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Article

AI-Enhanced Risk-Return Optimization in Islamic and Conventional Banking Portfolios

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ABSTRACT

Portfolio risk assessment in Islamic versus conventional banking requires advanced analytical approaches due to complex market dynamics and regulatory differences. Traditional optimization methods often fail to capture non-linear relationships and volatility patterns inherent in these distinct banking sectors. This study introduces an AI-enhanced framework combining Monte Carlo simulation with Solver-based optimization to compare market risks and determine optimal portfolio weights between Islamic and conventional banking stocks. The methodological innovation lies in integrating Microsoft Excel's GRG nonlinear AI solver for real-time portfolio optimization, addressing limitations of conventional Markowitz models. Using 194 daily price observations from LQ45 and JII70 indices (January-October 2024), we analyzed four banking stocks (BRIS, BTPS, BBCA, BBRI) through Monte Carlo VaR simulation with 10,000 iterations and AI-driven optimization at 95% confidence level. Mann-Whitney tests confirmed significant differences between Islamic and conventional banking returns and risk profiles. Results reveal Islamic banking portfolios demonstrate significantly higher risk (VaR: -4.18%, potential loss: IDR 4,180,169) compared to conventional portfolios (VaR: -1.65%, potential loss: IDR 1,652,541). AI optimization yielded distinct allocation strategies: Islamic portfolio (45.4% BRIS, 54.5% BTPS) versus conventional portfolio (74.5% BBCA, 25.4% BBRI). This research provides the first AI-integrated comparative framework for Islamic-conventional banking risk analysis, offering quantitative evidence that challenges assumptions about Islamic banking stability. The study demonstrates practical applications of machine learning in portfolio management for emerging markets, providing actionable insights for different investor risk profiles while advancing methodological approaches in Islamic finance research.

Keywords: Value at Risk (VaR), Monte Carlo Simulation, Portfolio Optimization, Islamic Banking, Conventional Banking.
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INTRODUCTION

In the meantime, many individuals choose to invest as a means of managing their finances and planning for their future. Among the various investment options available, investments in real sectors such as property and stock markets have become the most popular choices (Bodie et al., 2019; Paningrum, 2022). Both types of investments offer attractive potential returns, albeit with differing characteristics. Property investments tend to be more stable and experience gradual value appreciation over time (Wulandari et al., 2023). Conversely, stock investments can yield higher returns in a shorter period but come with significantly higher risks due to frequent price fluctuations (Bodie et al., 2019). Stock price movements are highly dynamic and can change drastically within days or even hours. These changes can be triggered by various factors, ranging from internal corporate issues to global economic conditions. For instance, when a company faces a management crisis, its stock prices can plummet rapidly (Paningrum, 2022). On a broader scale, the entire stock market can be shaken by market risk-price changes driven by global economic conditions, government policies, or political instability (Pasieczna, 2019).

The stock market in the financial sector, particularly banking, holds a unique position as it is considered a reflection of the overall economic condition. Banks play a crucial role in driving economic activity through services such as credit, savings, and investments. Bank stocks are an attractive choice for investors due to their stability and strategic role in the economy (Nurul & Raharjo, 2024). To facilitate investors, the Indonesia Stock Exchange (IDX) has created specific indices, such as LQ45 and JII70, which include highly liquid stocks that are easy to trade due to their large transaction volumes (Indonesia Stock Exchange, 2021). Given the high risks associated with stock investments, investors need effective methods to measure these risks. One widely used method is Value at Risk (VaR). This method has been extensively employed by experts and capital market practitioners to estimate potential losses investors might incur, as evidenced by studies conducted by Pasieczna (2019), Anam et al. (2017), Darman et al. (2023), and Anita & Riris (2021).

Several studies have analyzed VaR for banking stocks using the Historical Method and Markowitz Standard Deviation, but limited research specifically compared market risk between Islamic and conventional banking stocks using Monte Carlo Simulation. Previous studies have employed methods that are less effective in analyzing the complexities of market movements that do not always follow normal patterns. Therefore, this research aims to fill that gap by utilizing Monte Carlo Simulation, which provides a more comprehensive and flexible risk analysis. Referring to the recommendations of Nainggolan et al. (2020) and Anita & Riris (2021), this study will compare market risk between the Islamic and conventional banking sectors using VaR analysis with a Monte Carlo Simulation approach. This method was chosen for its ability to analyze complex conditions through relatively simple simulations (Priyantono et al., 2023).

Moreover, to generate the optimum weight of portfolios, Solver Optimization is used to equally distribute the investment diversifications based on the risk-weighted based on the Markowitch model. Solver Optimization is one of the AI features in Ms. Excel that solves complex mathematical formulations. The use of the Solver AI in the previous literature mainly focuses on the physics and chemistry area by using the distillation method (Hashemi et al., 2020; Vázquez et al., 2021). However, in this study, we attempt to utilise the AI feature to generate the proportional weight of investment based on the risk measured. It is hoped that this study will help investors better understand the risk profiles of both types of banking stocks, enabling them to make more informed investment decisions.

LITERATURE REVIEW

In financial theory, the relationship between risk and return on stocks is typically positive, meaning that higher risk is expected to yield higher returns (Bachrach & Galai, 1979). This idea stems from Modern Portfolio Theory (MPT) by Harry Markowitz, which posits that rational investors aim to maximize expected returns while minimizing risk (Bachrach & Galai, 1979; Maneemaroj et al., 2021). The Capital Asset Pricing Model (CAPM) builds on this concept, providing a quantitative relationship where the expected return of a security $E(R_i)$ is determined by its systematic risk, measured by beta β, and the overall market return $E(R_m)$. Mathematically, CAPM is expressed as:

$$E(R_i) = R_f + \beta_i(E(R_m) - R_f)$$

Whereas $E(R_i)$ is the expected rate of return on asset *i*, R_f is risk-free rate of return β_i is the extent to which an asset's return correlates with market returns and $E(R_m)$is expected market rate of return. Meanwhile, the Markowitz Optimal Portfolio Model is an approach in modern portfolio theory developed by Harry (1959) to assist investors in selecting an optimal combination of assets based on the trade-off between return and risk (Rahman, 2024). This model focuses on the concept of efficient diversification, where investors can reduce portfolio risk by combining assets that have low or negative correlations, using mathematical calculations involving variances and covariances between assets to determine optimal weights (Parulian et al., 2022). The result of this optimization is a set of efficient portfolios that form the efficient frontier, where each point represents an optimal combination of return and risk (Rahman, 2024). Despite its limitations, such as the assumption of normally distributed returns and reliance on historical data, the model remains a foundational element in investment management as it provides a systematic framework for portfolio optimization and understanding the relationship between risk and return in the context of the entire portfolio (Berger & Fieberg, 2016). The basic formulas used in portfolio optimization include the following:

$$\sigma_p^2 = \sum_{i=1}^{n}\sum_{j=1}^{n} w_i w_j Cov(r_i, r_j)$$

σ_p^2 = Portfolio's Variance

$Cov_{1,2}$ = Covariance between asset returns *i* and *j*

Value at Risk (VaR)

Value at Risk (VaR) emerges as a critical statistical tool for measuring potential financial losses. As Jorion (2007) defines, VaR provides investors with a mechanism to quantify "the maximum possible loss of a portfolio over a specific time horizon with a given confidence level" (Jorion, 2007). The research identifies three primary VaR calculation methods: Delta-Normal Simulation, Historical Simulation, and Monte Carlo Simulation. Pasieczna (2019) highlights the unique characteristics of each method, with Monte Carlo Simulation offering superior flexibility in handling complex risk scenarios. In this study Monte Carlo Simulation was preferred due to its ability to generate multiple random scenarios. As Priyantono et al. (2023) note, this method is "increasingly popular because of its ability to simulate complex conditions in a simple manner" (Priyantono et al., 2023).

There are three main approaches to calculating Value at Risk (VaR). First, the Delta-Normal Simulation assumes that asset returns follow a normal distribution. Second, Historical Simulation utilizes past data to estimate risk

(Jorion, 2007). Third, Monte Carlo Simulation generates various random scenarios to estimate risk. Among these methods, Monte Carlo Simulation is considered the most comprehensive as it can accommodate complex conditions through straightforward simulations (Jorion, 2007). Then what we will use in this study is var with a Monte Carlo simulation approach. Important formulas in VaR calculation include:

$$VaR_{1-\alpha} = \mu \frac{P}{L} - Z_{1-\alpha} . \sigma \frac{P}{L}$$

Where $\mu \frac{P}{L}$ is average or expected profit/loss, $Z_{1-\alpha}$ is *Z-score* for a given confidence level, $\sigma \frac{P}{L}$ is Standard Deviation that measures volatility or fluctuation.

Monte Carlo Simulation

According to Jorion, (2007) Monte Carlo simulation is a statistical method used to solve complex mathematical problems by performing random simulations to obtain representative results. This approach relies on the use of random numbers to generate various possible outcomes of a model or system and then analyzes the distribution of those outcomes to make predictions or estimations (Jorion, 2007). In many cases, Monte Carlo simulation is employed to address problems that are difficult to solve through analytical methods, such as probability calculations, determining expected values, or optimization under uncertainty (Indarwati & Kusumawati, 2021). This technique is widely applied across various fields, including finance, physics, engineering, and computer science (Indarwati & Kusumawati, 2021).

Monte Carlo simulation is highly relevant in the approach to calculating Value at Risk (VaR), a risk measure used to estimate the maximum potential loss that may occur in a portfolio or investment over a specified time, with a certain confidence level (Jorion, 2007). In VaR calculation, Monte Carlo simulation can be employed to simulate various scenarios of asset price movements or financial instrument values based on assumed probability distributions (Jorion, 2007). By performing random simulations of asset or portfolio value changes, Monte Carlo generates a distribution of possible outcomes, enabling the calculation of VaR, such as the maximum loss that is not likely to be exceeded with a given probability (e.g., 95% or 99%). This approach is particularly useful when the loss distribution is non-normal or difficult to estimate analytically, as Monte Carlo can handle a wide range of distributions and market uncertainties more flexibly (Rahman, 2024). The following are the steps of calculating the var portfolio with the monte carlo simulation approach:

1. Calculate daily return.

$$R_i = \frac{P_i - P_{i-1}}{P_{i-1}}$$

R_i = Return in the time period *i*

P_i = Price in the time period *i*

2. Calculate Mean and Standard Deviation

$$\bar{R} = \frac{\sum_{i=1}^{n} R_i}{n} \text{ and } \sigma = \sqrt{\frac{\sum_{i=1}^{n}(R_i - \bar{R})^2}{n}}$$

n = Number of time periods

σ = Standard Deviation daily return

3. Calculate Portfolio's Standard Deviation

$$\sigma_p = \sqrt{\sum_{i=1}^{n} \sum_{j=1}^{n} w_i w_j \sigma_i \sigma_j \rho_{ij}}$$

σ_p = Standard Deviation of the portfolio

$w_i w_j$ = Weight of asset *i* and *j* in the portfolio

$\sigma_i \sigma_j$ = Standard deviation of assets *i* and *j*

ρ_{ij} = Correlation coefficient between assets *i* and *j*

4. Calculate Expected Return portfolio

$$ER_p = W_0 \left(\left(\mu \frac{P}{L} 1 . w_1 \right) + \left(\mu \frac{P}{L} 2 . w_2 \right) \right) . \left(\frac{t}{n-1} \right)$$

W_0 = Initial investment funds

w_1 dan w_2 = Vector of weights of each asset 1 and 2 in the portfolio

t = Range of days to invest

n = Number of data or sampling days

5. Calculate Scenario VaR

$$VaR = ER_p - \left(W_0 \cdot \sigma_p \cdot Z_{(1-\alpha)} \cdot \sqrt{\frac{t}{n-1}}\right)$$

ER_p = Expected Return of the portfolio

σ_p = Standard Deviation of the portfolio

$Z_{(1-\alpha)}$ = Z-score for a given confidence level.

6. Repeating steps (2) to (5) as many times as the required Monte Carlo Simulation value (m) thus reflecting the various possible portfolio VaR values VaR1, VaR2, ..., VaRm.
7. Determine the percentile of the VaR value of Monte carlo simulation based on the confidence level used.

$$P_k = k \times (n+1)$$

k = Desired percentage in decimal form

n = Number of elements in the data

Generalized Reduced Gradient (GRG)

The Generalized Reduced Gradient (GRG) method is an algorithm used to solve nonlinear optimization problems with a general structure (Ruppert, 2001). This method is highly useful in various applications, including portfolio optimization, optimal control, and reliability system optimization (Smith & Lasdon, 1992). The GRG method works by reducing the dimensionality of the optimization problem by separating free and constrained variables, and then employing gradient-based techniques to find the optimal solution (Smith & Lasdon, 1992). GRG Nonlinear calculation can be done with ms. excel 2019 using the "Solver" function.

Mathematically when using the Nonlinear GRG method, the calculation works with the objective function $f(x)$ to be optimised, and for each iteration, the Solver calculates the gradient $\nabla f(x)$ which is used to find a better solution, with respect to predefined constraints (Ruppert, 2001). The solver tries to minimise the objective function with respect to the constraints with the minimize formula.

$$\min_{x_1,x_2} f\,(x_1,x_2) \text{ and } g_i(x_1,x_2) \le 0, i = 1,2,\dots,m$$

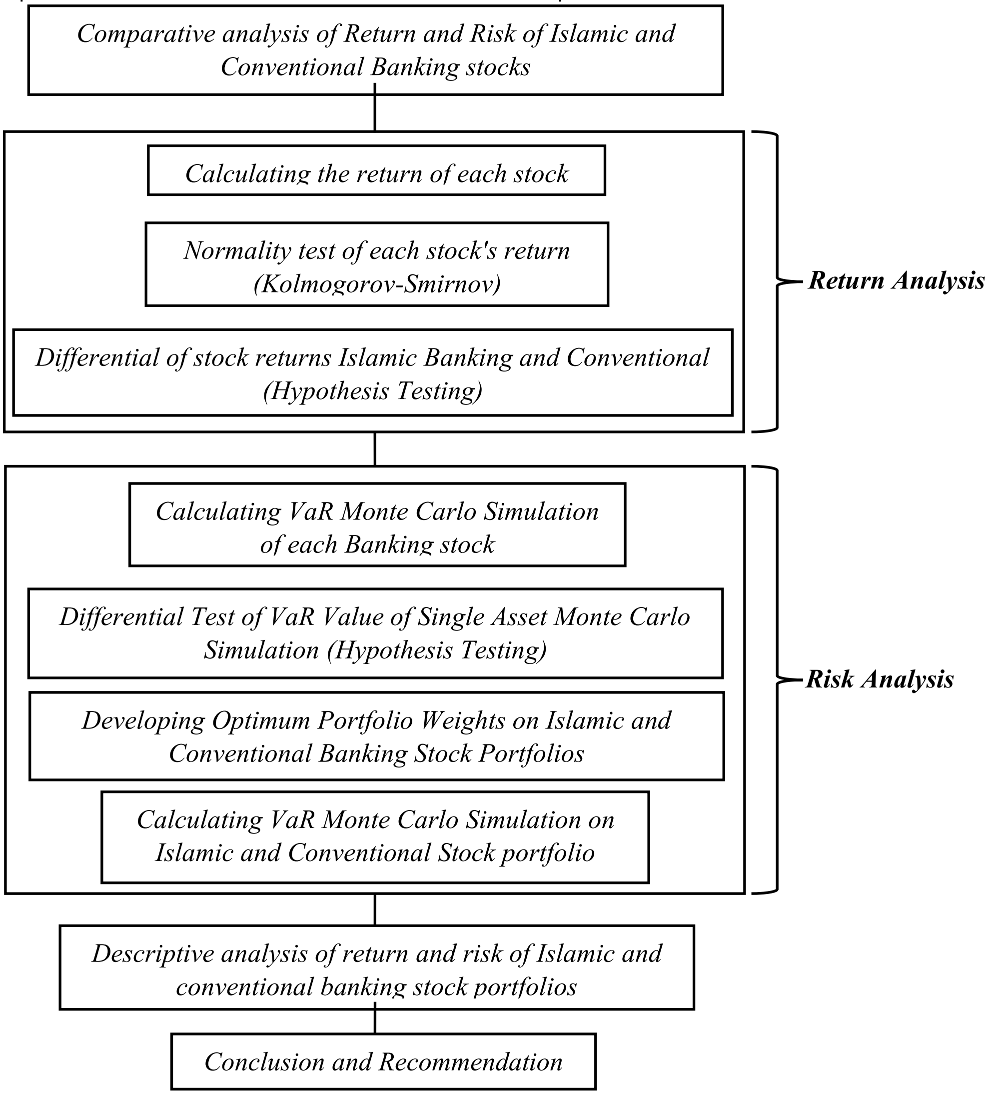
Which is $g_i(x_1,x_2)$ represents the constraint functions and mmm is the number of constraints (Ruppert, 2001; Smith & Lasdon, 1992). The solver utilizes the Generalized Reduced Gradient method to find the optimal solution in the solution space by iteratively approaching the optimal value (Smith & Lasdon, 1992).

METHODOLOGY

The methodology employed in this study adopts a descriptive comparative approach aimed at comparing Islamic and conventional banking stocks through a series of comprehensive hypothesis tests (Sugiyono, 2016). The research utilizes secondary data in the form of 194 daily closing stock prices from four issuers obtained from *www.yahoofinance.com*. Selected using a purposive sampling technique: two Islamic stocks (BRIS and BTPS) and two conventional stocks (BBCA and BBRI). These stocks are listed on the JII70 and LQ45 indices during the period from 1 January to 28 October 2024. On that date, the Indonesian stock market experienced significant fluctuations, with an optimistic opening at the beginning of the year and a decline in the JCI on 28 October 2024 which was influenced by global sentiment and foreign capital flows. The selection of the four stocks is based on the fact that there are only two Islamic stocks listed in the JII70 index, which are then compared with two conventional bank stocks from the LQ45 index, which have similar liquidity levels to ensure a relevant and fair comparison.

The data analysis process begins with calculating daily stock returns using standard mathematical formulas. Subsequently, the study conducts a normality test using the Kolmogorov-Smirnov method to examine the distribution of return data, followed by a Mann-Whitney test to identify significant differences between the returns of Islamic and conventional banking stocks. The primary method employed in this research is the calculation of Value at Risk (VaR) using the Monte Carlo Simulation approach, allowing risk analysis at a 95% confidence level over a 15-day horizon.

The artificial intelligence tool used in this study is Solver Optimization based on the GRG non-linear model. We utilise the Solver Optimization program, from Microsoft Excel for optimum portfolio formation using the Markowitz Model, as well as IBM SPSS 26 for statistical testing. This research adopts a quantitative approach with a focus on investment risk analysis, utilizing key variables such as stock returns, Value at Risk, and optimal portfolio composition. The ultimate objective of this methodology is to provide an in-depth understanding of the risk characteristics and performance of Islamic banking stocks compared to conventional banking stocks, employing advanced simulation techniques to explore potential losses and optimal investment strategies. From the previous theoretical explanation, the following are the steps in this research:



RESULT AND DISCUSSION

In this section, we discuss the results and analysis of the study including the descriptive statistics, the comparison of Value at Risk measurement between Islamic and conventional stocks and portfolio optimization utilising artificial intelligence called Solver Optimization.

Descriptive Statistics

Descriptive analysis provides an overview of the stock price fluctuations of four companies, namely BBCA, BBRI, BRIS, and BTPS, based on the analyzed data. The descriptive statistics presented include the minimum, maximum, and standard deviation values for each stock, which indicate the extent of price movement variations and the level of volatility.

Table 1. Descriptive Statistics of Stock Return

	N	Minimum	Maximum	Std. Deviation
R_BBCA	193	-0,038	0,041	0,013688
R_BBRI	193	-0,062	0,044	0,018662
R_BRIS	193	-0,094	0,096	0,027767
R_BTPS	193	-0,100	0,103	0,026012
Valid N (listwise)	193			

Source: Data processed by the author, 2024

BBCA exhibits relatively stable price fluctuations, with a range between -0.038 and 0.041 and a standard deviation of 0.013574. This indicates that BBCA's stock tends to experience less price movement and greater stability. In contrast, BBRI demonstrates larger price fluctuations, with a standard deviation of 0.018662. Despite its slightly negative return, BBRI's stock is more volatile compared to BBCA. For BRIS and BTPS, both show greater price volatility, with a standard deviation of 0.027767 for BRIS and 0.026012 for BTPS. BRIS displays higher price fluctuations, while BTPS shows substantial volatility with a negative return. Both of these stocks are considered riskier due to their more volatile price movements. The results of the descriptive statistics provide an indication that the returns of BBCA and BBRI tend to be more stable compared to BRIS and BTPS. To gain a deeper understanding of this, a normality test is conducted to assume that stocks with normally distributed returns are likely to exhibit greater stability.

Table 2. Normality Test of Daily Stock Returns

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
R_BBCA	0.062	193	0.068	0.989	193	0.130
R_BBRI	0.059	193	0.095	0.990	193	0.178
R_BRIS	0.090	193	0.001	0.975	193	0.001
R_BTPS	0.081	193	0.004	0.969	193	0.000

Source: Data processed by the author, 2024

Based on the results of the normality test with Kolmogorov-Smirnov, it can be seen that for BBCA and BBRI stocks, the significance value (Sig.) is more than 0.05, namely 0.068 and 0.095. Thus, the distribution of BBCA and BBRI stock returns is normally distributed. In contrast, for BRIS and BTPS, the Kolmogorov-Smirnov significance value is less than 0.05, namely 0.001 and 0.004, which means that the stock returns of these two companies are not normally distributed.

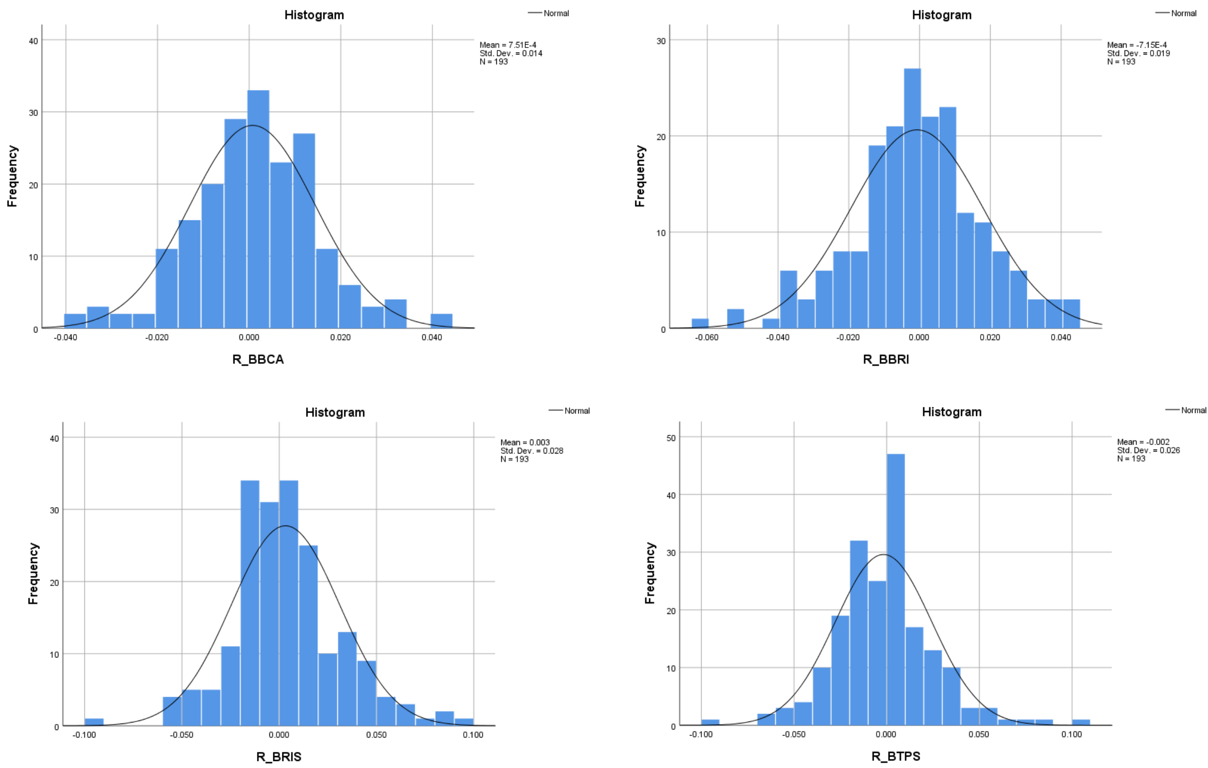


Figure 1. Normal Distribution Histogram of the Kolmogorov Smirnov Normality Test

However, looking at the normal distribution histograms of the four stocks above, almost BRIS and BTPS stock are still close to normal distribution. Although the level of normal distribution is not as high as BBCA and BBRI stock.

Table 3. Difference Test of Islamic and Conventional Banking Stock Returns

	Return
Mann-Whitney U	64942.500
Wilcoxon W	139633.500
Z	-3.085
Asymp. Sig. (2-tailed)	.002

Source: Data processed by the author, 2024

Based on the Asymp.Sig (2-tailed) value of 0.002 and the value is less than 0.05, it can be concluded that the value of Return on Islamic Banking Shares and Conventional Banking Stock in this study has a significant difference. And it can also be seen that the Z-score value is -3,085 which explains that the return on Islamic banking stock has a higher value than conventional banking.

Value at Risk (VaR) Monte Carlo Simulation on Single Asset

The following table displays the VaR value with Monte Carlo Simulation on a single asset. The number of iterations used is 10,000 iterations with an initial investment fund of IDR 100 million.

Table 4. Value at Risk (VaR) Monte Carlo Simulation on Each Stock

No	Stock Code	*VaR* $_{(1-a)}$	*VaR* @ 100 Million
1	BBCA	-2,19%	-Rp2.191.806
2	BBRI	-2,95%	-Rp2.947.552
3	BRIS	-4,78%	-Rp4.780.184
4	BTPS	-3,98%	-Rp3.982.545

Source: Data processed by the author, 2024

Table above illustrates the estimated maximum potential loss that could occur from an investment within a one-day period after October 25, 2024, at a 95% confidence level, with a simulation conducted using 10,000 iterations to model possible outcomes based on future stock price movements. BBCA has a Value at Risk (VaR) of -2.19%, meaning there is a 5% chance that investors could experience a loss exceeding 2.19% of their investment value. In contrast, BRIS stock has a VaR of -4.78%, making it the highest-risk stock compared to BBCA, BBRI, and BTPS. As shown in the "VaR@100 million" column, this indicates the nominal loss that could occur on an investment of IDR 100 million. For BBCA, with a VaR of -2.19%, the potential loss would be -IDR 2,191,806, meaning that an investor with a 100 million Rupiah investment in BBCA faces the risk of losing approximately IDR 2.19 million in an extreme situation, expected to occur only 5% of the time after October 25, 2024. The significant difference between the two VaR values can be explained in the table below:

Table 5. Differential Test of VaR Value of Monte Carlo Simulation of Islamic and Conventional Banking Stocks on a Single Asset

	Score_VaR
Mann-Whitney U	65107.500
Wilcoxon W	139798.500
Z	-3.031
Asymp. Sig. (2-tailed)	.002

Source: Data processed by the author, 2024

Based on the Asymp.Sig (2-tailed) value of 0.002 and the value is less than 0.05, it can be concluded that the VaR value of Islamic Banking Shares and Conventional Banking Shares in this study has a significant difference. And the Z-score value of -3,031 explains that the VaR value on Islamic banking stocks has a higher value than conventional banking stocks.

Portfolio Optimization

To find the optimum portfolio weight combination, we utilise the Solver Optimization feature in the Microsoft Excel tool based on the use of Nonlinear GRG calculations by minimizing the portfolio variance function in the Markowitz model optimum portfolio theory. Nonlinear GRG calculations also involve the return movement of the JCI, not only limited to existing portfolio returns. Because CAPM theory explains that efficient markets are highly correlated with the market. The following is the covariance matrix used to calculate portfolio variance:

Table 6. Covariance Matrix of Return in Each Portfolio

	BRIS	BTPS	JCI
BRIS	0,000781849	0,000171445	-1,63003E-05
BTPS	0,000171445	0,000679894	-1,32572E-05
JCI	-1,63003E-05	-1,32572E-05	5,7997E-05

	BBCA	BBRI	JCI
BBCA	0,000186554	0,00010182	9,16199E-06
BBRI	0,00010182	0,00034996	1,45687E-05
JCI	9,16199E-06	1,45687E-05	5,7997E-05

Source: Data processed by the author, 2024

Based on the covariance matrix values from the table above, it can be explained that the assets within the Islamic banking stock portfolio (BRIS and BTPS) exhibit a negative correlation with the Jakarta Composite Index (JCI), with correlation values of -1.63 and -1.33, respectively. This indicates that the movements of these two assets tend to move in the opposite direction to the JCI. In contrast, the assets within the conventional banking stock portfolio (BBCA and BBRI) show a very high correlation with the JCI, with correlation values of 9.16 and 1.45, respectively. This suggests that the movements of these two assets are more likely to follow the direction of the JCI. This can be illustrated in the chart below:

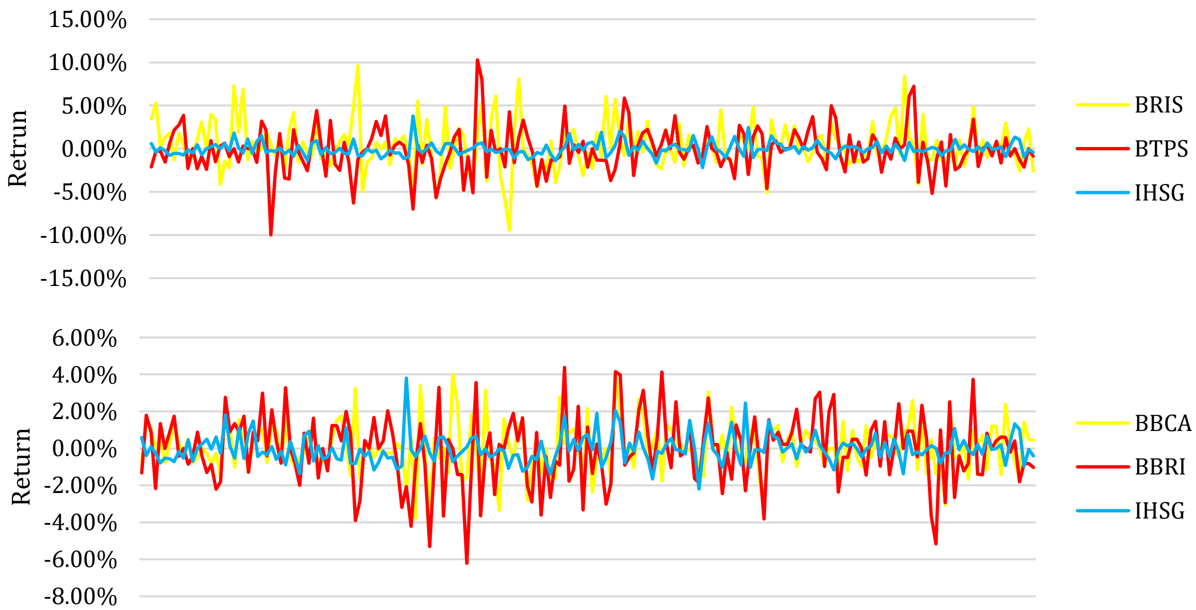


Figure 2. Chart of Correlation of Assets in The Portfolio Against The JCI

Based on the results of GRG Nonlinear calculations using the 'Solver' function in Ms. Excel 2019, with the aim of minimizing portfolio variance which is considered as risk, getting the following results:

Table 7. Markowitz Optimum Portfolio Weighting Model

No	Portfolio	Code	Portfolio Weight Optimum	Percentage
1	Islamic Banking Stocks	BRIS	0,454	45,4%
		BTPS	0,545	54,5%
2	Conventional Banking Stocks	BBCA	0,745	74,5%
		BBRI	0,254	25,4%

Source: Data processed by the author, 2024

In the Islamic banking stock portfolio, BRIS is assigned a weight of 45.4%, while BTPS receives a higher weight of 54.5%. Meanwhile, in the conventional banking stock portfolio, BBCA is allocated a weight of 74.5%, reflecting the belief that this stock is more stable and safer, with lower risk compared to BBRI, which is assigned a weight of only 25.4%.

Value at Risk (VaR) Monte Carlo Simulation on Islamic and Conventional Banking Portfolio

The calculation of the optimal portfolio weights will be used in the Monte Carlo simulation VaR calculation. The number of iterations used in the Monte Carlo simulation VaR analysis for the portfolio in this study is 10,000 iterations, with a confidence level of 95% and 15 days time horizon. The following are the Monte Carlo simulation VaR values for each portfolio:

Table 8. VaR Value of Monte Carlo Simulation of Each Portfolio

No	Portfolio	VaR $_{(1-\alpha)}$	*VaR* @ 100 Million
1	Islamic Banking Stocks	-4,18%	-Rp4.180.169
2	Conventional Banking Stocks	-1,65%	-Rp1.652.541

Source: Data processed by the author, 2024

Based on table above, it can be concluded that the Islamic banking stock portfolio carries a higher risk of loss compared to the conventional banking stock portfolio. For the Islamic banking stock portfolio, the potential loss is approximately 4.18% of the portfolio value over the calculated period, which, when applied to a value of Rp 100 million, could amount to IDR 4,180,169 within 15 days after October 25, 2024. In contrast, the potential loss for the conventional banking stock portfolio is significantly smaller, at 1.65%, or approximately IDR 1,652,541 from a value of IDR 100 million within 15 days after October 25, 2024.

Discussion

Discussion of this research, the author will highlight in terms of hypothesis testing that has been done. Based on the results of the return difference test that has been carried out, it states that the return on Islamic Banking stocks and Conventional Banking Stocks has a significantly different return value with a z-score value of -3.085 which indicates that the return value on Islamic banking stocks is higher than conventional banking stocks. Significant differences in returns on Islamic and conventional banking sector stocks are in line with CAPM theory which explains the relationship between risk and the rate of return on an asset by considering risk factors that cannot be avoided by investors, namely market risk or systematic risk (Bachrach & Galai, 1979; Reilly & Brown, 2012). The research shows that Islamic and conventional banking stocks have different characteristics, such as investment and financing policies, which can affect their returns. Islamic and conventional banking stocks, although operating in the same sector, have significant differences in terms of operating structure and compliance with sharia principles (Anita & Riris, 2021). Therefore, the returns that will be received also have significant differences (Anita & Riris, 2021).

However, it should also be noted that shares of Islamic banking stocks, namely BRIS and BTPS, have their own appeal, but also pose challenges for investors. For instance, BRIS offers the highest average return of 0.321%, indicating a promising profit opportunity. However, behind this potential lies a very high risk, as reflected in its standard deviation of 2.7767%, which shows that the stock price is highly volatile and can change drastically (Anita & Riris, 2021). Meanwhile, BTPS exhibits similar characteristics. Despite its negative average return of -0.172%, this stock still carries high risk, with a standard deviation of 2.6012%. This means that although its potential return is not as high as BRIS, its price fluctuations remain significant (Anita & Riris, 2021).

If we consider based on Value at Risk (VaR) measurement, the level of risk is associated with an asset (Jorion, 2007). It is used to assess the risk that an investor is willing to accept over a specified period and with a certain confidence level (Jorion, 2007). Investing in the capital market offers high returns but also entails significant risks that must be accepted by investors (Tandelilin, 2017). In this study, the CAPM theory, which links asset risk to market risk, was supported by the results, showing a significant difference in VaR between Islamic banking and conventional banking stocks using the Monte Carlo Simulation approach. The Mann-Whitney test revealed an Asymp. Sig. value of 0.002 (<0.05), indicating a statistically significant difference in risk levels between the two stock types. This finding aligns with previous studies by Dewi et al. (2024), Cahyani & Fajar (2020), and Suryadi et al. (2021), who also observed significant differences in risk and returns between Islamic and conventional banking stocks.

The significant difference in VaR values between Islamic and conventional banking stocks reflects variations in risk levels associated with each type of stock (Humayrah & Prima Sari, 2023). VaR measures the potential losses within a certain period, with differences indicating how volatile and sensitive the stocks are to market fluctuations (Jorion, 2007). According to the Capital Asset Pricing Model (CAPM), risk differences are linked to stock beta, which indicates the level of risk related to market movements (Alecia & Erric, 2020). The implication is that Islamic and conventional banking stocks may offer different returns, with riskier stocks potentially yielding higher returns but with greater uncertainty (Pasieczna, 2019). Therefore, investors should consider these risk differences when making investment decisions, adjusting their strategies according to their risk profile (Tandelilin, 2017), and for those investing in Islamic banking stocks, adherence to Shariah principles is also important (Adenan et al., 2021).

According to Harry (1959) it explains the importance of diversification in a portfolio. And in this study, the optimal portfolio construction using the Markowitz Portfolio Model resulted in stock combinations for the Islamic Banking Stock Portfolio (45.4% BRIS and 54.5% BTPS) and the Conventional Banking Stock Portfolio (74.5% BBCA and 25.4% BBRI). These portfolios were designed to minimize risk and maximize returns, aiming to reduce risk fluctuations and create a more balanced and diversified portfolio. The results show that the Islamic Banking Stock Portfolio has a VaR of -4.18% (-Rp4,180,169), while the Conventional Banking Stock Portfolio has a VaR of -1.65% (-Rp1,652,541). This finding contradicts the hypothesis stating that the Islamic Banking Stock Portfolio should have a lower VaR.

Based on these results, investors can choose a portfolio according to their risk tolerance level. Aggressive investors, who are willing to accept higher risks for potentially greater returns, may opt for the Islamic Banking Stock Portfolio despite its higher loss risk (Kubilay & Bayrakdaroglu, 2016). Conservative investors, who prioritize stability and low risk, are more suited to the Conventional Banking Stock Portfolio, as it has a lower risk (Muna & Khaddafi, 2022). Meanwhile, moderate investors, seeking a balance between risk and return, may choose the Conventional Banking Stock Portfolio, which offers better stability while still providing reasonable potential returns (Kubilay & Bayrakdaroglu, 2016).

CONCLUSION AND RECOMMENDATION

This study reveals significant risk differentials between Islamic and conventional banking portfolios, with Islamic stocks demonstrating higher volatility (VaR: -4.18% vs -1.65%). However, these findings require critical interpretation beyond surface-level statistical differences. The higher risk profile of Islamic banking stocks may reflect structural factors including: (1) market maturity disparities, as Islamic banks operate within a relatively nascent regulatory framework compared to established conventional banking systems; (2) liquidity constraints inherent in Shariah-compliant investment restrictions; and (3) limited diversification opportunities due to sectoral screening requirements.

Our Monte Carlo simulation, while sophisticated, relies on historical price data that may not capture regime shifts, regulatory interventions, or evolving market sentiment toward Islamic finance. The study period (January-October 2024) coincides with significant monetary policy adjustments by Bank Indonesia, potentially skewing volatility measures. Furthermore, the AI-driven Solver optimization, despite its computational advantages, remains constrained by the same historical data limitations and assumes static correlations that may not hold during market stress periods.

The observed risk patterns challenge traditional CAPM assumptions about efficient markets. Islamic stocks' negative correlation with JCI (-1.63 for BRIS, -1.33 for BTPS) suggests potential diversification benefits inadequately explored in our Markowitz optimization framework. This contradiction between theoretical expectations and empirical findings warrants deeper investigation into Islamic finance-specific risk factors.

Recommendations

For Future Research:

1. Multi-regime Analysis: Incorporate regime-switching models to capture structural breaks in Islamic vs conventional banking performance during different economic cycles
2. Confounding Variables Control: Integrate macroeconomic variables (inflation, monetary policy, regulatory changes) into risk models to isolate sector-specific effects
3. Behavioral Finance Integration: Examine investor sentiment differentials toward Islamic vs conventional banking through survey-based research complementing quantitative analysis
4. Extended Temporal Scope: Conduct longitudinal studies spanning multiple economic cycles to validate stability of observed risk patterns

For Practitioners:

1. Dynamic Risk Management: Implement adaptive portfolio rebalancing mechanisms that account for regime changes rather than static optimization weights

2. Multi-factor Risk Models: Develop Islamic finance-specific risk factors beyond traditional Fama-French models to better capture Shariah-compliance premiums
3. Regulatory Arbitrage Awareness: Consider regulatory environment changes that may differentially impact Islamic vs conventional banking performance

Methodological Improvements:

1. Hybrid AI Approaches: Combine machine learning algorithms (neural networks, support vector machines) with traditional optimization to capture non-linear relationships inadequately addressed by GRG Solver
2. Stress Testing Integration: Incorporate scenario analysis and extreme value theory to assess tail risks beyond VaR limitations
3. Real-time Data Integration: Develop dynamic models using high-frequency data to capture intraday volatility patterns potentially missed in daily observations

Study Limitations Acknowledgment: This research represents an initial exploration rather than definitive conclusions about Islamic-conventional banking risk differentials. The observed patterns may reflect temporary market conditions, regulatory transitions, or data-specific artifacts requiring validation through expanded datasets and alternative methodological approaches.

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