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STRENGTHENING SYARIAH FINANCIAL MARKETS WITH GARCH-BASED STOCK PRICE FORECASTING AND VAR-RISK ASSESSMENT

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ABSTRACT

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Indonesia, as the largest Muslim-majority country, has significant potential to enhance its Shariah financial sector, which has been growing rapidly, around 7.43% from 2023 to 2024, and contributing to the national economy. However, political and natural disasters have influenced the economy and Shariah-compliant stocks. This study focuses on forecasting Shariah-compliant stock prices using Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models and estimating investment risks via Value at Risk (VaR) for four Islamic banks listed in IDX: BRIS, BTPS, BANK, and PNBS. The findings indicate that GARCH models effectively capture stock price dynamics and provide accurate 10-day forecasts. Additionally, the models reliably predict VaR, validated through backtesting at various confidence levels. These insights are valuable for financial regulators and risk managers, aiding in policy design to ensure market stability by enabling the implementation of measures such as stricter capital reserve requirements for institutions with high-risk exposure and mandatory adoption of advanced risk management techniques like dynamic stress testing. Such policies not only mitigate systemic risks during periods of financial volatility but also enhance the overall resilience and robustness of the financial system. For investors, accurate risk predictions support informed decision-making, enhance portfolio protection, and optimize risk management.

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1. INTRODUCTION

As the world's largest Muslim-majority country, Indonesia has substantial potential for developing its Shariah financial sector. Islamic finance, which operates by Islamic legal principles, has been warmly received in Indonesia due to its alignment with the beliefs of the majority of its population. The Shariah-compliant stocks, introduced in 2011, regulated by the Otoritas Jasa Keuangan (Financial Services Authority — OJK) and the Majelis Ulama Indonesia (Indonesian Ulema Council — MUI), serve as concrete evidence of the rapid growth of Islamic finance in Indonesia [1]. In the Indonesian Islamic Financial Development Report 2023, with Islamic banking assets increasing by 11.21% by 2023, coupled with the Islamic capital market growing by 7.43%, and the non-bank Islamic financial industry experiencing an impressive increase of 12.98%, the demand for sophisticated risk management strategies is apparent [2]. This trend indicates that the Islamic financial industry is expanding and has substantial potential to support national economic development [2]. In line with this potential, the Indonesian government and financial institutions continue to innovate and develop a more diverse range of Islamic financial products to meet market needs.

Islamic investments include a variety of instruments designed to follow Sharia principles in Islam, including Sharia-compliant stocks, Sukuk (Islamic bonds), Sharia mutual funds, and Sharia deposits [3], [4], [5], [6]. Sharia-compliant stocks are issued by companies that operate by Sharia principles, avoiding involvement in businesses prohibited in Islam, such as gambling, alcohol production, and usury (interest). Consequently, Sharia-compliant stocks attract many investors who seek to combine financial aspects with Islamic moral and ethical principles [7], [8]. The introduction of Sharia-compliant stocks in Indonesia aims to provide investment options aligned with religious beliefs and develop a more sustainable Islamic financial sector. This initiative reflects the Indonesian government's commitment to promoting financial inclusion that encompasses all segments of society, including those prioritizing Sharia principles in their economic and financial activities.

In Indonesia, there are four Islamic banks listed on IDX: PT Bank Syariah Indonesia Tbk (BRIS), PT Bank BTPN Syariah Tbk (BTPS), PT Bank Aladin Syariah Tbk (BANK), and PT Bank Panin Dubai Syariah Tbk (PNBS). The frequently unstable market conditions create challenges for investors, particularly concerning stock price predictions and investment risk management. For instance, it is suspected that due to internal political issues or to foster healthy competition among Islamic banks in Indonesia, as well as risk concentration considerations, the Muhammadiyah Political Party withdrew up to Rp15 trillion from Bank Syariah Indonesia (BSI), one of the most prominent Islamic banks in Indonesia [9], [10], [11]. Withdrawing Muhammadiyah money does not significantly affect price changes; Islamic bank stock is more sensitive to the issue of increasing interest rates. IDX and OJK need to enhance education, transparency, and investment frameworks to rebuild trust and ensure the competitiveness of Islamic Banks Stocks Focusing on improving service quality, product innovation, and regulatory adaptation is crucial for the sustainability and growth of the Islamic financial sector. In addition to eliminating prohibited elements under Islamic law, Islamic investment risk management must adopt principles of justice, social responsibility, and sustainability to provide long-term benefits for all stakeholders.

Political problems, especially Islamic parties, affect Islamic banks, i.e., the potential volatility in Sharia-compliant stocks. The volatility is influenced by global market conditions, regulatory changes, domestic politics, and market sentiment [12]. The volatility may lead to investment values fluctuating significantly within a short period, increasing investors' risk of substantial losses, especially if stock prices suddenly plummet. Effective investment is crucial to mitigate these risks and protect investor portfolios [13]. One strategy in investment is to model historical data to forecast stock prices accurately.

High volatility in data cannot be adequately addressed with linear models, necessitating nonlinear time series modelling. Many researchers stated that financial data is characterized by non-normal distribution, skewed, leptokurtic, and heavy-tailed [14], [15], [16], [17], [18], [19], [20], [21]. In addition, they also observed that financial data exhibit volatility characteristics that lead to heteroskedasticity [22], [23], [24]. In 1982, Engle proposed the Autoregressive Conditional Heteroskedasticity (ARCH) model to accommodate heteroskedasticity. Subsequently, in 1986, Bollerslev generalized and simplified the ARCH model into the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model [25]. The ARCH/GARCH model has demonstrated strong performance in managing heteroskedasticity [26], [27], [28].

The financial data also tends to have leverage effect. The leverage effect refers to the phenomenon where price volatility tends to increase more after a sharp price drop compared to an equally significant price rise [29]. Standard GARCH models cannot capture this leverage effect because they only consider the magnitude of the shock without accounting for its positive or negative sign [30]. The Family GARCH (Asymmetric GARCH), *i.e.*, T-GARCH, N-GARCH, AP-ARCH, and GJR-GARCH, are proposed to capture the leverage effect. Using both symmetric and asymmetric GARCH models, Othman *et al.* investigated Bitcoin prices and concluded that Bitcoin exhibits persistent volatility and lacks a leverage effect [31]. This means that following a negative shock, stock prices usually become more unstable and fluctuate more than after a positive shock. One primary reason for the leverage effect is market psychology; a sharp price decline heightens investor anxiety, leading to most significant price fluctuations. Marobhe and Pastory investigated the volatility dynamics of stock returns on the Dar es Salaam Stock Exchange (DSE). They found that the E-GARCH (1,1) model provides evidence of a leverage effect related to stock returns, which can negatively impact the capital structure of companies [32]. Their findings showed that the GARCH model predicts stock price volatility effectively and offers deeper insights into stock market dynamics, including in Sharia-compliant markets. This research underscores the importance of adapting GARCH models within the context of markets adhering to Sharia principles.

Investment risks must be carefully measured and managed to ensure long-term returns. Measuring investment risks is significant for maintaining investors' risk appetite and avoiding unpredicted losses. Value at Risk (VaR) analysis can be used to calculate the potential risk of investments [33]. The VaR estimates the maximum possible loss over a specified period at a given confidence level (1% or 2.5%), enabling banks to manage investment risks more effectively. Implementing GARCH to model stock price and calculation of VaR to measure investment risk are used to be Sharia-compliant to overcome investment losses.

This research will focus on forecasting the stock prices of the four Islamic banks in Indonesia—BRIS, BTPS, BANK, and PNBS—using family GARCH models. Value at Risk (VaR) calculations will also be performed to identify, measure, and manage the investment risks associated with Sharia-compliant finance. Therefore, this research aims to improve the accuracy of stock price forecasts and investment risk in Islamic banks, thus providing better protection for investors.

2. RESEARCH METHODS

2.1 Data Sources

The introduction of **Table 1** is preceded by a detailed description of the study's focus and dataset to enhance clarity and flow, t. This study examines four listed Islamic banks in Indonesia, namely Bank Syariah Indonesia (BSI), Bank Aladin Syariah (BANK), Bank Tabungan Pensiunan Syariah (BTPS), and Bank Panin Dubai Syariah (PNBS). Stock price data for these banks were retrieved from Yahoo Finance, covering May 2018 to July 2024, with slight variations in the starting dates for each bank's data series. This selection of Islamic banks, each representing a different market segment, allows for a comprehensive stock performance analysis within Indonesia's Islamic banking industry.

Table 1 provides a detailed overview of the stock indices and the number of observations available for each bank, facilitating a clearer understanding of the data used in this research. The stock price data for BRIS, BTPS, and BANK have been collected from their respective inception dates, while the initial observation date for PNBS was set to November 2, 2020. This choice is based on the observation that before this period, the price data pattern for PNBS exhibited static characteristics over an extended duration. The static nature of the data pattern may indicate minimal price fluctuations, which may obscure the dynamic analysis required to develop an effective model.

Table 1. Overview of Sharia Bank Stocks in Indonesia

Stock Index	Description	Date	Number of Observations
BRIS	PT Bank Syariah Indonesia Tbk (BRIS) was known as BRI Syariah before merging with Bank Syariah Mandiri and BNI Syariah in 2021. The company was established in 2017 when PT Bank Rakyat Indonesia (Persero) Tbk acquired Bank Jasa Arta. The merger aims to combine the advantages owned by the three banks to provide a better and broader range of services.	2018-05-09 - 2024-07-30	1510

Stock Index	Description	Date	Number of Observations
BTPS	PT Bank BTPN Syariah Tbk (BTPS) was a sharia business unit of Bank Tabungan Pensiunan Nasional (BTPN) before becoming a separate entity on 14th July 2014. The bank currently has 26 branches across Indonesia. It offers sharia financing and funding services, focusing on Indonesian underprivileged productive families.	2018-05-08 - 2024-07-30	1510
BANK	PT Bank Aladin Syariah Tbk (BANK) is a digital-based Syariah bank in Indonesia. It was known as Bank Net Syariah before changing its name to Aladin Bank. The bank collaborates with some businesses, like Alfamart and Halodoc, to combine online and offline elements to provide banking services.	2021-02-01 - 2024-07-30	822
PNBS	PT Bank Panin Dubai Syariah Tbk (PNBS) is a subsidiary of PT Bank Panin Tbk, focusing on Sharia banking services. The bank offers various banking and financial products, such as fund products (saving, checking, deposits, etc), fund programs, service products, financing products (mortgage, car loan, working capital, multi-finance, etc), and treasury products.	2020-11-02 - 2024-07-30	882

2.2 Methods

This study employs two key approaches for modelling stock prices and estimating investment risk: Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models for volatility forecasting and Value at Risk (VaR) for risk assessment.

a) Stationary Testing of Data

The first step in the analysis involves testing for stationarity in the stock price data. Two main types of stationarity, mean stationarity and variance stationarity, are examined. Mean stationarity implies that the mean value of the data does not change over time, while variance stationarity indicates that the variance remains constant throughout the period. Mean stationarity can be tested using the Augmented Dickey-Fuller (ADF) test. The ADF test is conducted by regressing the **Equation (1)[25]**.

$$\Delta Y_t = \pi_0 + +\rho Y_{t-1} + \sum_{i=1}^{m} \varphi_i \Delta Y_{t-1} + \varepsilon_t \tag{1}$$

where ε_t representing the pure error component that is characterized as white noise, and $\Delta Y_{t-1} = (Y_{t-2} - Y_{t-1})$, $\Delta Y_{t-2} = (Y_{t-3} - Y_{t-2})$, and so on. ΔY_t denotes the change in the value of variable Y at time t. π_0 is the intercept, while π_1 is the time trend coefficient that captures the influence of time on changes in Y. The coefficient ρ measures the effect of previous values on the current change (ΔY_t). If $\rho \to 1$, it indicates that the data tends to revert to the mean **[34]**. Furthermore, variance stationarity is examined using the Box-Cox transformation. If $\lambda_{BC} \neq 1$, the data needs to be transformed using the **Equation (2)**.

$$y' = \begin{cases} \dfrac{y^{\lambda_{BC}} - 1}{\lambda_{BC}}; & \text{if } \lambda_{BC} \neq 0 \\ \log y; & \text{if } \lambda_{BC} = 0 \end{cases} \tag{2}$$

Here, y' represents the individual data points. Since the transformation applies only to positive data, if the time series contains zeros or negative values, a constant must be added to shift all values into the positive range before applying the transformation. To apply the Box-Cox transformation, one typically uses maximum likelihood estimation (MLE) to determine the optimal λ, the value that best stabilizes variance and normalizes the data. Once the optimal λ is identified, the data are transformed using the corresponding formula. The transformation stabilizes the variance, making the variance the data more consistent over time **[35]**. This is particularly beneficial when the data exhibit patterns like exponential growth or periodic increases in variability. The Box-Cox transformation also enhances model interpretability and performance. Addressing issues like non-linearity and heteroscedasticity allows simpler linear models to capture the underlying structure of the data effectively [36].

If the stock price data exhibits non-stationarity in mean and variance, it can lead to errors in statistical inference. If the data is non-stationary, methods such as differencing or transformation such as differencing or Box-Cox transformations are applied to stabilize the data, thereby enhancing the validity and relevance of the analysis conducted [25].

b) ARIMA Modelling

After achieving stationarity, an Auto-Regressive Integrated Moving Average (ARIMA) model is applied to capture the time-series structure of the stock prices. The ARIMA (p, d, q) model equation using the backshift operator is defined in Equation (3) [25].

$$\left(1-\phi_p B\right)(1-B)^d Y_t=\left(1+\theta_q\right) e_t \tag{3}$$

where B is the backshift operator, and it holds that $(1-B)Y_t = Y_t - Y_{t-1}$. The ARIMA (p, d, q) model is a time series analysis approach that combines three components: autoregression (AR), differencing (I for "integrated"), and moving averages (MA). Each component has a distinct meaning. The p parameter (autoregressive order) represents the number of lagged past values used to predict the current value, capturing the linear relationship between the current and previous observations. The d parameter (degree of differencing) indicates how many times the data needs to be differenced to achieve stationarity, effectively removing trends or seasonality. For instance, if $d = 1$, the model analyzes changes between consecutive time points. The q parameter (moving average order) captures the influence of past random shocks or errors on the current value by including a specified number of lagged error terms. These parameters allow ARIMA to model complex patterns in time series data, accounting for trends, seasonality, and random noise, making it a versatile tool for forecasting and analysis.

c) Model ARIMA Residual Diagnostic

The best-fitting ARIMA model for each bank is selected based on the lowest Akaike Information Criterion (AIC). Residual diagnostics tests, including the Ljung-Box test (to check for autocorrelation) and the Jarque-Bera test (for normality), are conducted to ensure that the residuals of the ARIMA model are white noise.

d) GARCH Modelling for Volatility

The residuals from the ARIMA model are used to model volatility using the GARCH family models, which account for the heteroscedasticity observed in the stock price data. Time series data from financial markets tends to exhibit high volatility, reflecting trading reactions to various news and real-world events. A key characteristic of financial time series is the presence of periods of high volatility followed by periods of stability [37]. High volatility can lead to heteroskedasticity. Engle developed the Autoregressive Conditional Heteroscedasticity (ARCH) model [38], which was later expanded by Bollerslev into the Generalized ARCH (GARCH) model [15] into the Generalized ARCH (GARCH) model. The GARCH process of order (P, Q) is formulated in Equation (4) [33]. The GARCH (1,1) model is defined as:

$$\begin{gathered}z_t=\sigma_t \varepsilon_t, \\ \sigma_t^2=\omega+\sum_{i=1}^P \alpha_i z_{t-i}^2+\sum_{j=1}^Q \beta_j \sigma_{t-j}^2\end{gathered} \tag{4}$$

where ε_t is the error component of the mean model with $\varepsilon_t \sim NIID(0, \sigma_t^2)$, $\omega > 0$ is a constant, $\alpha_i \geq 0$ are the ARCH parameters, and $\beta_j \geq 0$ are the GARCH parameters, with the condition that $\alpha_i + \beta_j < 1$. The GARCH effect captures long-term volatility, indicating that past data continues to influence current price changes.
Financial data often exhibit asymmetric characteristics, meaning the market response to price changes is not always balanced (leverage effect/asymmetric volatility). The leverage effect is

defined as the negative correlation between shocks in returns and volatility; in other words, there is an increase in the amplitude of volatility fluctuations when a decline in stock prices occurs. If the leverage effect persists over an extended period, it leads to negative skewness in the return data distribution [39].

The leverage effect in the data can be identified through the sign bias test by obtaining the residuals from the GARCH model and then regressing them with the model presented in Equation (5) [40].

$$\hat{\varepsilon}_t^2 = \zeta_0 + \zeta_1 N_{t-1}^- + u_t \tag{5}$$

with,

$$N_{t-1}^- = \begin{cases} 1, & \text{if } \varepsilon_{t-1}^2 < 0 \\ 0, & \text{elsewhere} \end{cases}$$

The model approaches that can be utilized when asymmetric volatility occurs include the Family GARCH models, such as Non-linear GARCH (N-GARCH) [41], Threshold GARCH (T-GARCH) [19], Asymmetric Power ARCH (AP-ARCH) [42], and Glosten-Jagannathan-Runkle GARCH (GJR-GARCH) [16]. The Family GARCH (1,1) model can generally be expressed in Equation (6) [43].

$$\sigma_t^\lambda = \omega + \alpha\sigma_{t-1}^\lambda\big(|z_{t-1} - \eta_2| - \eta_1(z_{t-1} - \eta_2)\big)^\delta + \beta\sigma_{t-1}^\lambda \tag{6}$$

which is defined by the parameter λ, and the parameter δ transforms the absolute value function according to rotation (η_1) and shifting (η_2). In Equation (6), the parameters β and α measure the persistence effects and shocks on volatility, respectively. The sign effect is represented by λ, while the strength of the time horizon is indicated by δ. Higher-order models within the Family GARCH tend to increase model instability. Thus the GARCH (1,1) model is selected to minimize this risk [44]. Additionally, various studies have demonstrated that GARCH (1,1) often outperforms more complex models in terms of forecasting accuracy. Research indicates that GARCH (1,1) provides superior predictions, particularly for long-term forecasting, due to its ability to effectively model volatility persistence over time without leading to overfitting of the data.

Higgins & Bera proposed the N-GARCH model, where small shocks are not different from large shocks, specifically $\delta = \lambda$ [41]. This indicates that both rotation and shifting are zero, *i.e.*, $\eta_1 = \eta_2 = 0$. Therefore, the N-GARCH (1,1) model can be expressed in Equation (7).

$$\sigma_t^\lambda = \omega + \alpha\sigma_{t-1}^\lambda(|z_{t-1}|)^\delta + \beta\sigma_{t-1}^\lambda \tag{7}$$

The T-GARCH model accommodates regime changes in volatility. The choice of model used depends on the characteristics and needs of the data being analyzed [45] The T-GARCH (1,1) model can be expressed in Equation (8) and Equation (9) [33].

$$\sigma_t^2 = \omega + (\alpha + \lambda\eta_{t-1})z_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{8}$$

where η_{t-1} is a negative indicator of e_{t-1}:

$$\eta_{t-1} = \begin{cases} 1 & \text{if } z_{t-1} < 0, \\ 0 & \text{if } z_{t-1} \geq 0, \end{cases} \tag{9}$$

and $\alpha, \lambda,$ and β is a non-negative parameter that satisfies conditions similar to those in the GARCH model. The T-GARCH model uses zero as the threshold to differentiate the effects of past shocks.

Ding *et al.* presented the AP-ARCH model, which provides a general class of volatility models capable of effectively capturing characteristics such as fat tails, excess kurtosis, and leverage effects **[42]**. The AP-ARCH (1,1) model can be expressed in **Equation (10)** as follows.

$$\sigma_t^\delta = \omega + \alpha(|z_{t-1}| - \gamma z_{t-1})^\delta + \beta\sigma_{t-1}^\delta \tag{10}$$

The GJR-GARCH (1,1) model is designed to capture the long-term impact of negative shocks that may lead to asymmetric leverage volatility effects, and it can be expressed in **Equation (11)**.

$$\sigma_t^2 = \omega + \alpha_1 z_{t-1}^2 + \beta_1\sigma_{t-1}^2 + \gamma z_{t-1}^2 d_{t-1} \tag{11}$$

with the dummy variable d_t controlling the impact of shocks in such a way that:

$$d_t = \begin{cases} 1; \text{ if } z_t < 0 \\ 0; \text{otherwise} \end{cases}$$

e) Value at Risk (VaR) Estimation

The second part of this study's analysis focuses on assessing investment risk through stock returns. There are various types of risks in the financial market, such as credit, operational, and market risks. One commonly used metric for measuring the magnitude of investment risk is Value at Risk (VaR). VaR represents the maximum loss of a financial position over a specified time at a certain probability level **[33]**.

Return data, derived from price data, is a crucial measure in financial analysis that reflects the change in the value of an asset over time. Returns are calculated to help investors understand investment performance and assess associated risks. Let P_t and P_{t-1} denote the closing prices of a stock index at times t and $t-1$, respectively; then the return can be computed using **Equation (12)**.

$$R_t = \log\left(\frac{P_t}{P_{t-1}}\right) \tag{12}$$

The use of logarithmic returns in financial analysis has several advantages, with one of the primary reasons being its ability to eliminate the effects of dividends from return calculations.

The steps for the VaR analysis begin with establishing an ARIMA-GARCH model on the logarithmic returns of the stock prices of Islamic banks. This involves obtaining the return values, modelling the mean of the return values using the Box-Jenkins ARIMA approach, and subsequently modelling the heteroskedasticity of the residuals from the ARIMA model using Family GARCH.

f) Backtesting of VaR

To ensure the accuracy of the VaR predictions using the employed model, backtesting of VaR will be conducted. This backtesting involves comparing the predicted VaR with the actual losses incurred. The process includes comparing the number of days where actual losses exceed VaR (exceedance) with the expected number of exceedances **[46]**, **[47]**.

Kupiec's test is one of the methods used to assess the accuracy of VaR models **[48]**. This test helps identify whether the observed number of exceptions falls within the expected range, thus ensuring that the VaR model is well-calibrated and reliable **[49]**. The Kupiec method involves two key tests: Proportion of Failures (POF) and Time Until First Failure (TUFF) **[50]**.

The POF test aims to examine whether the proportion of actual losses exceeding VaR (referred to as "exceptions" or "violations") aligns with the chosen confidence level in the VaR model. The POF test utilizes the binomial distribution to test the null hypothesis that the proportion of violations corresponds to the confidence level. The VaR model is deemed inaccurate if the test results indicate that the proportion of exceptions significantly differs from the expected value. The statistical calculation for the POF test is expressed using **Equation (13)** as follows **[50]**.

$$LR_{POF} = -2\ln\left(\frac{(1-p)^{n-x}p^{x}}{(1-\hat{p})^{n-x}\hat{p}^{x}}\right) \sim \chi_1^2 \quad (13)$$

where n is the number of observations, x is the number of observations that exceed VaR, p is the confidence level of VaR, and $\hat{p} = \frac{x}{n}$ is the observed proportion of violations. The overall stages of the research are summarized in a flowchart presented in **Figure 1** as follows.

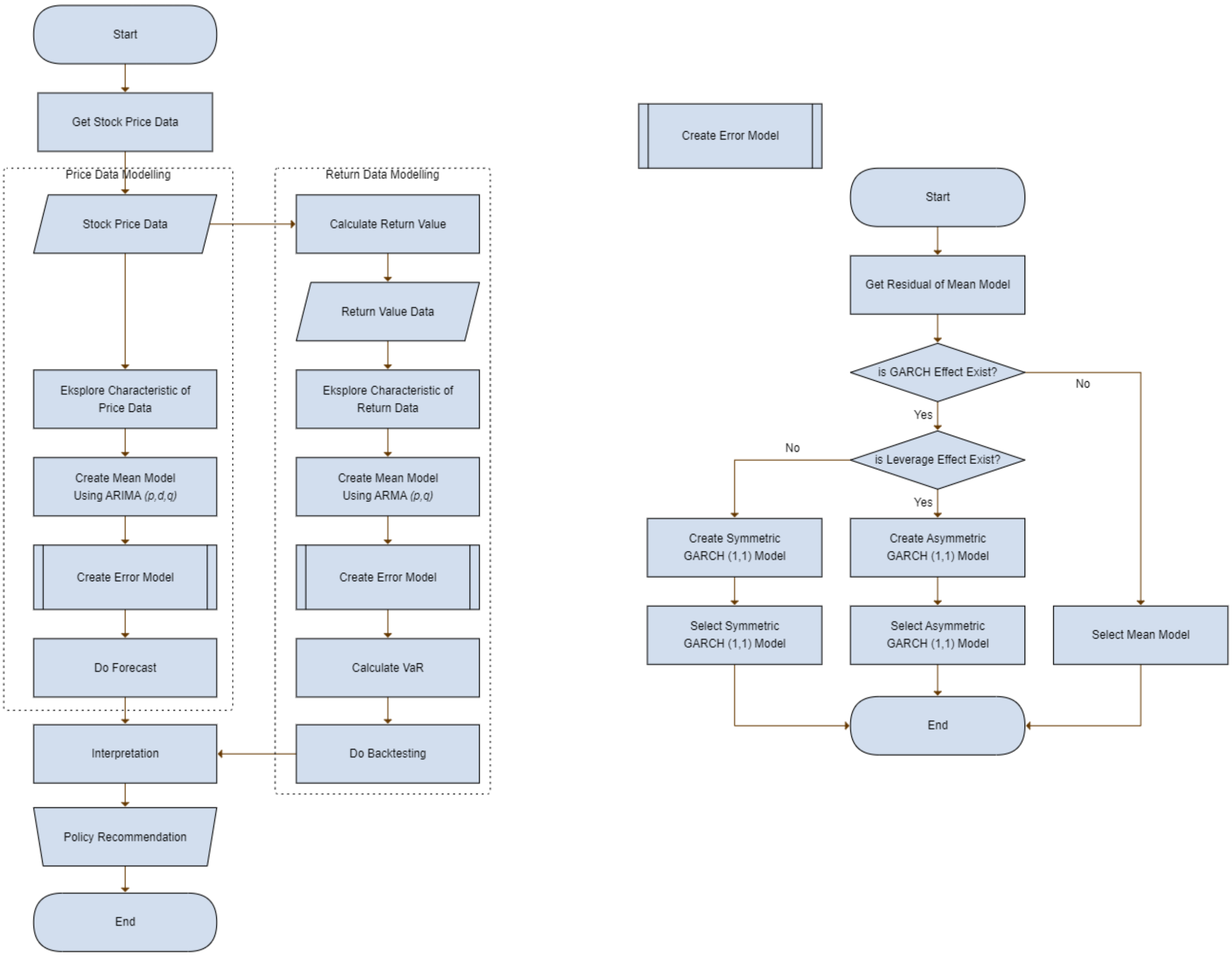

Figure 1. Flowchart of Research (source: Authors' Document)

3. RESULTS AND DISCUSSION

3.1 Stock Price Modelling

The price movement graphs of four Islamic banking stocks in Indonesia—BRIS, BTPS, BANK, and PNBS—are presented in **Figure 2**. Overall, the graphs indicate a price spike in early 2021 for BRIS, BTPS, and BANK, followed by a decline. The historical prices of BTPS and BANK show a downward trend from late 2021 to July 2024. Similarly, PNBS's stock price has declined since 2022, with very low prices below IDR 100. In contrast, BRIS's stock price has exhibited an upward trend from 2022 until the end of the research period in July 2024. This situation highlights the uniqueness of each Islamic stock as a response to the economic conditions in Indonesia and globally.

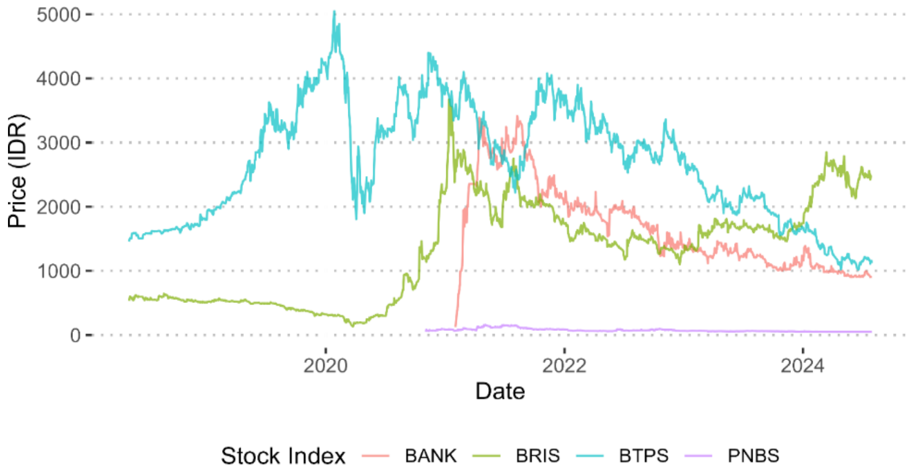

Figure 2. Volatility and Trends in Indonesian Sharia Banking Stocks

Table 2 presents the descriptive statistics of stock prices. For BRIS, BTPS, and BANK stocks, the skewness values are close to zero (0.27, 0.05, and 0.70), and the kurtosis values are near three (2.05, 1.98, and 2.64), indicating that the price distributions of these stocks tend to be approximately normal. However, for PNBS stock, the high skewness value (1.53) and kurtosis value (5.00) suggest a highly skewed and leptokurtic distribution, indicating significant deviations from normal distribution characteristics. Skewness reflects the asymmetry of the data distribution. If the distribution is positively skewed, it has a longer right tail. However, kurtosis measures the "tailedness" or the propensity for extreme values in the data. High kurtosis, indicative of a leptokurtic distribution, suggests a higher frequency of extreme values than a normal distribution. If the standard normality assumption is applied to data with high kurtosis, the model may underestimate the likelihood of extreme events, leading to unreliable risk and volatility assessments. Incorporating heavy-tailed distributions, such as the Student's t-distribution, allows the GARCH component to handle the clustering of extreme values better, ensuring more robust and realistic modelling of volatility dynamics. Addressing skewness and kurtosis in ARIMA-GARCH modelling ensures that the models accurately reflect the underlying data properties, leading to improved forecasts and more reliable insights.

Table 2. Statistic Descriptive of Stock Price Data

Stock Index	Stock Price			
	Mean	**St. Dev.**	**Skewness**	**Kurtosis**
BRIS	1293.70	770.26	0.27	2.05
BTPS	2694.93	891.62	0.05	1.98
BANK	1689.10	662.29	0.70	2.64
PNBS	75.11	24.47	1.53	5.00

The average value for each of the four stock prices was modeled using the ARIMA model. Using the Augmented Dickey-Fuller (ADF) test, the stationarity test for the mean indicated that only BNK datasets are stationary. Consequently, the data were differenced once and transformed. After differencing, each stock price was stationary in the mean, which showed a p-value of 0.01, which is less than the actual level of 0.05. ADF test results on each stock price are shown in **Table 3**.

Table 3. ADF Test Result in Each Stock Price

Stock Index	Price		Return	
	Statistic	***p*-value**	**Statistic**	***p*-value**
BRIS	-1.830	0.650	-11.124	< 0.01
BTPS	-1.987	0.584	-11.933	< 0.01
BANK	-6.293	< 0.01	-12.397	< 0.01
PNBS	-2.976	0.165	-9.681	< 0.01

The best ARIMA model was determined based on the lowest Akaike Information Criterion (AIC) value. The selection of the best model and the results of the residual assumption tests are summarized in **Table 4**.

Table 4. Best Model and Residual Diagnostic of Stock Price Model

Stock Index	ARIMA Order			Jarque-Bera Test (p-value)	Ljung-Box Test (p-value)	ARCH-LM Test	
	p	d	q			Lag	p-value
BRIS	1	1	0	< 0.001	0.975	1	< 0.001
						2	< 0.001
						3	< 0.001
						4	< 0.001
BTPS	0	1	2	< 0.001	0.995	1	< 0.001
						2	< 0.001
						3	< 0.001
						4	< 0.001
BANK	3	1	0	< 0.001	0.958	1	< 0.001
						2	< 0.001
						3	< 0.001
						4	< 0.001
PNBS	2	1	3	< 0.001	0.917	1	< 0.001
						2	< 0.001
						3	< 0.001
						4	< 0.001

Table 4 presents the results of the best ARIMA models and residual diagnostics for four stock indices: BRIS, BTPS, BANK, and PNBS. The residual diagnostics include the Jarque-Bera test for normality, the Ljung-Box test for autocorrelation, and the ARCH-LM test for heteroskedasticity. The ARIMA model order varies across the stock indices, with the parameters p, d, and q denoting the autoregressive, integrated, and moving average components, respectively.

The residual diagnostics in Table 4 indicate that the residuals of the ARIMA models for all stock indices do not follow a normal distribution, as shown by the Jarque-Bera test with p-values below 0.001. Additionally, the Ljung-Box test confirms that the residuals are free from autocorrelation, with p-values above 0.05 for all indices. However, the ARCH-LM test reveals significant heteroskedasticity, as the p-values are less than 0.001 across multiple lags, indicating that the variance of the residuals is not constant over time.

Based on the residual diagnostics results in Table 4, it can be concluded that the residuals of the ARIMA model do not follow a normal distribution, exhibit non-autocorrelation, and display heteroskedasticity, as indicated by the p-value < 0.001. In addition to not fulfilling residual diagnostics in the ARIMA model, the asymmetry of data characteristics is also a reason for modelling the Family GARCH. The next step is to model the residuals using the Family GARCH (1,1) approach, with the statistics presented in Table 5.

Table 5. Selection of the Best GARCH Model of Stock Price

Stock Index	Mean Model	Error Model	AIC	BIC
BRIS	ARIMA (1,1,0)	GARCH (1,1)	-0.057	-0.043
		GJR-GARCH (1,1)	-0.063	-0.045
		T-GARCH (1,1)	-0.848	-0.831
		N-GARCH (1,1)	-0.762	-0.744
		AP-ARCH (1,1)	**-0.862**	**-0.841**
BTPS	ARIMA (0,1,2)	GARCH (1,1)	-1.347	-1.329
		GJR-GARCH (1,1)	-1.352	-1.331
		T-GARCH (1,1)	-1.814	-1.794
		N-GARCH (1,1)	-1.772	-1.751
		AP-ARCH (1,1)	**-1.859**	**-1.834**
BANK	ARIMA (3,1,0)	GARCH (1,1)	5.091	5.124
		GJR-GARCH (1,1)	5.093	5.132
		T-GARCH (1,1)	5.471	5.510
		N-GARCH (1,1)	**4.950**	**4.989**
		AP-ARCH (1,1)	4.951	4.996
PNBS	ARIMA (2,1,3)	GARCH (1,1)	-4.446	-4.404
		GJR-GARCH (1,1)	-4.444	-4.396

Stock Index	Mean Model	Error Model	AIC	BIC
		T-GARCH (1,1)	-4.696	-4.648
		N-GARCH (1,1)	**-4.752**	**-4.704**
		AP-ARCH (1,1)	-4.745	-4.692

Table 5 presents the results of the Family GARCH (1,1) model analysis for the four stock datasets, indicating variations in model fit. The BRIS stock is modeled using ARIMA (1,1,0) AP-ARCH (1,1), while BTPS is modeled with ARIMA (0,1,2) AP-ARCH (1,1). The BANK stock is represented by ARIMA (3,1,0) N-GARCH (1,1), and PNBS is modeled with ARIMA (2,1,3) N-GARCH (1,1). The estimated parameters are presented in **Table 6**.

Table 6. Parameter Estimation of ARIMA-GARCH Model of Stock Price

Terms	Dependent Variable: P_t			
	BRIS	BRIS	BRIS	BRIS
Mean Model				
ϕ_1	**0.041 (0.001)**		-0.050 (0.037)	**-0.155 (0.041)**
ϕ_2			-0.063 (0.035)	**-0.716 (0.045)**
ϕ_3			-0.044 (0.036)	
θ_1		**0.057 (0.001)**		-0.085 (0.060)
θ_2		**0.009 (0.000)**		**0.711 (0.039)**
θ_3				**-0.248 (0.040)**
Error Model				
ω	**0.005 (0.003)**	**0.013 (0.002)**	0.160 (0.108)	**0.000 (0.000)**
α	**0.069 (0.015)**	**0.059 (0.003)**	**0.030 (0.010)**	**0.209 (0.023)**
β	**0.938 (0.016)**	**0.924 (0.004)**	**0.892 (0.019)**	**0.653 (0.004)**
λ	**0.502 (0.062)**	**0.318 (0.025)**	**4.000 (0.337)**	**2.977 (0.062)**
η_1	-0.108 (0.127)	0.181 (0.119)		
Goodness of Fit Model				
Number of Observations	1532	1532	844	904
AIC	-0.9	-1.9	5	-4.8
BIC	-0.8	-1.8	5	-4.7
RMSE	0.419	0.514	3.769	0.202
MAE	0.121	0.089	2.26	0.031

**the value in parentheses represents the standard error value*
***bold text indicates statistically significance at the 5% level*

Table 6 presents the estimation of ARIMA-GARCH parameters for the four stock prices. The mean model for BRIS and BTPS stock prices indicates that AR and MA parameters significantly impact the model, with the values of ϕ and θ exhibiting several significant signs. Specifically, the parameter ϕ_1 for BRIS is significant with a positive value (0.041), while θ_1 and θ_2 for BTPS are significant with positive (0.057) and negative (0.009) signs, respectively. For error model, by the AP-ARCH model approximation, the values of α (0.069 and 0.059) and β (0.938 and 0.924) refers to stability and volatility shifts for both stocks. In addition, BANK and PNBS by the ARIMA-N-GARCH model give varying results. BANK has significant values for α (0.030) and β (0.892) which indicates that the short-term of past volatility continues affecting the present period. Meanwhile, statistic λ (4.000) indicates data has extremely high volatility. However, PNBS shows that α (0.209) and β (0.653) are significant which means it also has short-term volatility even its effect lower than BANK. The goodness of fit concludes that the model fits well with small AIC and BIC as well as RMSE and MAE. The small values of Goodness of Fit indicators mean the model can forecast the actual precisely (see **Figure 3**).

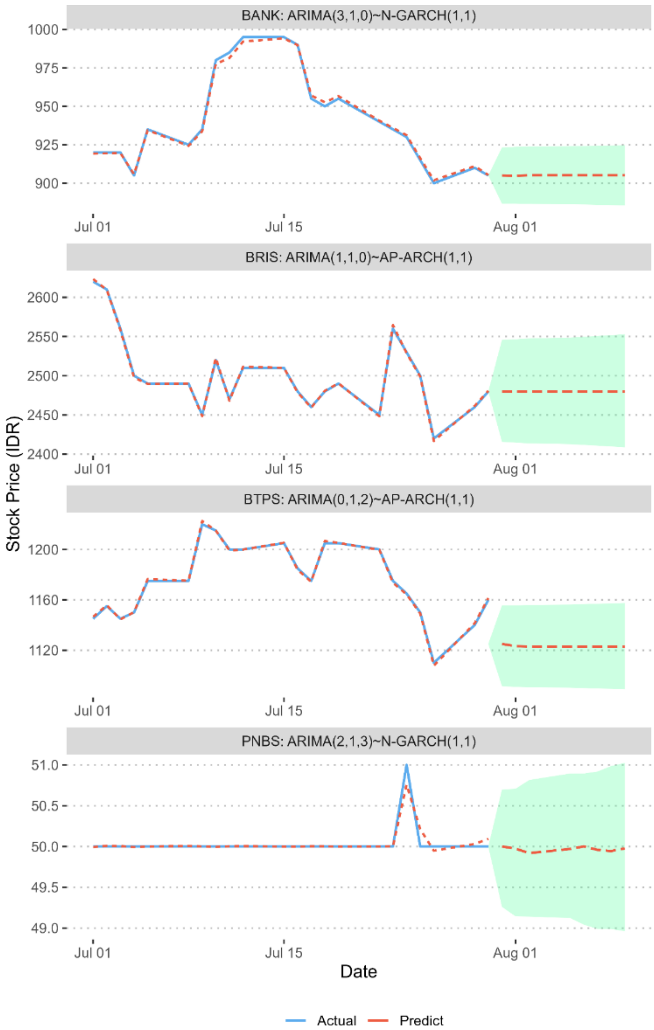

Figure 3. Comparison of Actual Price and Predicted Value and Forecasting Results

The visualization of forecast results for the next ten days (July 31, 2024- August 9, 2024) can be seen in **Figure 3**. Between July 31, 2024, and August 9, 2024, BANK, BRIS, BTPS, and PNBS stock prices displayed distinct trends. BANK experienced a slight increase, with its stock price rising marginally from IDR 904.869 to IDR 905.079, indicating a stable upward trend. BRIS remained constant at IDR 2480.000 throughout the period, showcasing no price movement. BTPS initially showed a minor decrease, dropping from IDR 1123.137 to IDR 1122.799, after which it stabilized. In contrast, PNBS exhibited some fluctuation, starting at IDR 49.973, dipping slightly to IDR 49.919, and then recovering to IDR 49.982. The forecasting is represented by the dashed line and the shaded green area on the graph, which provide a visual representation of the model's confidence level/prediction range. It has been proved that the developed model effectively captures the dynamics of the stock prices, though the forecasts are stable, with small volatility for each stock. The ARIMA causes this small volatility of the forecast mean model, which has a short-term effect **[51]** and Islamic bank stocks have more excellent stability cause they can be predicted based on our model and also in line with the implementation of Islamic principles in stock investment **[52]**, **[53]**.

Stable stock price forecasts can be a consideration for financial policy decisions for policy-makers and investors in navigating stock market dynamics to encourage an investment environment that leads to enhanced investor confidence, secures safer investment, offers consistent returns, and promotes more inclusive economic growth. In addition, stability reduces the long-term planning risks and capital investment, which is essential for sustainable business growth and development **[54]**, **[55]**.

3.2 Return Value Modelling

Figure 4 illustrates the log-return of the four stocks which show evidence of volatility. In early 2020, shock of return as the effect of COVID-19 can be found in both BRIS and BTPS. Moreover, in the middle of 2022, the Ukraine conflict greatly affected the economy, leading to global financial market shock **[56]**. The "shock" caused by the war was a significant factor in slowing economic growth to 3.1 percent in 2022 and is also why the OECD predicted it would further decline to 2.2 percent in 2023. According to the report, the war has had its most severe impact on Europe's economy, where growth in 2023 is expected to be a mere 0.3 percent [57].

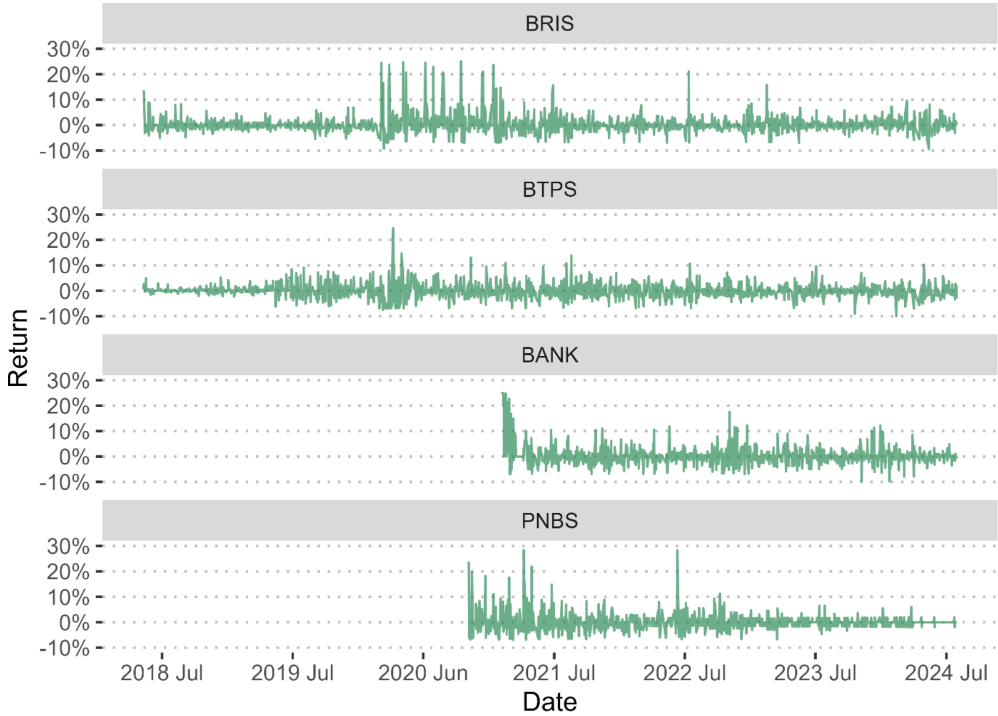

Figure 4. Volatility and Trends of 4 Sharia Banking Stocks' Return Value

Table 7 shows that the stock returns for BRIS, BTPS, BANK, and PNBS exhibit low mean values with varying degrees of volatility, as indicated by their standard deviations. The return distributions are positively skewed, particularly for BRIS, BANK, and PNBS, while BTPS has moderate skewness. High kurtosis values across all indices indicate leptokurtic distributions, suggesting the presence of fat tails and potential extreme returns. Overall, the series is stationary in both mean and variance, as confirmed by the Box-Cox method.

Table 7. Statistic Descriptive of Return Value Data

Stock Index	Stock Price			
	Mean	**St. Dev.**	**Skewness**	**Kurtosis**
BRIS	0.0016	0.036	2.72	18.62
BTPS	0.0002	0.029	1.14	10.60
BANK	0.0033	0.045	2.98	18.76
PNBS	0.0007	0.038	2.92	21.20

Table 8 provides the results of the best ARMA models and their residual diagnostics for the return values of four stock indices: BRIS, BTPS, BANK, and PNBS. The ARMA model parameters represent the autoregressive and moving average components, respectively. The residual diagnostics of the ARMA models highlight significant statistical findings. The errors from the four ARMA models exhibit ARCH effects, as confirmed by the LM test. Additionally, the residuals display a non-normal distribution, indicated by the Jarque-Bera test, while the Ljung-Box test reveals the absence of autocorrelation. These findings suggest that the basic ARMA models are insufficient for capturing the underlying volatility characteristics of the data, necessitating the development of a more sophisticated model to account for the ARCH effects present in the residuals.

The residuals derived from the ARMA models can be used as input for constructing Family GARCH models. These models are designed to handle the time-varying volatility and heteroskedasticity identified by the ARCH-LM test, providing a more sophisticated approach that captures the underlying volatility structure of the data. By incorporating GARCH models, we can better account for the dynamic nature of the residuals, improving the overall model fit and predictive accuracy.

Table 8. Best Model and Residual Diagnostic of Return Value Model

Stock	ARMA Order		Jarque-Bera Test	Ljung-Box Test	ARCH-LM Test	
	p	*q*	(*p*-value)	(*p*-value)	Lag	*p*-value
BRIS	1	1	< 0.001	0.916	1	< 0.001
					2	< 0.001
					3	< 0.001
					4	< 0.001
BTPS	0	2	< 0.001	0.990	1	< 0.001
					2	< 0.001
					3	< 0.001
					4	< 0.001
BANK	2	0	< 0.001	0.104	1	< 0.001
					2	< 0.001
					3	< 0.001
					4	< 0.001
PNBS	4	0	< 0.001	0.822	1	< 0.001
					2	< 0.001
					3	< 0.001
					4	< 0.001

Family GARCH modelling, both symmetric and asymmetric, illustrated in Table 9. These GARCH models are specifically designed to capture the volatility clustering and time-varying nature of financial time series data. By utilizing the residuals, the GARCH models aim to provide a more accurate representation of the data's behavior, allowing for better risk assessment and forecasting capabilities. This approach enhances the robustness of the analysis, ultimately leading to improved insights into the dynamics of the financial series being studied.

Table 9. Selection of the Best Family GARCH Model of Return Value

Stock Index	Mean Model	Error Model	AIC	BIC
BRIS	ARMA (1,1)	GARCH (1,1)	-4.283	-4.262
		GJR-GARCH (1,1)	-4.297	-4.272
		T-GARCH (1,1)	-4.238	-4.214
		N-GARCH (1,1)	-4.286	-4.261
		AP-ARCH (1,1)	**-4.317**	**-4.289**
BTPS	ARMA (0,2)	GARCH (1,1)	-4.518	-4.497
		GJR-GARCH (1,1)	-4.532	-4.508
		T-GARCH (1,1)	**-4.547**	**-4.523**
		N-GARCH (1,1)	-4.542	-4.517
		AP-ARCH (1,1)	-4.546	-4.518
BANK	ARMA (2,0)	GARCH (1,1)	-3.900	-3.867
		GJR-GARCH (1,1)	-3.900	-3.861
		T-GARCH (1,1)	-3.619	-3.580
		N-GARCH (1,1)	**-3.982**	**-3.943**
		AP-ARCH (1,1)	-3.978	-3.933
PNBS	ARMA (4,0)	GARCH (1,1)	-4.191	-4.148
		GJR-GARCH (1,1)	-4.191	-4.143
		T-GARCH (1,1)	-3.968	-3.920
		N-GARCH (1,1)	**-4.233**	**-4.185**
		AP-ARCH (1,1)	-4.230	-4.177

**Bold text indicates the best model based on AIC and BIC values*

Table 9 shows that the Asymmetric GARCH models have lower AIC and BIC values than the Symmetric GARCH models. BRIS is modeled by AP-ARCH, BTPS by T-GARCH, and BANK and N-GARCH models PNBS. The AP-ARCH model is well-suited for long-term volatility forecasting due to its sensitivity to past shocks and ability to capture persistent volatility patterns. The T-GARCH model excels in short-term volatility forecasting by effectively capturing leverage effects and asymmetries. The N-GARCH model offers a nonlinear approach that can be applied to short-term and long-term volatility forecasting, depending on the specific market conditions and data characteristics [58], [59]. The estimated parameters used to model the return values are presented in Table 10.

Table 10. Parameter Estimation of ARMA-Family GARCH Model of Return Value

Terms	Dependent Variable: R_t			
	BRIS	BTPS	BANK	PNBS
Mean Model				
μ	0.000 (0.001)	0.000 (0.000)	-0.001 (0.001)	0.000 (0.000)
ϕ_1	**-0.641 (0.203)**		-0.051 (0.042)	**-0.146 (0.042)**
ϕ_2			-0.054 (0.039)	-0.009 (0.042)
ϕ_3				-0.029 (0.041)
ϕ_4				**-0.093 (0.043)**
θ_1	**0.670 (0.195)**	0.010 (0.031)		
θ_2		**-0.062 (0.027)**		
Error Model				
ω	0.000 (0.000)	**0.001 (0.000)**	0.000 (0.000)	0.000 (0.000)
α	**0.032 (0.001)**	**0.104 (0.016)**	**0.081 (0.024)**	**0.064 (0.011)**
β	**0.920 (0.005)**	**0.906 (0.015)**	**0.653 (0.018)**	**0.895 (0.021)**
λ	**3.423 (0.187)**		**3.994 (0.049)**	**2.977 (0.041)**
η_1	**0.205 (0.029)**	**0.246 (0.075)**		
Goodness of Fit Model				
Number of Observations	1531	1531	**843**	903
AIC	-4.3	-4.5	-4	-4.2
BIC	-4.3	-4.5	-3.9	-4.2
RMSE	0.036	0.029	0.046	0.038
MAE	0.021	0.02	0.026	0.022

**The value in parentheses indicates the standard error value*
bold text indicates significance at the 5% level

Table 10 shows that BRIS modelled by ARMA (1,1) AP-ARCH (1,1) with mean model parameters are ϕ_1 (-0.641) and θ_1 (0.670) as well as error model parameters are α (0.032) and β (0.920). This BRIS is also indicated existence of leverage effect based on significant λ (3.423). Furthermore, BTPS is fitted by ARMA (0,2) T-GARCH (1,1) with θ_2 (-0.062), α (0.104) and β (0.906) indicating substantial changes in volatility. The rotation parameter (η_1) for both BRIS and BTPS are significant. BANK and PNBS are modelled by the ARMA (2,0) N-GARCH (1,1) and ARMA (4,0) N-GARCH (1,1) respectively. Both models have λ (3.994 and 2.997), revealing a strong leverage effect. In general, Table 10 also shows the goodness-of-fit of the chosen models have small AIC and BIC as well as RMSE and MAE means the constructed models are adequate well capturing volatility of historical data.

Figure 5 displays the visualization of the example of VaR at the 2.5% and 5% levels for the four stocks, with red lines for 5% VaR and blue lines for 2.5% VaR. The grey dots represent actual returns, the blue dots represent returns that exceed the 2.5% VaR threshold, and the red dots denote returns that exceed the 5% VaR threshold but do not surpass the 2.5% VaR threshold. Both red and blue dots represent overpredicted losses, necessitating greater risk management attention. If the exceedance rates—where actual returns fall below the Value at Risk (VaR) thresholds—are higher than expected, the model underestimates the risk associated with the portfolio or individual stocks. This underestimation could imply that the assumed distributions of returns, model parameters, or historical data used to calculate the VaR may not adequately capture the actual risk dynamics.

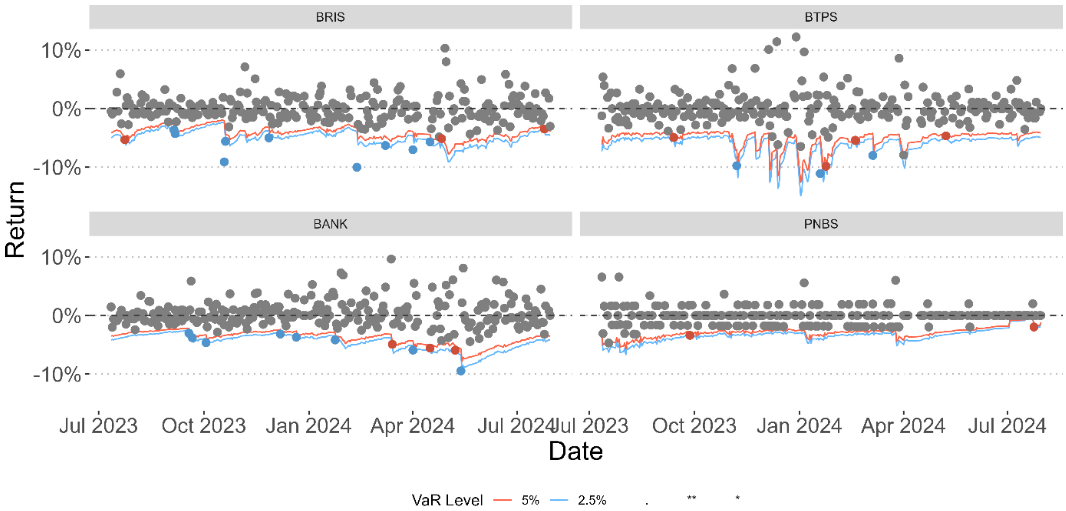

Figure 5. **Value at Risk 5% and 2.5% of ARMA-Asymmetric GARCH Model**

Backtesting was conducted using Kupiec's Proportion of Failures (POF) test to evaluate the accuracy of the VaR calculations in predicting extreme losses. The Kupiec's POF test was performed using an in-sample dataset of 250 observations. Table 9 presents the results of the Kupiec test for various VaR levels and concludes that the chosen model for each stock is well-implemented to predict VaR.

Table 11. **Kupiec Test Results for Different VaR Levels Across Stocks**

Stock	VaR 5%			VaR 2.5%			VaR 1%		
	No. of Exc.	Stat. test	*p*-value	No. of Exc.	Stat. test	*p*-value	No. of Exc.	Stat. test	*p*-value
BRIS	12	0.021	0.116	9	1.095	0.705	4	0.769	0.620
BTPS	7	3.009	0.917	3	2.139	0.856	3	0.095	0.242
BANK	11	0.197	0.343	8	0.462	0.503	1	1.176	0.722
PNBS	2	14.127	> 0.999	0	12.659	> 0.999	0	5.025	0.975

4. CONCLUSIONS

This study applied advanced GARCH family models and Value at Risk (VaR) analysis to forecast stock prices and assess investment risk in four major Islamic banks in Indonesia: BANK, BRIS, BTPS, and PNBS—as evidenced by the fitted value graphs closely mirroring the actual values. The results demonstrate that the GARCH family models effectively capture the volatility dynamics of Shariah-compliant stock prices, providing accurate 10-day forecasts. For example, BRIS remained constant at IDR 2480.000 throughout the period, showcasing no price movement from 31 July 2024 to 9 August 2024. Both symmetric and asymmetric GARCH models were used to account for volatility clustering and the leverage effect, which are prominent features of financial time-series data. The findings reveal that:

a. BRIS and BANK exhibited more stable stock price trends with lower volatility, as modeled by ARIMA-APARCH and ARIMA-NGARCH, respectively.

b. BTPS and PNBS exhibit higher volatility than BRIS and BANK primarily due to their smaller size, lower market liquidity, higher risk exposure, and sensitivity to market sentiment and regulatory changes. These factors make their stock prices more reactive to positive and negative news, leading to more significant fluctuations. Reflecting the dynamic nature of their stock price movements, they were best modeled using ARIMA-TGARCH and ARIMA-NGARCH.

c. The VaR analysis indicated that all four stocks offer a relatively stable investment environment, with well-calibrated models successfully predicting the risk of losses at various confidence levels.

These results offer valuable insights for investors seeking to optimize portfolio management and manage risk based on their risk appetite. By applying these models, investors can better anticipate market conditions, manage risks, and implement strategies to promote sustainable growth in Islamic banking stocks.

The broader implications of this study are that accurate stock price forecasts and risk management techniques, such as GARCH and VaR, can enhance investor confidence in Islamic bank stocks. These tools contribute to fostering more transparent, stable, and resilient Islamic bank stocks, supporting development in banking stocks that become conditionally applied to other stocks, provided they exhibit the same volatility characteristics as our data. The data may require separate analysis and appropriate modelling even if fluctuations occur due to regulations, economic changes, or other factors if the volatility pattern differs.

In many situations, volatility changes over time, and such volatility may occur in our data. The standard GARCH model may not accommodate these changes in each regime. As proposed by **[60]** and implemented by **[61]**, **[62]**, and **[63]**, the Markov-Switching GARCH (MS-GARCH) model can capture the changing parameters of the model due to shifts in volatility levels across different regimes. Therefore, to effectively capture volatility based on regimes, such as local government regulations, global economic changes, and other factors clustering volatility, we consider using Markov-Switching within the GARCH family of models.

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