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Market Risk Assessment of the Indonesian Composite Stock Price Index (IHSG) Using Monte Carlo Simulation and Backtesting During the Rupiah Exchange Rate Shock

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ABSTRACT

This study aims to quantify the market risk of the Indonesian Composite Stock Price Index (IHSG/JKSE) during a period of heightened macroeconomic uncertainty coinciding with a sharp depreciation of the Indonesian Rupiah (IDR). This research used daily closing prices of IHSG from January 2, 2023 to June 5, 2026 (813 trading days) were used. Missing observations caused by market holidays were imputed via the Last Observation Carried Forward (LOCF) method. Log-returns were computed and their distributional properties examined through descriptive statistics, the Jarque-Bera normality test, and the Augmented Dickey-Fuller (ADF) unit root test. Market risk was estimated as Value-at-Risk (VaR) at the 95% confidence level using Monte Carlo simulation with 10,000 iterations, drawing random returns from a normal distribution parameterized by the empirical mean and standard deviation. Model validity was assessed using Kupiec's proportion-of-failures backtesting procedure. The result shows that the daily IHSG log-return exhibits a negative mean (μ= -0.000249), volatility of σ= 0.010851, negative skewness (-1.3644), and total kurtosis of 12.0664 (excess kurtosis = 9.066), confirming a heavy-tailed, non-normal distribution (Jarque-Bera p < 0.001). The ADF test confirms stationarity at the level. The Monte Carlo VaR at the 95% confidence level is -1.8065%, equivalent to a maximum potential loss of IDR 17,902,811 for a one-billion-rupiah portfolio. Backtesting produced exactly 41 actual violations against 41 expected violations (failure rate = 5.04%), confirming that the model is statistically valid and robust for capturing downside market risk.

*Keyword***:** *Value-at-Risk; Monte Carlo Simulation; IHSG; Backtesting; Market Risk*

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1. Introduction

Global macroeconomic uncertainty has intensified substantially in recent years, placing considerable pressure on financial stability across emerging market economies. Indonesia is no exception: the sustained depreciation of the Indonesian Rupiah against the US Dollar has occurred concurrently with marked declines in the Composite Stock Price Index (IHSG). Currency depreciation commonly triggers capital outflows from domestic equity markets, amplifies return volatility, and elevates market risk for investors and portfolio managers (Syalsabila et al., 2025).

The quantification of market risk has long been central to financial risk management, and Value-at-Risk (VaR) remains the dominant industry standard. VaR is formally defined as the maximum loss, at a specified confidence level (1 - alpha), that a portfolio may incur over a given time horizon (Kasse et al., 2021; McNeil et al., 2015) . Despite its widespread adoption, the conventional parametric VaR framework relies on the assumption that financial returns follow a normal distribution, a premise that is routinely violated in practice. Daily financial return series frequently exhibit negative skewness, excess kurtosis (fat tails), and volatility clustering, properties that render the Gaussian assumption inadequate under turbulent market conditions (Cont, 2001; Tsay, 2010).

Monte Carlo simulation offers a flexible nonparametric alternative for VaR estimation. By generating thousands of hypothetical future return paths from the empirical statistical distribution of historical data, the approach circumvents the restrictive normality assumption and provides a richer characterization of the tail distribution (Jorion, 2007). However, the practical utility of any VaR model depends on its empirical validity, which must be assessed through backtesting, a procedure that compares ex-post actual return violations against the model's ex-ante predictions (Kupiec, 1995).

A defining feature of financial return distributions that contributes to fat tails is volatility clustering, the tendency of large return shocks to be followed by further large shocks. This phenomenon was formally characterized by Engle (1982) through the Autoregressive Conditional Heteroscedasticity (ARCH) model, later generalized by Bollerslev (1986) into the GARCH framework. In the presence of volatility clustering, the assumption of independent, identically distributed returns underpinning standard Monte Carlo VaR becomes a meaningful approximation rather than a strict description of reality.

Monte Carlo simulation offers a flexible alternative for VaR estimation. By generating thousands of hypothetical future return paths from the empirical statistical distribution of historical data, the approach circumvents the restrictive normality assumption and provides a richer characterization of the tail distribution (Glasserman, 2003; Jorion, 2007). However, the practical utility of any VaR model depends on its empirical validity, which must be assessed through backtesting, a procedure that compares ex-post actual return violations against the model's ex-ante predictions (Kupiec, 1995).

Prior research in the Indonesian context has predominantly focused on sectoral portfolios or on parametric GARCH-based approaches (Kasse et al., 2021; Syalsabila et al., 2025). Studies specifically examining aggregate index-level risk via Monte Carlo simulation while rigorously accounting for the prevailing exchange-rate shock and subjecting the model to formal backtesting remain sparse. Recent contributions by Sulistianingsih et al. (2022) and Takaishi (2023) have advanced Monte Carlo-based risk frameworks, but direct application to the IHSG during a crisis episode has yet to be systematically addressed. This study addresses that gap. Using daily IHSG data from January 2, 2023 to June 5, 2026, we apply Monte Carlo simulation to estimate one-day VaR at the 95% confidence level, conduct a full suite of distributional diagnostic tests, and validate the model using Kupiec's proportion-of-failures test.

2. Method

This study employs a quantitative approach using secondary data comprising the daily closing prices of the IHSG (Yahoo Finance ticker: ^JKSE) over the period January 2, 2023 to June 5, 2026, yielding 813 trading days of observations.

2.1 Data Preprocessing and Missing Value Treatment

Stock exchange holidays generate calendar gaps in trading-day time series. To preserve the daily periodicity of the data without distorting the return distribution, missing observations were imputed using the Last Observation Carried Forward (LOCF) method, which substitutes each missing price with the most recent observed closing price. Log-returns were subsequently computed as:

$$r_t = ln\left(\frac{P_t}{P_{t-1}}\right) \tag{1}$$

where P_t denotes the IHSG closing price on trading day t. Log-returns are preferred to simple returns in financial econometrics because they are time-additive, bounded from below by -1, and more approximately symmetric around the mean (Tsay, 2010).

2.2 Diagnostic Tests

Prior to simulation, the return series was subjected to the following diagnostic procedures:

a. **Descriptive Statistics**: mean (μ), standard deviation (σ), skewness, and excess kurtosis were calculated to characterize the empirical distribution.
b. **Jarque-Bera Test**: The null hypothesis of normality was tested using the Jarque-Bera statistic, which combines empirical skewness (S) and excess kurtosis (K_{excess}) as $JB = \left(\frac{n}{6}\right)\left[S^2 + \left(\frac{K_{excess}^2}{4}\right)\right]$, where K_{excess} = total kurtosis - 3. Rejection of H_0 at α = 0.05 indicates a statistically significant departure from normality (Jarque & Bera, 1987).
c. **Augmented Dickey-Fuller (ADF) Test**: Stationarity was examined by testing the null hypothesis of a unit root in the return series (Dickey & Fuller, 1979). Rejection of H_0confirms that the series is stationary at the level, a prerequisite for the simulation framework employed here.

Financial return series characteristically deviate from normality through two empirically robust properties: negative skewness (asymmetric left tails reflecting crash propensity) and excess kurtosis (fat tails reflecting a higher probability of extreme outcomes than predicted by the normal distribution). Cont (2001) catalogued these as fundamental stylized facts of asset return distributions, and their presence in IHSG returns is consistent with broader evidence from emerging equity markets.

2.3 Monte Carlo VaR Estimation

The Monte Carlo simulation generates N = 10,000 synthetic one-day returns by drawing independently from a normal distribution parameterized by the empirical mean ($\hat{\mu}$) and standard deviation ($\hat{\sigma}$) of the historical return series:

$$r_{sim} \sim N(\hat{\mu}, \hat{\sigma}^2), \quad \text{i = 1, 2, ..., 10,000} \tag{2}$$

This specification deliberately assumes normality in the simulation despite the empirically demonstrated non-normality of actual IHSG returns. This is a recognized limitation of the standard Monte Carlo VaR approach (Glasserman, 2003). The simulation is not intended to replicate the exact empirical distribution but to produce a tractable, widely comparable risk estimate; its adequacy is then evaluated empirically through backtesting. Extensions using non-normal kernels such as the Student-t distribution or historical resampling (bootstrapping) are documented in McNeil et al. (2015) and remain a direction for future work.

The one-day VaR at confidence level (1 - α) is defined as the α-th quantile of the simulated return distribution:

$$VaR_{1-\alpha} = Q_\alpha(r_{sim}) \tag{3}$$

For this study, α = 0.05 (95% confidence level). The corresponding monetary loss for an initial portfolio value V_0= IDR 1,000,000,000 is:

$$L = |VaR_{0.95}| \times V_0 \tag{4}$$

2.4 Kupiec Proportion-of-Failures Backtesting

The validity of the VaR model was assessed using the proportion-of-failures (POF) test proposed by Kupiec (1995). For each of the T = 813 observation days, a violation indicator I_t is defined as:

$$\begin{gathered} I_t = 1, \text{if } r_t < VaR_{0.95}, \\ I_t = 0, \text{ otherwise} \end{gathered} \tag{5}$$

The total number of violations is V = sum(I_t). Under the null hypothesis that the model is correctly specified, V follows a Binomial(T, α) distribution, so the expected number of violations is E[V] = T x α = 813 x 0.05 = 40.65 ≈ 41. The empirical failure rate is $FR = \frac{V}{T}$, which should be close to α = 0.05 for a well-calibrated model.

Kupiec's POF test evaluates this formally via a likelihood ratio statistic:

$$LR_{POF} = -2ln[(1-\alpha)^{T-V} \times \alpha^V] + 2ln[(1-FR)^{T-V} \times FR^V] \tag{6}$$

Under H0, $LR_{POF} \sim \chi^2_{(1)}$. The model is deemed valid if LR_{POF} falls below the critical value at a chosen significance level, indicating that the observed failure rate is statistically consistent with the theoretical probability α. The simple failure-rate comparison reported in the Results section (FR = 5.04% vs. 5.00%) is a descriptive summary. Full statistical inference requires the LR_{POF} statistic, which is reported in Table 2.

3. Result and Discussion

3.1 Descriptive Statistics and Diagnostic Test Results

Table 1 summarizes the descriptive statistics of IHSG daily log-returns over the study period. The daily log-return mean of -0.000249 reflects the net downward drift in IHSG over the study period, driven primarily by the sharp market decline recorded from mid-2025 through mid-2026 as visible in Figure 1. The daily standard deviation of 0.010851 (approximately 1.09%) is consistent with the elevated volatility regime observed during the Rupiah depreciation episode. The strongly negative skewness (-1.3644) indicates that the left tail of the return distribution is substantially heavier than the right, implying that large negative daily returns (crashes) occur with greater frequency and magnitude than equivalently positive ones. The total kurtosis of 12.0664 (excess kurtosis = 9.066, where the normal benchmark is zero) confirms pronounced leptokurtosis. Note that R's moments::kurtosis() function returns total kurtosis, not excess kurtosis; the Jarque-Bera statistic is computed on excess kurtosis (K_{excess}= 9.066), which yields the reported JB = 3,036.7. Together, these two moments characterize what Tsay (2010) terms a heavy-tailed, asymmetric financial return distribution.

Table 1. Descriptive Statistics of IHSG Daily Log-Returns (January 2023 - June 2026)

Statistical Parameter	Estimated Value
Number of Observations (T)	813 days
Mean Return ($\hat{\mu}$)	-0.000249
Daily Volatility ($\hat{\sigma}$)	0.010851
Skewness	-1.3644
Total Kurtosis	12.0664 (Excess Kurtosis = 9.066)
Jarque-Bera Statistic	3,036.7 ($p < 0.001$)
ADF Statistic (p-value)	-8.7582 ($p = 0.01$, stationary)

The Jarque-Bera test strongly rejects the null hypothesis of normality ($p < 0.001$). This finding is consistent with a large body of empirical evidence on the non-normality of daily equity returns in emerging markets (Syalsabila et al., 2023). The ADF test likewise rejects the null of a unit root ($p < 0.001$), confirming that the log-return series is stationary at the level. This is the expected outcome for properly constructed log-returns: differencing of log-prices yields a stationary series under standard financial time series theory (Tsay, 2010). Stationarity is a necessary condition for the validity of the empirical parameter estimates used in the simulation.

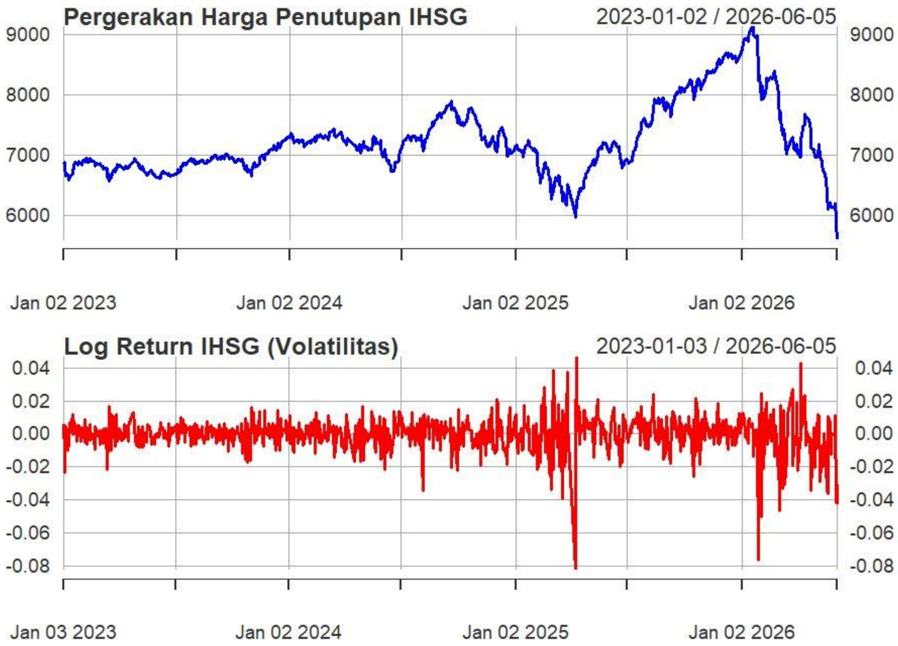

Figure 1. IHSG Closing Price Movement and Log-Return Volatility (January 2, 2023 - June 5, 2026)

Figure 1 presents the historical trajectory of IHSG closing prices and the corresponding log-return volatility over the study period. The upper panel of Figure 1 reveals two distinct market phases: a broad uptrend from January 2023 through the peak near 9,000 in early 2026, followed by an abrupt and severe correction that brought the index to approximately 5,700 by June 2026, representing a drawdown of roughly 37% from the peak. The lower panel exhibits pronounced volatility clustering: periods of low-amplitude daily fluctuations are clearly interrupted by clusters of high-amplitude movements coinciding with the 2025-2026 market correction. Volatility clustering is a well-documented stylized fact of financial time series (Tsay, 2010) and is formally captured by ARCH-class models; its presence here supports the characterization of the IHSG return distribution as non-normal and justifies the empirical parameterization approach used in the Monte Carlo simulation.

Volatility clustering of this nature was formally modelled by Engle (1982) and Bollerslev (1986) using ARCH/GARCH frameworks, which capture the time-varying conditional variance of financial returns. Its presence here confirms that the IHSG return process during this period does not satisfy the i.i.d. assumption of standard Monte Carlo simulation. The backtesting procedure in Section 3.3 is therefore critical for assessing whether the i.i.d.-based VaR estimate remains adequately calibrated in practice despite this violation.

3.2 Monte Carlo VaR Estimation

Using the empirical parameter estimates ($\hat{\mu}$ = -0.000249, $\hat{\sigma}^2$ = 0.010851), 10,000 hypothetical one-day returns were simulated from $N(\hat{\mu}, \hat{\sigma}^2)$. The 5th percentile of this simulated distribution constitutes the 95% confidence-level VaR estimate.

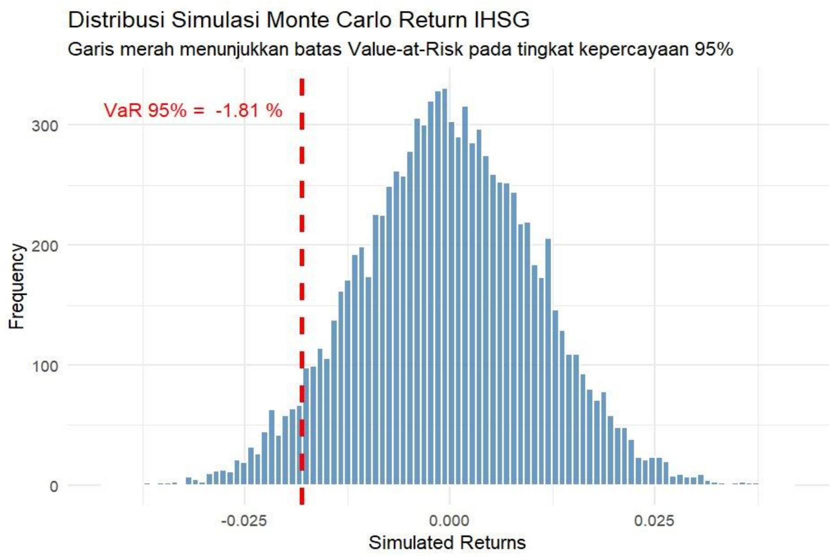

Figure 2. Simulated Return Distribution from Monte Carlo Simulation with 95% VaR Threshold (Red Dashed Line)

Figure 2 shows that the simulated return distribution is approximately bell-shaped around the empirical mean, which is expected given that returns were drawn from a normal distribution. The red dashed vertical line marks the 5th percentile, yielding:

VaR(95%) = -1.8065%

This value is interpreted as follows: holding a portfolio indexed to IHSG, an investor can be 95% confident that the single-day loss will not exceed 1.8065% of portfolio value. Equivalently, there is a 5% probability that the daily loss will exceed this threshold. For an initial portfolio of IDR 1,000,000,000, the monetary risk exposure is:

L = 0.0179 x IDR 1,000,000,000 = IDR 17,902,811

This figure provides a concrete daily loss threshold for capital reserve planning. Under the Basel III regulatory framework, financial institutions are required to hold capital sufficient to cover VaR exceedances at a 99% confidence level over a 10-day horizon; the 95% one-day estimate can be scaled to longer horizons under the square-root-of-time approximation, though this scaling assumes i.i.d. returns and should be applied with caution given the volatility clustering observed.

A complementary risk measure that addresses a known limitation of VaR is Conditional Value-at-Risk (CVaR), also termed Expected Shortfall (ES), defined as the expected loss given that the loss exceeds the VaR threshold. Acerbi & Tasche (2002) demonstrated that CVaR is a coherent risk measure satisfying subadditivity, a property VaR lacks. For the IHSG series with excess kurtosis of 9.0664, CVaR would provide a more conservative and theoretically superior characterization of extreme tail losses and is recommended as a direction for future work.

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3.3 Model Validation: Kupiec Backtesting

Table 2 reports the backtesting results across the full 813-day observation window. The backtesting results in Table 2 are noteworthy. Over 813 trading days, the model predicted an expected number of violations of 40.65, or effectively 41 days on which actual log-returns would fall below the -1.8065% VaR threshold. The observed number of violations was exactly 41, producing an empirical failure rate of FR = 41/813 = 5.04%, which differs from the theoretical rate of 5.00% by only 0.04 percentage points. The Kupiec LR_{POF} statistic is effectively zero, and the associated p-value approaches 1.00, providing no statistical grounds to reject the null hypothesis of correct model specification.

Table 2. Summary of Kupiec Proportion-of-Failures Backtesting Results

Backtesting Parameter	**Value**
Total Observation Days (T)	813
Confidence Level (1 - α)	95%
Theoretical Failure Rate (α)	5.00%
Expected Violations (T x α)	40.65 ≈ 41
Actual Violations (V)	41
Empirical Failure Rate (FR = V/T)	5.04%
Kupiec LR_{POF} Statistic	~0.00 (p ≈ 1.00)
Model Validity Decision	Valid (H0 not rejected)

This result warrants careful interpretation. The near-perfect alignment between observed and expected violation counts is, in part, a consequence of the simulation design: Monte Carlo VaR draws from a normal distribution parameterized by the same empirical moments $N(\hat{\mu}, \hat{\sigma}^2)$ that describe the historical data. The simulated quantile therefore captures the scale of the distribution well, even if it does not replicate the exact shape of the heavy-tailed empirical distribution. In effect, the normal-distribution assumption introduces compensating errors in the tails: it slightly underestimates the probability of extreme losses (beyond -3 sigma) but slightly overestimates the probability of moderate losses. Across a finite observation window such as 813 days, these errors can cancel to produce a failure count very close to the theoretical expectation.

This outcome aligns with findings by Sulistianingsih et al. (2022), who demonstrated that Monte Carlo-based VaR frameworks calibrated on empirical moments can produce well-calibrated backtesting results even when the underlying return distribution deviates from normality, provided the observation window is sufficiently long. Takaishi (2023) similarly found that VaR models parameterized by standard deviation remain adequate for index-level risk at 95% confidence but may underestimate risk at higher confidence levels (e.g., 99%) where the power-law tail becomes dominant.

The practical implication is clear: the Monte Carlo VaR model, calibrated with empirical mean and standard deviation and evaluated over 813 trading days, provides a statistically reliable daily risk threshold for IHSG during this high-volatility period. Portfolio managers can use the IDR 17,902,811 figure as a daily loss tolerance boundary for a one-billion-rupiah equity index position.

4. Conclusion

This study applied Monte Carlo simulation to estimate the one-day 95% Value-at-Risk of the Indonesian Composite Stock Price Index (IHSG) during the episode of Rupiah exchange rate depreciation spanning January 2023 to June 2026. Diagnostic analysis confirmed that IHSG daily log-returns are stationary, non-normally distributed, negatively skewed, and leptokurtic, reflecting the heavy-tailed behavior typical of equity markets under stress. These properties render conventional parametric VaR methods unreliable without distributional adjustments.

The Monte Carlo simulation, calibrated on empirical return moments, produced a daily VaR of -1.8065% at the 95% confidence level, corresponding to a maximum potential daily loss of IDR 17,902,811 for a one-billion-rupiah portfolio. Kupiec backtesting over the full 813-day window yielded exactly 41 actual violations against 41 theoretically expected violations (empirical failure rate = 5.04%), and the LR_{POF} statistic failed to reject the null of correct model specification. The model is therefore statistically valid for quantifying market risk in the Indonesian equity market under current conditions.

For practitioners, the estimated VaR threshold provides a daily capital adequacy benchmark amid persistent Rupiah weakness. Future research should explore non-normal simulation kernels (Student-t distribution, historical resampling), Conditional VaR (Expected Shortfall) as a coherent complement to VaR (Acerbi & Tasche, 2002), and GARCH-based conditional volatility models to account for the time-varying variance structure documented in this study.

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