Error	Beta	t-value	Sig.	Direction
Constant	6.452	0.850	–	7.595	0.000	
Stock Volatility	88.358	5.669	0.962	15.587	0.000	Positive
Stock Liquidity	-1.748	1.034	-0.087	-1.691	0.093	Negative
Stock Return	-46.156	9.435	-0.302	-4.892	0.000	Negative

Source: processed data 2026

Based on the table, the following regression equation is obtained:

VaR = 6.452 + 88.358 Volatility -1.748 Liquidity -46.156 Return. This regression equation shows that stock volatility has a positive effect on Value at Risk, while stock liquidity and stock returns have a negative effect on Value at Risk.

Hypothesis Testing

Hypothesis testing was conducted using multiple linear regression analysis through partial tests (t-test) and simultaneous tests (F-test) at a 5% significance level ($\alpha = 0.05$).

Partial Test Results (t-Test)

Table 6.
Partial Test Results (t-Test)

Independent Variable	Coefficient (B)	t-value	Sig.	Direction	Decision
Stock Volatility	88.358	15.587	0.000	Positive	H1 Accepted
Stock Liquidity	-1.748	-1.691	0.093	Negative	H2 Rejected
Stock Return	-46.156	-4.892	0.000	Negative	H3 Accepted

Source: processed data 2026

Explanation of Table 6.

1. Stock volatility has a positive and significant effect on VaR ($p < 0.05$), therefore, H1 is accepted.
2. Stock liquidity does not have a significant effect on VaR ($p > 0.05$), so H2 is rejected.
3. Stock returns have a negative and significant effect on VaR ($p < 0.05$), therefore, H3 is accepted.

Simultaneous Test Results (F Test)

Table 7.
Simultaneous Test Results (F Test)

Independent Variables	Dependent Variable	F-value	Sig.	Conclusion	Decision
Volatility, Liquidity, Return	Value at Risk	88.600	0.000	Significant	H4 Accepted

Source: processed data 2026

The F-test shows that volatility, liquidity, and stock returns jointly have a significant effect on VaR ($p < 0.05$). Thus, H4 is accepted, and the regression model is declared statistically sound.

Results of the Coefficient of Determination (R^2) Test.

The coefficient of determination is used to measure the ability of the independent variables, namely stock volatility, stock liquidity, and stock returns, to explain the variation in the dependent variable, Value at Risk (VaR).

Table 8.
Results of the Coefficient of Determination (R^2)

Model	R	R Square	Adjusted R Square	Std Error
1	0,834	0,696	0,688	5,22657

Source: processed data 2026

Based on the results of the Coefficient of Determination (R^2) test, the coefficient of determination (R Square) value of 0.696 indicates that 69.6% of the variation in Value at Risk can be explained by stock volatility, stock liquidity, and stock returns, while the remaining 30.4% is explained by other variables outside the research model.

The Adjusted R Square value of 0.688 indicates that after adjusting for the number of independent variables and sample size, the model is still able to explain 68.8% of the variation in Value at Risk.

The relatively high coefficient of determination value indicates that the regression model used in this study has a strong ability to explain the investment risk of small-cap stocks on the Indonesia Stock Exchange.

Analysis of the Effect of Stock Volatility on Value at Risk

The regression results show that stock volatility has a positive and significant effect on Value at Risk (VaR), with a coefficient of 88.358 and a significance level of 0.000 (< 0.05). This finding indicates that an increase in small-cap stock volatility directly increases the potential maximum loss measured using VaR at a 95% confidence level. Theoretically, this result is consistent with Portfolio Theory, which places variance or standard deviation as the primary measure of risk. In the Monte Carlo approach, volatility is a key parameter shaping the return distribution, so higher volatility widens the distribution tail (left-tail risk).

This finding confirms that volatility is the main determinant of downside risk in small-cap stocks on the Indonesia Stock Exchange.

Effect of Stock Liquidity on Value at Risk

Stock liquidity has a negative coefficient of −1.748 with a significance level of 0.093 (> 0.05), indicating that it does not significantly affect VaR. Conceptually, low liquidity can increase risk because it raises transaction costs and price impact. However, in a VaR model based on a normal return distribution, the risk captured is primarily market risk rather than liquidity risk. Therefore, variations in liquidity are not directly reflected in annual VaR estimates.

This result indicates that, in the context of Monte Carlo simulation-based risk measurement, liquidity is not a major determinant of maximum loss risk in small-cap stocks.

Effect of Stock Returns on Value at Risk

Stock returns have a negative and significant effect on VaR, with a coefficient of −46.156 and significance of 0.000 (< 0.05). This means that the higher the stock return, the lower the estimated potential maximum loss. Statistically, an increase in average return shifts the distribution to the right, reducing the magnitude of extreme losses.

This finding is consistent with the risk–return tradeoff concept, where better stock performance tends to reduce the probability of downside risk. Thus, VaR is influenced not only by volatility but also by the mean return parameter.

Simultaneous Effect and Coefficient of Determination

The simultaneous test shows that volatility, liquidity, and return jointly have a significant effect on VaR ($F = 88.600$; $p = 0.000$). The coefficient of determination test shows an Adjusted R^2 value of 0.688, indicating that 68.8% of the variation in VaR can be explained by the three variables in the model. This value is considered strong in financial research based on market data, indicating that the model has good explanatory power. However, 31.2% of the risk variation is still influenced by other factors such as macroeconomic conditions and market sentiment.

Theoretical Implications

This study strengthens the relevance of Portfolio Theory in the context of small-cap stocks in emerging markets. The finding that volatility has a positive and significant effect on Value at Risk (VaR) confirms that return variance remains the main determinant of downside risk. This shows that classical risk approaches based on standard deviation still have strong explanatory power in market structures with high uncertainty such as the Indonesia Stock Exchange.

In addition, the negative and significant effect of returns on VaR indicates that risk estimation is determined not only by return dispersion but also by the mean return parameter. Conceptually, this result reinforces the normal distribution approach in Monte Carlo simulation, where VaR is simultaneously influenced by mean and variance. Therefore, this study contributes empirically to the risk management literature by demonstrating the integration of the risk–return relationship in quantitative risk measurement.

The insignificance of liquidity on VaR indicates that VaR models based on normal distributions represent market risk more than liquidity risk. This finding opens opportunities for developing risk models that explicitly integrate liquidity risk components, especially for small-cap stocks that structurally tend to have low liquidity.

Practical Implications

Practically, the results confirm that small-cap stock portfolio risk management should prioritize volatility control as the dominant factor shaping maximum loss risk. Investment managers can implement volatility monitoring, VaR-based risk limits, and diversification strategies to reduce risk exposure.

The negative effect of returns on VaR also indicates that improved stock performancecontributes to lower downside risk. Therefore, fundamental-based stock selection strategies and performance consistency are important within a risk management framework.

Although the model has strong explanatory power, the findings indicate that conventional VaR does not fully capture liquidity risk. Thus, in practical risk management, VaR should be complemented with stress testing and scenario analysis to obtain more comprehensive risk estimates.

CONCLUSION

Overall, the research results indicate that volatility is the dominant factor in determining the downside risk of small-cap stocks. Stock returns act as a risk-reducing factor, while liquidity is not proven significant in the annual normal distribution-based VaR model.

These findings reinforce the relevance of Portfolio Theory and modern risk management approaches in the context of emerging markets. The implication is that risk management of small-cap stock portfolios should prioritize volatility control and return optimization to minimize potential losses.

Study Strengths, Limitations, and Suggestions

This research has several strengths. First, it integrates Value at Risk (VaR) estimation through Monte Carlo simulations with panel data regression analysis, resulting in a comprehensive and empirically based risk measurement. Second, the focus on small-cap stocks on the Indonesia Stock Exchange provides an empirical contribution to the risk management literature in emerging markets. Third, the model demonstrates strong explanatory power with an adjusted R^2 value of 0.688, indicating that volatility, liquidity, and returns can explain substantial variation in risk.

However, this study has limitations. VaR estimation still uses the assumption of a normal distribution, which potentially ignores the fat tails characteristic of stock returns.

Furthermore, liquidity risk has not been fully accommodated in the model, and there are indications of heteroscedasticity and mild autocorrelation that could affect estimation efficiency. Macroeconomic variables have also not been included in the research model.

Future research is recommended to use non-normal distributions or Extreme Value Theory, develop liquidity-adjusted VaR, and add macroeconomic variables and robust estimation methods to improve the accuracy of risk measurement.

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