RANGE : Jurnal Pendidikan Matematika
e-ISSN :2685-2373

Volume 7, Nomor 1, Juli 2025, pp. 204-213

Investment Risk Analysis Using Value at Risk With Monte Carlo Simulation

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Received: May 25th 2025. Accepted: June 6th 2025. Published: July 31st 2024

ABSTRACT

This study aims to evaluate and compare the investment risk levels of three primary financial instruments in Indonesia: the Indonesia Composite Index (IHSG), Bank Central Asia (BCA) with code BBCA stock, and gold. Using the Value at Risk (VaR) approach based on Monte Carlo simulation, the research integrates these assets into a unified risk assessment model, providing a more comprehensive perspective than prior studies that typically examine individual assets or use historical estimation methods. Monthly historical price data from April 2024 to March 2025 were obtained from the Indonesia Stock Exchange and the Central Bureau of Statistics. The analysis involved calculating asset returns, means, and standard deviations, followed by 10,000 Monte Carlo simulation iterations to generate potential future price paths and estimate losses under market uncertainty. The results, at a 95% confidence level, show that IHSG carries the highest investment risk, with a VaR of IDR 9,331.16, followed closely by BBCA stock at IDR 9,210.31. Gold exhibited the lowest risk level, with a VaR of IDR 6,896.86, confirming its role as a more stable and less volatile investment compared to equity-based assets. These findings highlight the reliability of gold as a defensive asset during turbulent market conditions. The application of Monte Carlo simulation effectively captures the non-normal distribution of returns and accommodates complex market behaviors, making it a robust tool for financial risk modeling. This research offers meaningful insights for investors, analysts, and academics in optimizing portfolio strategies and improving risk management decisions.

Keywords: Gold; IHSG; Investment Risk; Monte Carlo Simulation; Value at Risk (VaR).

How to Cite: Clara, N. C. & Rakhmawati, F. (2025). Investment Risk Analysis Using Value at Risk With Monte Carlo Simulation. *Range: Jurnal Pendidikan Matematika*, 7(1), 204-213.

Introduction

Investment is a fundamental economic activity aimed at achieving long-term financial growth. As noted by (Handayani & Thariq, 2022), investment refers to the allocation of resources whether capital, time, or assets by individuals or organizations with the expectation of generating future returns. Investment instruments vary widely, encompassing stocks, bonds, mutual funds, real estate, and precious metals like gold (Abdullaevich, 2020). However, despite their potential for profit, all investment vehicles are inherently subject to risk. These risks include, but are not limited to, market risk, liquidity risk, and interest rate risk, each of which can negatively impact the value of an asset (Mutia Evi Kristhy et al., 2022).

In light of these uncertainties, implementing effective risk management is crucial. A well-structured risk management approach allows investors to detect potential threats, evaluate their consequences, and take preventive actions to reduce possible losses (Arta, 2021; Mapadang, 2021). In

Indonesia's capital market, the Indonesia Composite Index (Indeks Harga Saham Gabungan or IHSG) is widely used as a benchmark to evaluate the overall performance of listed stocks. The IHSG provides a comprehensive snapshot of price trends across the market (Agustina et al., 2025).

Monitoring movements in stock indices is crucial because it allows investors to understand prevailing market dynamics, whether bullish, bearish, or stable. This insight helps them adjust their investment strategies accordingly (Abdul Basit, 2019; Ahmad Taslim, 2016). Risk in the capital market is closely linked to price volatility, which directly affects the valuation of investment assets. As highlighted by (Rahmany, 2019), the fluctuating nature of asset prices introduces a significant degree of uncertainty, especially for equity-based instruments and market indices.

A clear example of this can be seen in the case of PT Bank Central Asia (BBCA), a prominent blue-chip stock known for its consistent performance and strong investor appeal. Nevertheless, even high performing stocks like BBCA are susceptible to broader market fluctuations, making short and long term price predictions challenging (Saputra & Widiantoro, 2024; Vaddhano, 2022). In contrast, gold is typically perceived as a more stable investment asset. Due to its historical value retention and role as a safe haven during economic turmoil, many investors turn to gold for long term security (paningrum, 2022).

Seasoned investors often construct diversified portfolios that include multiple asset classes to maximize returns while managing risk exposure (Urwah et al., 2024). In such cases, risk assessment becomes a vital part of the decision-making process. One of the most widely recognized methods for measuring investment risk is VaR, which estimates the potential maximum loss of an asset or portfolio within a given time frame and confidence level (Perli Iswanto & Aditya Rian Ramadhan, 2024; Akbar et al., 2020).

Several prior studies have utilized various approaches to calculate VaR. For example, (Anam et al., 2020) applied the variance-covariance method to assess bond portfolios, while (Yuliah & Triana, 2021) employed Monte Carlo simulation to analyze corporate assets. However, research that directly compares the investment risks of the IHSG, BBCA stock, and gold using Monte Carlo simulation in a single framework remains limited.

Monte Carlo simulation is a probabilistic computational technique that relies on repeated random sampling to estimate the distribution of possible outcomes in a stochastic process. In the context of financial risk assessment, this method simulates a large number of possible return scenarios by incorporating statistical inputs such as mean returns and standard deviations. These simulations produce a full distribution of potential asset values over time, which allows for the estimation of Value at Risk (VaR) without assuming a normal distribution of returns. This is a significant advantage over conventional VaR methods like historical or variance-covariance approaches, which often rely on restrictive assumptions about market behavior. The ability of Monte Carlo simulation to accommodate nonlinearities, skewness, and fat tails makes it particularly robust for modeling complex and volatile financial environments. It has gained popularity as a risk analysis tool because it generates random scenarios based on historical data and statistical patterns, without being confined to the assumption of normal distribution (Sucita, 2022; Bima et al., 2024). This adaptability makes it especially reliable in highly uncertain or volatile market conditions (Darman Saputra et al., 2023).

Monte Carlo simulation is a computational technique that uses repeated random sampling to model the probability distribution of potential outcomes. In financial risk analysis, it allows for the generation of thousands of possible return scenarios by incorporating both the expected return (mean) and volatility (standard deviation) into a stochastic process. Unlike traditional VaR methods that assume normal distribution and linear relationships, Monte Carlo simulation captures non-linear dynamics and non-normal return distributions, making it particularly suitable for complex and volatile markets. This flexibility enables a more accurate estimation of extreme losses, which is crucial for robust investment risk assessment (Bima et al., 2024; Sucita, 2022).

The novelty of this study lies in its integrated analysis of three key investment instruments in Indonesia the IHSG, BBCA stock, and gold within a unified VaR framework using Monte Carlo simulation. By incorporating these assets into a single comparative study, this research not only contributes to the growing body of empirical literature on risk management but also offers valuable practical insights for investors seeking to navigate diverse market conditions more effectively.

Accordingly, the central research question addressed in this study is: “What is the maximum potential loss (Value at Risk) of the Indonesia Composite Index (IHSG), BBCA stock, and gold at a 95% confidence level using Monte Carlo simulation?” The findings of this research are expected to serve as a reference for investors, financial analysts, and academics alike in understanding and quantifying investment risks across different asset classes in the Indonesian financial market.

Methods

This research adopts a quantitative approach to evaluate and compare the investment risks associated with three financial instruments: the Indonesia Composite Index (IHSG), shares of PT Bank Central Asia (BBCA), and gold. The study utilizes secondary data in the form of historical monthly closing prices for IHSG, BBCA stock, and gold. These data were collected from the official website of the Indonesia Stock Exchange www.idx.co.id and the Central Bureau of Statistics (BPS). The observation period spans from April 2024 to March 2025, selected to reflect recent market trends while maintaining relevance to current economic conditions.

The research procedure was carried out through several stages. First, data were collected in the form of monthly closing prices for IHSG, BBCA, and gold. The data then underwent a preprocessing stage to ensure completeness and to convert them into a more structured format. Next, return calculations were performed, where the monthly returns for each asset were computed using the cleaned data. This was followed by the calculation of the mean and standard deviation of the returns, using RStudio as the primary analytical tool. Subsequently, the Value at Risk (VaR) was estimated using the Monte Carlo simulation method, by simulating return values based on the previously obtained parameters. The simulation was run for 10,000 iterations. The maximum potential loss was then determined at the 95% confidence level, based on the simulated portfolio values. Finally, the results were interpreted to identify the risk level associated with investing in IHSG, BBCA stock, and gold.

The following outlines the research method workflow that was carried out accordingly:

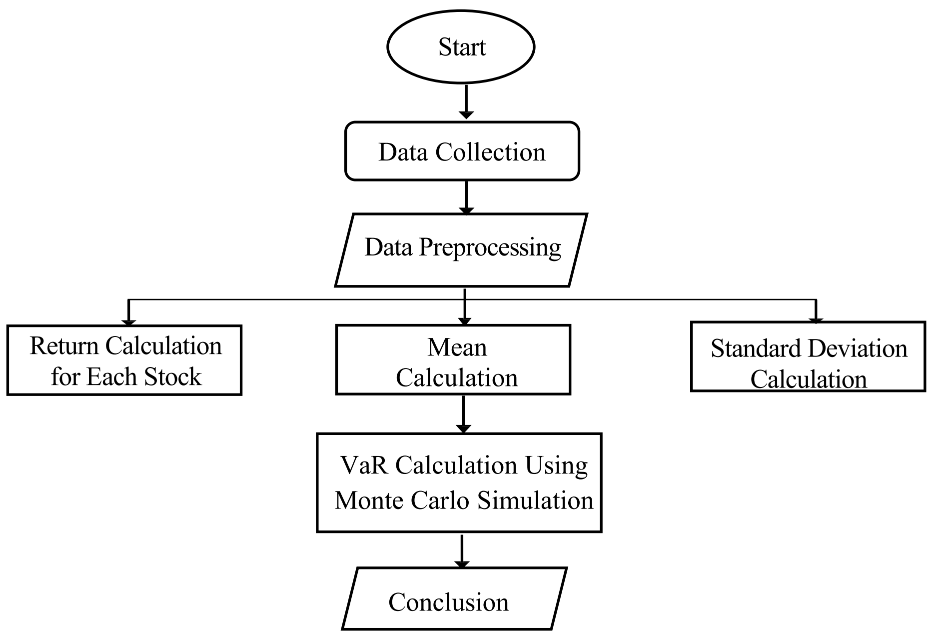

***Figure 1**. Research Flow Diagram*

Based on the flowchart above, this study aims to deliver a comprehensive and statistically reliable estimation of Value at Risk (VaR) for IHSG, BBCA stock, and gold. The insights generated are intended to help investors better understand the relative risk exposure of each asset, thereby supporting more accurate and strategic portfolio decision-making.

Results and Discussion

Monthly returns for IHSG, BBCA, and gold were calculated using the respective closing prices of each asset. As shown in Table 1, these original price figures serve as the foundational data used to calculate the returns for each asset.

Table 1. *Monthly Closing Prices of IHSG, BBCA, and Gold*

Date	BBCA	IHSG	Gold
1/4/2025	9800	7205.06	1115208
1/5/2025	9250	7117.42	1115629
1/6/2025	9925	7036.19	1131888
1/7/2025	10275	7139.63	1146888
1/8/2025	10325	7325.98	1172711
1/9/2025	10326	7694.53	1178869
1/10/2025	10250	7642.13	1259736
1/11/2025	10000	7505.26	1261007
1/12/2025	9675	7046.99	1289310
1/1/2025	9450	7163.21	1304793
1/2/2025	8425	7030.06	1399822
1/3/2025	8500	6519.66	1458176

Source*: www.idx.co.id dan https://www.bps.go.id/id*

Figure 2 presents the initial step of the analysis, which involves calculating returns from historical closing prices using RStudio.

```
# 1. Install dan load package
library(ggplot2)
IHSG <- read.csv("C:/IHSG.csv")
View(IHSG)
##data structure
str(IHSG)
summary(IHSG)
head(IHSG)
# 3. Clear column names (remove spaces)
names(IHSG) <- trimws(names(IHSG))
# 4. Rename the date column for ease of use
names(IHSG)[names(IHSG) == "date.month.year"] <- "Date"
#5. Convert date column to Date format
IHSG$Date <- as.Date(IHSG$Date, format = "%d/%m/%Y")
# 6. Sort by date
IHSG <- IHSG[order(IHSG$Date), ]
# 7. Calculate the log-return of the 'close' price
IHSG$return <- c(NA, diff(log(IHSG$close)))
returns <- na.omit(IHSG$return)
```

Figure 2*. IHSG, BBCA, and gold return calculation process*

Table 2 summarizes the computed monthly returns of the three selected assets BBCA stock, the IHSG, and gold covering the period from April 2024 to March 2025. As the data for April 2024 serve as the starting point, the return for that month is not available (NA) due to the absence of preceding price data.

Table 2. *The Return Values of Gold, IHSG, and BBCA*

Date	BBCA	IHSG	Gold
1/4/2024	NA	NA	NA
1/5/2024	-0.05776	-0.0371	0.0004
1/6/2024	0.070433	0.009345	0.0145
1/7/2024	0.034657	0.030729	0.0132
1/8/2024	0.004854	0.055616	0.0223
1/9/2024	9.68E-05	-0.01879	0.0052
1/10/2024	-0.00739	0.006104	0.0663
1/11/2024	-0.02469	-0.06262	0.001
1/12/2024	-0.03304	-0.00484	0.0222
1/1/2025	-0.02353	0.00413	0.0119
1/2/2025	-0.11481	-0.12552	0.0703
1/3/2025	0.008863	-0.0371	0.0408

The calculated returns form the basis for evaluating each asset's average return and its standard deviation, both of which are vital for quantifying expected performance and associated risk. The mean return indicates the average monthly gain or loss, while the standard deviation reflects the variability or volatility of returns over time. Figure 3 displays the RStudio code used to perform these calculations.

```
# 8. Estimation of the normal distribution of returns
mu <- mean(returns)
sigma <- sd(returns)

```

Figure 3*. RStudio code for calculating mean return and standard deviation*

Table 3 presents the computed average return and standard deviation for each asset over the analysis period. Notably, gold exhibits a positive average return of 2.44%, with relatively low volatility, making it a relatively stable investment. In contrast, both the IHSG and BBCA display negative mean returns (-0.96% and -0.91% respectively), accompanied by higher levels of volatility, suggesting a greater degree of risk exposure.

Table 3. *Mean Returns and Standard Deviations*

Asset	μ	σ
Gold	0,0244	0,02387
IHSG	-0,0096	0,051
BBCA	-0,0091	0.0365

These statistical parameters serve as critical inputs for the Monte Carlo simulation process used to estimate potential future losses.

Following the derivation of statistical inputs, a Monte Carlo simulation consisting of 10,000 iterations is executed to model potential price paths for each asset. This stochastic technique involves generating thousands of possible future scenarios based on historical return characteristics specifically the mean and standard deviation of each asset class.

By simulating future returns and prices, the study calculates hypothetical losses for each scenario. From the distribution of these losses, the Value at Risk (VaR) at the 95% confidence level is determined. This metric represents the maximum estimated loss that an investor could incur under normal market conditions in 95 out of 100 cases.

Figure 4 displays the RStudio code applied to assess investment risk using the Value at Risk (VaR) approach through Monte Carlo simulation. This code simulates a wide range of possible future price movements based on historical return data, allowing the estimation of the maximum potential loss under typical market conditions. The results provide insights into the risk level associated with each financial instrument analyzed.

```
# 9. Monte Carlo Simulation
set.seed(123)
n_simulasi <- 10000
simulated_returns <- rnorm(n_simulasi, mean = mu, sd = sigma)

# 10. Calculate simulated loss for portfolio value
nilai_portofolio <- 100000  # Contoh: $100.000
simulated_losses <- nilai_portofolio * simulated_returns

# 11. Calculate Value at Risk (VaR) 95%
VaR_95 <- -quantile(simulated_losses, probs = 0.05)

# 12. Show results
cat("Value at Risk (VaR) 95% is:", round(VaR_95, 2), "USD\n")

# 13. Visualization of simulation results
ggplot(data.frame(simulated_losses), aes(x = simulated_losses)) +
  geom_histogram(bins = 50, fill = "skyblue", color = "black") +
  geom_vline(xintercept = -VaR_95, color = "red", linetype = "dashed") +
  labs(title = "Distribution Monte Carlo Simulation - Value at Risk (99%)",
       x = "Loss (USD)", y = "Frequency") +
  theme_minimal()
```

***Figure 4**. RStudio code for VaR calculation using Monte Carlo simulation*

Based on the RStudio code execution shown in Figure 3, the investment risk for each asset was successfully estimated and is presented in Table 4. This table outlines the Value at Risk (VaR) at a 95% confidence level, calculated through 10,000 Monte Carlo simulations. The data provide a comparative view of the potential losses associated with IHSG, BBCA, and gold under typical market conditions, supporting a clearer assessment of each asset's risk exposure.

***Table 4**. Value at Risk (VaR) at 95% Confidence Level*

Asset	VaR at the 95% confidence level
Gold	6896,86
IHSG	9331,16
BBCA	9210,31

The VaR outcomes presented in Table 4 highlight the differing levels of financial risk across the three investment instruments. Gold demonstrates the smallest estimated loss, suggesting greater price stability and lower volatility. In contrast, both IHSG and BBCA exhibit significantly higher VaR values, indicating a higher degree of risk. These results provide a useful benchmark for comparing the risk-return profiles of each asset under normal market conditions.

Such findings reinforce the view that gold remains a more resilient investment choice, particularly in times of financial turbulence, thereby supporting its role as a traditional safe-haven asset. On the other hand, the relatively elevated VaR values of IHSG and BBCA reflect the inherent volatility of equity markets. This aligns with prior research which consistently shows that stock-based instruments tend to respond more sharply to market shifts.

Conclusion

This research analyzed the risk levels associated with investments in gold, BBCA stock, and the IHSG using the Value at Risk (VaR) approach enhanced by Monte Carlo simulation. The analysis revealed that IHSG carried the greatest potential loss, recording a VaR of 9331.16, followed by BBCA stock at 9210.31. In contrast, gold had the lowest risk level, with a VaR of 6896.86. These outcomes highlight gold as the most stable investment among the three, especially during periods of market volatility. Monte Carlo simulation proved to be an effective tool in estimating financial risk, as it accommodates non-normal return distributions, providing greater flexibility and realism in risk modeling.

The findings deliver practical insights for investors aiming to mitigate portfolio risks, emphasizing the advantages of Monte Carlo-based VaR in uncertain market conditions. This approach supports more informed and responsive investment decisions. However, the study is constrained by a short data period (April 2024 – March 2025) and limited asset diversity. Future studies are encouraged to use longer time spans, include broader asset classes, or compare different VaR methodologies to gain a more comprehensive understanding of investment risk.

Acknowledgement

Author would like to thank all parties who have contributed to writing this article.

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