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Comparison of black-scholes models using historical volatility and garch volatility in collar strategy as hedging efforts for towr and tbig stocks

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Abstract

Purpose: This study aims to examine the implementation of option contracts using the Black-Scholes model with Historical Volatility and GARCH Volatility through a collar strategy, as a means of protecting stock value in the telecommunications sector. The research focuses on managing risk in stock investments, particularly for TOWR and TBIG stocks, in both crisis and non-crisis conditions.

Research methodology: The study applies the Black-Scholes model using two types of volatility—Historical and GARCH—within a collar strategy framework to evaluate its effectiveness in mitigating risks associated with TOWR and TBIG stocks under varying market conditions.

Results: For TOWR stocks, GARCH performs better in non-crisis conditions with three-month maturity, while Historical Volatility is superior in some shorter-maturity scenarios under both market conditions. For TBIG stocks, GARCH outperforms in all crisis scenarios with three-month maturity, whereas Historical Volatility leads in certain stable, short-term conditions.

Conclusion: The effectiveness of volatility methods in the Black-Scholes model depends on stock type, market conditions, and maturity, with GARCH better for high volatility and longer terms, while Historical suits stable, short-term scenarios.

Limitation: The study is limited to two telecommunications stocks and does not include empirical testing using live trading data, which could provide deeper validation of the proposed strategies.

Contribution: This research contributes to the understanding of how investment strategies like collar options can be optimized using appropriate volatility models. Investment involves the allocation of money or capital with the aim of gaining profit.

Keywords: *Black-Scholes, Collar, GARCH Volatility, Historical Volatility, Option Contract*

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1. Introduction

Telecommunications is any transmission, delivery, and/or reception of information in the form of signs, signals, writing, images, sounds, and voices through wire, optical, radio, or other electromagnetic systems. Telecommunication Towers are structures designed to support telecommunication equipment constructed in accordance with the requirements of telecommunication service providers. To reach locations that are not covered by existing telecommunication networks, telecommunication infrastructure, specifically Telecommunication Towers, is essential. Consequently, companies operating in the telecommunications infrastructure sector continue to grow. Hence, investing in stocks in the telecommunications infrastructure industry is still viable. Investing in stocks can yield high profits, but also carries the potential for significant losses. Therefore, hedging strategies in stock investments are necessary to minimize potential losses while still securing profits (Afifah, Hasanah, & Irfany, 2023; Parela, Hudalil, Ariswandy, & Pradana, 2022; Premananda & Risadi, 2023; Rahmawati & Hadian, 2022; Suaduon, Syarif, & Nugraha, 2020; Syarif, Rumengan, & Gunawan, 2021).

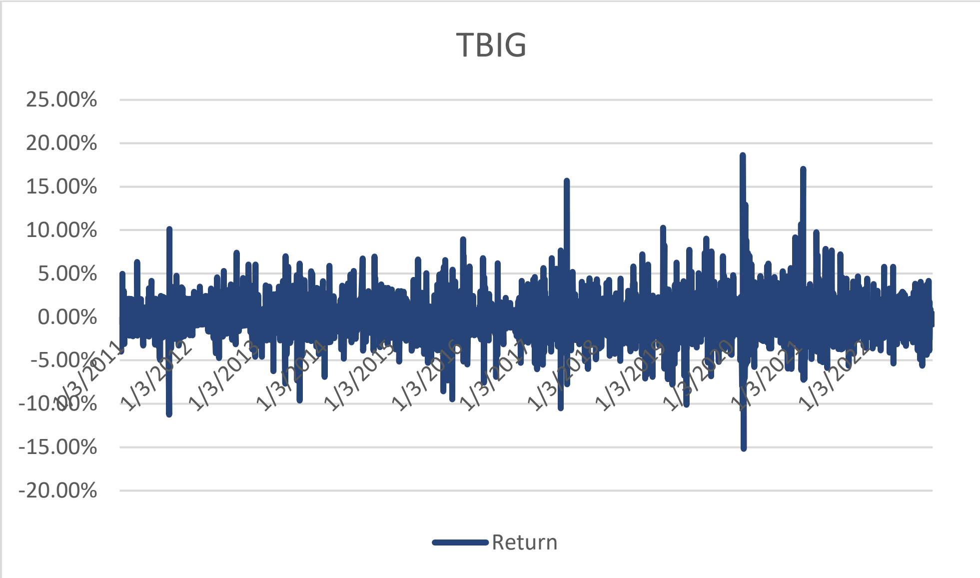


Figure 1. TBIG Return Stocks 2011-2022

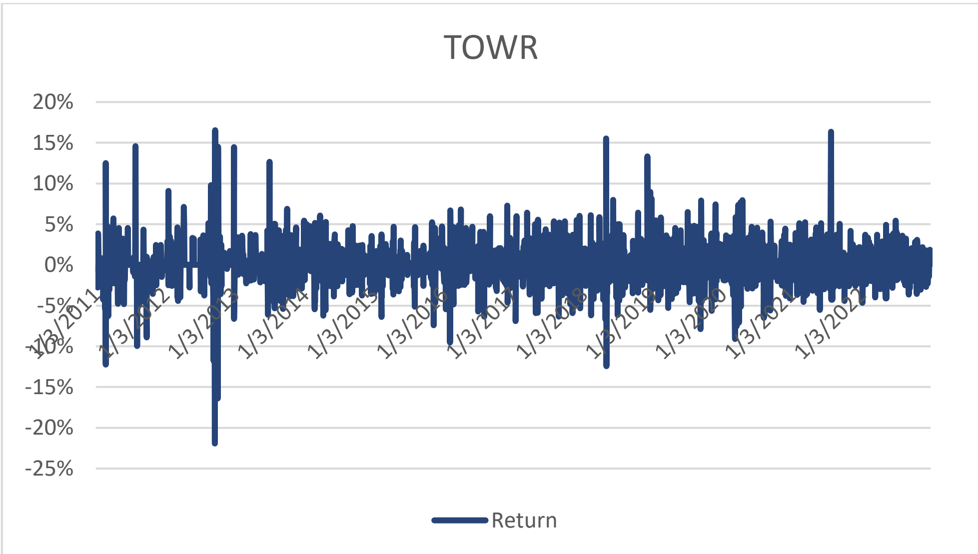


Figure 2: TOWR Return Stocks 2011-2022

The yield values for TBIG and TOWR stocks are illustrated in Figures 1 and 2. From the figures, it can be observed that the maximum profit achieved is 18.64% with a maximum loss of -15.18% for the TBIG stock. For the TOWR stock, the maximum profit is 16.54%, while the maximum loss is -21.92%. With such a wide range of yield values, hedging is necessary to minimize losses while achieving defined profits. This study employs option contracts as hedging mechanisms. This research delves into the calculation of calls using the Black-Scholes model with historical volatility and the Black-Scholes model with GARCH volatility, utilizing a collar strategy. According to (Eun, 2010) the collar strategy is a combination of a covered call option and protective put option. The collar strategy offers limited profit potential, but provides hedging at a low cost or even at no cost if the purchase price of put options equals the selling price of call options.

2. Literature Review

Hendrawan and Arifin (2023) investigated the implementation of option contracts using Black-Scholes and GARCH models on the Jakarta Islamic Index with a collar strategy. GARCH was employed to determine the volatility variance in the Black-Scholes calculations, which were then compared to calculations using historical volatility. During a crisis, options with GARCH and collar strategies yielded an average profit of 3.07% for 1-month options and 7.01% for 3-month option contracts. In non-crisis periods, options with GARCH Volatility and collar strategy resulted in an average profit higher by 0.16% for 1-month options but decreased by 1.45% for 3-month option contracts. The collar strategy produced maximum volatilities of 12.71%, 15.18%, and 17.14%, respectively. It was also found that the GARCH model outperformed the Black-Scholes model based on AMSE values during a crisis for 1-month and 3-month options, as well as in non-crisis for 1-month options.

Hendrawan, Laksana, and Aminah (2020) and Syarif and Riza (2022) examined IHSG volatility from to 2009-2018 using the Long Strangle strategy and tested its accuracy with AMSE on two historical volatility models: the Black-Scholes model and the GARCH volatility model based on the ARIMA lag model. The research indicated that the GARCH model was more accurate than Black-Scholes for 1-month and 2-month call options with results of 0.26% and 0.92%, respectively, whereas for 1-month and 2-month put options, the Black-Scholes model was more accurate with values of 0.18% and 0.26%, respectively. For a 3-month timeframe, both put and call options were more accurately predicted by Black-Scholes with values of 2% and 0.31%, respectively.

Isynuwardhana and Surur (2018) conducted a study and analysis of the return rates of option contracts using long straddle and long-strangle strategies and concluded that the long straddle strategy was significantly more profitable. According to Lee and Kim (2015), the collar strategy can be used as a hedging strategy. Basson, Van den Berg, and Van Vuuren (2018) stated that the zero-cost collar (ZCC) and long butterfly (LB) strategies yielded the best returns on an index with moderate volatility and good performance. According to Eun (2010) the collar strategy is a combination of a covered call option and protective put option. The collar strategy provides limited profit potential but offers hedging at a low or no cost if the purchase price of put options is the same as the selling price of call options (Mas'adah, Asngadi, & Hirmantono, 2021; Rumengan, Syarif, Rumengan, & Wibisono, 2020; Suharto, Ningsih, & Ali, 2022; Suharto & Yuliansyah, 2023).

3. Methodology

3.1 Option Theory

Options include derivative instruments aimed at granting the right to exchange assets in the future at predetermined rates of price, time, and quantity. A call option provides the right to purchase shares within a specified period at an agreed upon time and price. Call options are used when the current stock price is higher than the agreed upon price. On the contrary, a put option grants the right to sell a certain number of shares at an agreed-upon time and price. The buyer of the put option holds the right to sell shares, while the seller of the option has an obligation to buy shares. Put options are utilized when the current stock price is lower than the agreed-upon price (Suharto, Japlani, & Ali, 2021; Yahya & Yani, 2023).

3.2 Volatility

Volatility is the degree of price fluctuation in a stock or security over time. Volatility can be considered when calculating the probability or risk of a stock. High volatility indicates high risk, whereas low volatility indicates low risk for that stock. Historical Volatility and Implied Volatility are types of volatility (Shettima, Abdussalam, & Olayinka, 2023). Implied Volatility provides an outlook on a stock's future based on investors' perspectives. Historical Volatility represents the price variance of an asset over a specific period. The volatility can be calculated as follows:

$R_t = LN\left(\frac{S_t}{S_{t-1}}\right)$…………………………….…………………………….. (1)

Next, we calculated the average daily price change (R_m) over a specific period (n).

$R_m = \frac{\sum n\, R_t}{n}$………………………….…………………………...…. (2)

Next, we determined the average variation in daily price changes (standard deviation).

$HV = \sqrt{\frac{\sum(R_t - R_m)^2}{n-1}}$……………………………….……………...…… (3)

Next, we calculate the annual historical volatility as a percentage, multiplied by the square root of 252 (the average number of trading days in a year).

$annual\ HV = \sqrt{252} * HV$……………………….……………….... (4)

3.3 *GARCH Volatiltiy*

GARCH (Generalized Autoregressive Conditional Heteroscedasticity) model is an extension of the ARCH (Autoregressive Conditional Heteroscedasticity) model. This model was developed to avoid excessively high orders in the ARCH model, as proposed by (Engle & Bollerslev, 1986) emphasizing parsimony or selecting simpler models to ensure positive variance. The ARCH/GARCH model was used to model time-varying risk. The GARCH model, first developed from the ARCH model introduced by (Engle & Bollerslev, 1986) to address issues with the ARCH model.

Autoregressive (AR) conditions have several requirements, such as data stationarity, where the data are around the mean line or have a constant mean of the observation variance. Stationarity can be tested using the augmented Dickey–Fuller (ADF) test, ensuring that the data are not far from the mean line on the graph. In this model, conditional variance is influenced by past residuals and lagged conditional variance (Hardianti & Widarjono, 2017). The GARCH model can be explained as follows:

$\sigma_t^2 = \alpha_0 + \alpha_1 e_{t-1}^2 + \cdots + \alpha_p e_{t-p}^2 + \lambda_1 \sigma_{t-1}^2 + \cdots + \lambda_q \sigma_{t-q}^2$………………….(5)

Where:

p = represents the ARCH component

q = represents the GARCH component

$et{-}p$ = variable from p periods ago.

The time period that influences the model is limited to the GARCH model.

Engle and Bollerslev (1986) proposed GARCH (1,1) modeling in volatility modeling with σ_n^2 calculated from the long-term average variance level, V_L, also from σ_{t-1}^2 and u_{n-1}. According to (Capiński & Kopp, 2012), the GARCH (1,1) equation is as follows:.

$\sigma_n^2 = \gamma V_L + \alpha u_{n-1}^2 + \beta \sigma_{n-1}^2$……………….………………………………..(6)

If γ represents V_L, α represents u_{n-1}^2, and β represents σ_{n-1}^2, then the overall constants follow the following equation:

$\gamma + \alpha + \beta = 1$…………………………….……………….………….....…....(7)

In GARCH (1,1), it indicates that σ_n^2 is based on the latest observation of u^2 and the latest estimate of the variance level. The more general GARCH (p,q) model calculates σ_n^2 from p observations on u^2 and the latest q estimates of the variance level. If it is specified that ω= γV_L, then the GARCH (1,1) model can be written as:

$\sigma^2 = \omega + \alpha u_{n-1}^2 + \beta \sigma_{n-1}^2$ ……………………………………………….(8)

After ω, α, and β are estimated, you can then calculate γ as $1 - \alpha - \beta$. The long variance V_L can be calculated as ω⁄γ. For a stable GARCH process, it will satisfy the equation $\alpha + \beta < 1$.

3.4 *Black Scholes Model*

The Black-Scholes model serves as the basis for determining the fair pricing of both call and put options. The Black-Scholes model utilizes six variables to determine an option's price, including volatility, option type, stock price, time, strike price, and risk-free interest rate. According to (Capiński & Kopp, 2012), the Black-Scholes equation for a call option is as follows:

$C = SN(d1) - e^{-RfT}\, XN(d2)$……………………………………………...(9)

The formula for the put option is as follows:.

$P = Xe^{-RfT}\,N(-d2) - SN(d1)$……….…………………………………….(10)

$d1 = \left(\ln \frac{[S/X]+\left[Rf-\frac{\sigma^2}{2}\right]}{\sigma\sqrt{T}}\,T\right)$……………………….……………………….(11)

$d2 = d1 - \sigma\sqrt{T}$……..…………………………………………………..(12)

Where:
S = Spot stock price
X = Exercise/execution price
T = Time to maturity
Rf = Risk-free interest rate
σ = Stock price variance/volatility
N = Cumulative standard normal distribution

3.5 Collar Strategy

According to Eun (2010) the collar strategy is a combination of buying underlying stocks/indices, covered call options, and protective put options. This option limits both positive and negative returns and serves as a useful tool to mitigate high price volatility and achieve a more stable price. The collar option strategy is executed by simultaneously buying put options and selling call options on held stock. A payoff diagram for the collar option is shown in Figure 3.

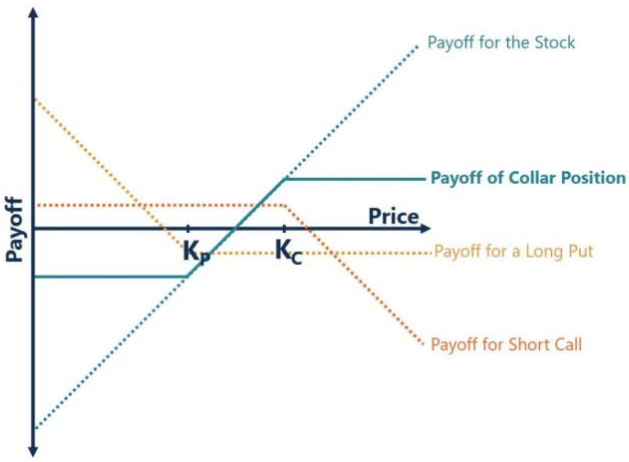


Figure 3. Payoff diagram of the collar strategy

A put option provides profits when the stock price in the market is lower than the put option's strike price (KP), because the stock price is protected from significant declines. Meanwhile, stock profits are limited to the strike price of the call option (KC) because the call option is exercised only if the market price is higher than KC. The collar strategy offers limited profits, but provides hedging at a low cost or even at no cost if the purchase price of put options is the same as the selling price of call options.

4. Results and discussions

4.1 Descriptive Data Characteristics

In this study, closing stock price data for TOWR and TBIG were obtained from finance.yahoo.com for the period 2011-2022. Below is an example of closing stock price data used.

Table 1. Closing Stock Prices for TOWR

Date	Close Price
1/3/2011	259
1/4/2011	255
1/5/2011	259

1/6/2011	258
1/7/2011	260
1/10/2011	257
1/11/2011	258
1/12/2011	251
1/13/2011	250
1/14/2011	260
1/17/2011	260
1/18/2011	258
1/19/2011	258

Table 2. Closing Stock Price for TBIG

Date	Close Price
1/3/2011	259
1/4/2011	255
1/5/2011	259
1/6/2011	258
1/7/2011	260
1/10/2011	257
1/11/2011	258
1/12/2011	251
1/13/2011	250
1/14/2011	260
1/17/2011	260
1/18/2011	258
1/19/2011	258

4.2 *Results of Historical Volatility Calculation*

1. Calculating Historical Volatility of TOWR Stock for a 1-month Period

The calculation of Historical Volatility is based on daily price changes in the stock market, where Rt is the natural logarithm of today's stock price (St) divided by the previous day's stock price (St-1). The data used for the 1-month period calculation were from January 3, 2011, to November 30, 2022.

If on January 4, 2011, the stock price (S_t) is 259 and the previous day's stock (S_{t-1}) is 255, then using the formula R_t is found to be $R_t = LN\left(\frac{259}{255}\right)$ = = -1.56%. After determining the value of R_t, the next step is to calculate the average daily price change (R_m) over a specified period (n) using the formula $R_m = \frac{\sum n\, R_t}{n}$, where $\sum$n R_t is the sum of R_t values in the data used. For a 21-day period, $R_m = \frac{\sum 21\, R_t}{21}$ = -0.000741.

Knowing the value of R_m, the Historical Volatility (HV) can be calculated with the formula $HV = \sqrt{\frac{\sum (R_t - R_m)^2}{n-1}}$. HV is obtained by summing the differences between R_t and R_m, squaring the sum, dividing it by the number of data points minus one, and then taking the square root. The resulting HV was 0.0129. The annual HV is obtained by multiplying this value by the square root of 252 (the average number of trading days in a year), giving an annual HV of 0.20516.

Table 3. shows the calculation of Historical Volatility for TOWR stock over a 1-month period

Date	Price Close	Rt	Rm	Rt - Rm	HV	annual HV
03/01/2011	259					
04/01/2011	255	-0.0156	-0,0007	-0,0148	0.0129	0.2051
05/01/2011	259	0.0156	-0,0007	0.0163	0.0129	0.2051
06/01/2011	258	-0.0039	-0,0007	-0.0031	0.0129	0.2051

07/01/2011	260	0.0077	-0,0007	0.0085	0.0129	0.2051
10/01/2011	257	-0.0116	-0,0007	-0.0109	0.0129	0.2051
11/01/2011	258	0.0039	-0,0007	0.0046	0.0129	0.2051

Source: Processed data

2. Calculating Historical Volatility for TOWR Stock - 3-month period

The same calculation is performed for a 3-month period using data from January 3, 2011, to September 30, 2022. The resulting values are presented in Table 4

Table 4 shows the calculation of Historical Volatility for TOWR stock over a 3-month period

Date	Closing Price	Rt	Rm	Rt - Rm	HV	annual HV
03/01/2011	259					
04/01/2011	255	-0.0156	0.00054	-0.0161	0.0317	0.5037
05/01/2011	259	0.0156	0.00054	0.0150	0.0317	0.5037
06/01/2011	258	-0.0039	0.00054	-0.0044	0.0317	0.5037
07/01/2011	260	0.0077	0.00054	0.0071	0.0317	0.5037
10/01/2011	257	-0.0116	0.00054	-0.0121	0.0317	0.5037
11/01/2011	258	0.0039	0.00054	0.0033	0.0317	0.5037

Source: Processed data

3. Calculating Historical Volatility for TBIG Stock - 1-month period

In calculating the Historical Volatility of TBIG stock for the 1-month period, the data used covers the period from January 3, 2011, to November 30, 2022. Subsequently, the calculation was performed following the procedure applied to the TOWR stock, yielding the following values:

Table 5. shows the calculation of Historical Volatility for TBIG stock over a 1-month period

Date	Closing Price	Rt	Rm	Calculation Rt and Rm	HV	annual HV
03/01/2011	500					
04/01/2011	520	0.0392	0,0005912	0.0386	0.0253	0.4025
05/01/2011	530	0.0190	0,0005912	0.0185	0.0253	0.4025
06/01/2011	535	0.0094	0,0005912	0.0088	0.0253	0.4025
07/01/2011	520	-0.0284	0,0005912	-0.0290	0.0253	0.4025
10/01/2011	500	-0.0392	0,0005912	-0.0398	0.0253	0.4025
11/01/2011	500	0.0000	0,0005912	-0.0006	0.0253	0.4025

Source: Processed data

4. Calculating Historical Volatility for TBIG Stock - 3-month period

Moving on to the calculation of Historical Volatility for TBIG stock over a 3-month period, the data used spans from January 3, 2011, to September 30, 2022. The calculation is performed in a manner consistent with the procedure applied to the TOWR stock, resulting in the following values:

Table 6. shows the calculation of Historical Volatility for TBIG stock over a 3-month period

Date	Closing Price	Rt	Rm	Rt - Rm	HV	annual HV
03/01/2011	500					
04/01/2011	520	0.0392	0,0005951	0.0386	0.0175	0.2792
05/01/2011	530	0.0190	0,0005951	0.0185	0.0175	0.2792
06/01/2011	535	0.0094	0,0005951	0.0088	0.0175	0.2792
07/01/2011	520	-0.0284	0,0005951	-0.0290	0.0175	0.2792
10/01/2011	500	-0.0392	0,0005951	-0.0386	0.0175	0.2792
11/01/2011	500	0.0000	0,0005951	-0.0006	0.0175	0.2792

Source: Processed data

Based on Tables 3 to 6, the annual Historical Volatility (HV) values are obtained. Subsequently, these standard deviation values are utilized as historical volatility inputs in the Black-Scholes model.

4.3 Results of GARCH Volatility Calculation

To calculate the volatility value using GARCH, it is necessary to test for stationarity and heteroskedasticity in the data used. Stationarity testing was conducted to determine whether the initial data had a stable dispersion. Data are considered stationary if the Augmented Dickey Fuller (ADF) test yields a value of less than 5%.

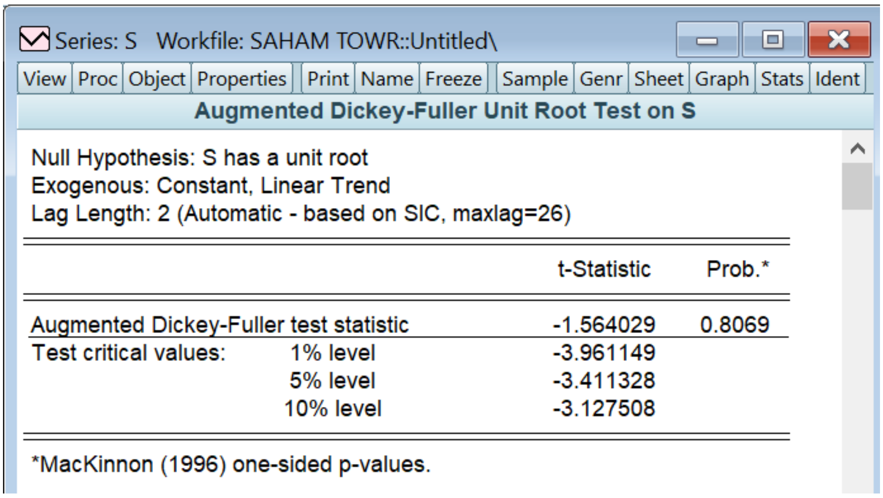


Figure 4: Stationarity Testing of TOWR Stock Closing Price Data

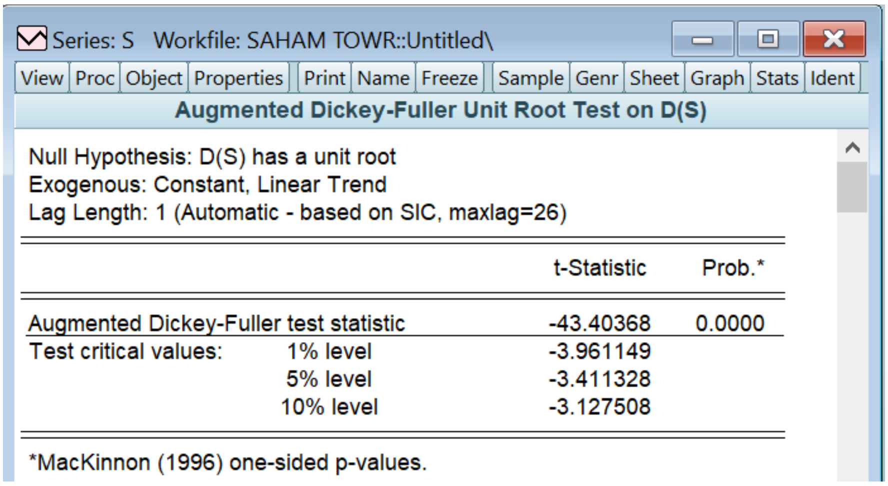
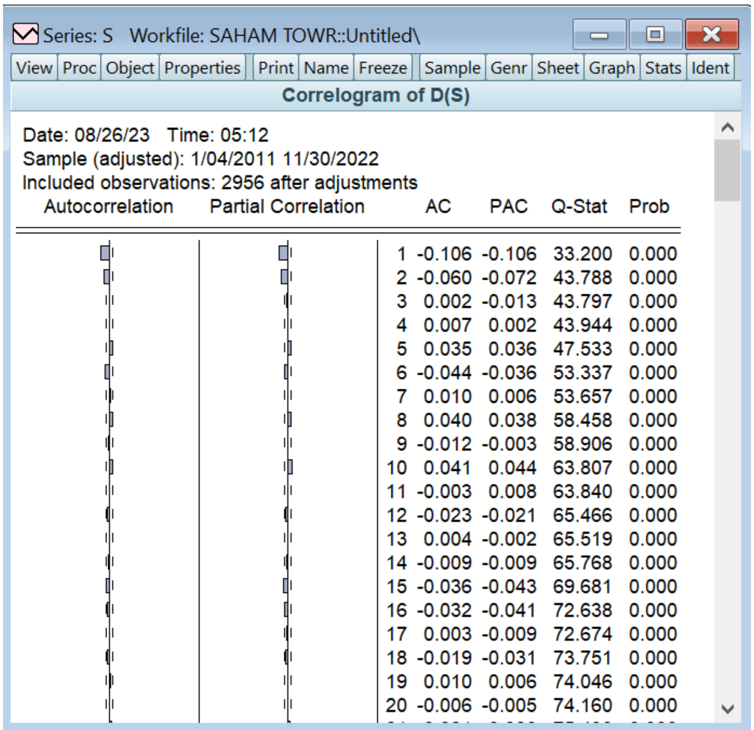


Figure 5: Stationarity Testing of TOWR Stock Closing Price Data - 1st Difference

4.4 Mean Model Estimation

The AR, MA, and ARMA models can be identified from their autocorrelation (ACF) and Partial Correlation (PACF). Subsequently, from the bar chart, the best model possibilities can be identified using the rule that PACF column data are used to determine the maximum order of AR(p) and ACF column data are used to determine MA(q).



Series: S Workfile: SAHAM TOWR::Untitled\
View | Proc | Object | Properties | Print | Name | Freeze | Sample | Genr | Sheet | Graph | Stats | Ident

Correlogram of D(S)

Date: 08/26/23 Time: 05:12
Sample (adjusted): 1/04/2011 11/30/2022
Included observations: 2956 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.106	-0.106	33.200	0.000
		2	-0.060	-0.072	43.788	0.000
		3	0.002	-0.013	43.797	0.000
		4	0.007	0.002	43.944	0.000
		5	0.035	0.036	47.533	0.000
		6	-0.044	-0.036	53.337	0.000
		7	0.010	0.006	53.657	0.000
		8	0.040	0.038	58.458	0.000
		9	-0.012	-0.003	58.906	0.000
		10	0.041	0.044	63.807	0.000
		11	-0.003	0.008	63.840	0.000
		12	-0.023	-0.021	65.466	0.000
		13	0.004	-0.002	65.519	0.000
		14	-0.009	-0.009	65.768	0.000
		15	-0.036	-0.043	69.681	0.000
		16	-0.032	-0.041	72.638	0.000
		17	0.003	-0.009	72.674	0.000
		18	-0.019	-0.031	73.751	0.000
		19	0.010	0.006	74.046	0.000
		20	-0.006	-0.005	74.160	0.000

Figure 6: ACF and PACF of TOWR Data

In Figure 5, the correlogram indicates that the ARMA models used are AR(1) and MA(2). These values were determined from the spikes observed in the Autocorrelation and Partial Correlation. AR(1) and MA(2) are then used as the Mean Model calculation, with the following results.

Table 7. AIC Results for GARCH Models

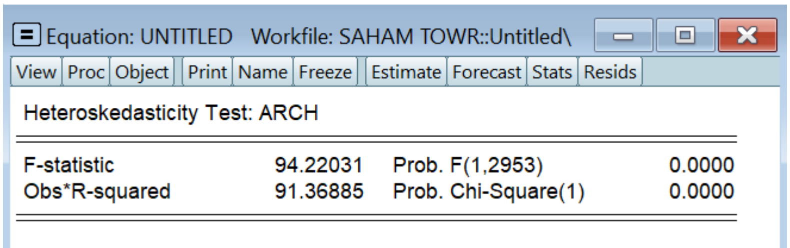
	AIC
AR(1)	10.04002
MA(1)	10.03830
AR(2)	10.04772
MA(2)	10.04774
ARIMA(1,1,1)	10.03634
ARIMA(1,1,2)	10.03545
ARIMA(2,1,1)	10.03539
ARIMA(2,1,2)	10.04792

Source: Processed data

The results of the mean estimation of each model are displayed in Table 7. The best model was determined by comparing the values of the Akaike Information Criterion, where the smallest AIC value was obtained for the ARIMA(2,1,1) model. Therefore, this model was used in the subsequent GARCH calculations.

4.5 Heteroscedasticity Effect Test

After estimating the mean model, the best model obtained is ARIMA(2,1,1). Subsequently, a test for heteroscedasticity effects in the residuals of the best method was conducted.



Equation: UNTITLED Workfile: SAHAM TOWR::Untitled\

Heteroskedasticity Test: ARCH

F-statistic	94.22031	Prob. F(1,2953)	0.0000
Obs*R-squared	91.36885	Prob. Chi-Square(1)	0.0000

Figure 7. Heteroscedasticity Effect Test

The heteroskedasticity effect was tested using the ARCH LM test, with a significance level of 0.05. As shown in Figure 6, the LM test yielded a value of 0.0000. Therefore, there is an ARCH effect in the data from the ARIMA(2,1,1) model when the probability value is <0.05.

4.6 Model Estimation and Model Verification for GARCH

From Figure 7, it is observed that the ARIMA (2,1,1) model exhibits GARCH effects. Consequently, we proceed with the verification of the GARCH model being utilized.

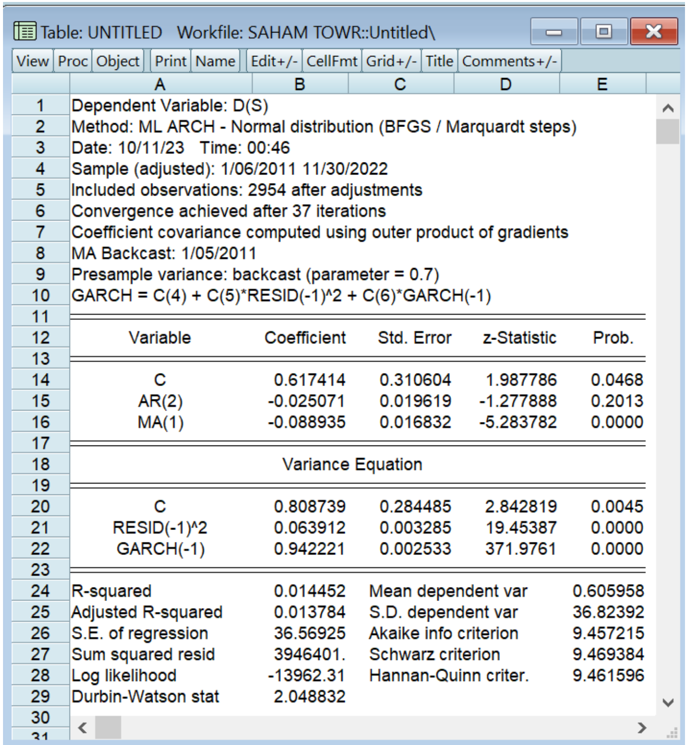


Table: UNTITLED Workfile: SAHAM TOWR::Untitled\

Dependent Variable: D(S)
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 10/11/23 Time: 00:46
Sample (adjusted): 1/06/2011 11/30/2022
Included observations: 2954 after adjustments
Convergence achieved after 37 iterations
Coefficient covariance computed using outer product of gradients
MA Backcast: 1/05/2011
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.617414	0.310604	1.987786	0.0468
AR(2)	-0.025071	0.019619	-1.277888	0.2013
MA(1)	-0.088935	0.016832	-5.283782	0.0000
Variance Equation				
C	0.808739	0.284485	2.842819	0.0045
RESID(-1)^2	0.063912	0.003285	19.45387	0.0000
GARCH(-1)	0.942221	0.002533	371.9761	0.0000

R-squared	0.014452	Mean dependent var	0.605958
Adjusted R-squared	0.013784	S.D. dependent var	36.82392
S.E. of regression	36.56925	Akaike info criterion	9.457215
Sum squared resid	3946401.	Schwarz criterion	9.469384
Log likelihood	-13962.31	Hannan-Quinn criter.	9.461596
Durbin-Watson stat	2.048832		

Figure 8. Verification of the ARIMA (2,1,1) model on GARCH(1,1)

The GARCH (1, 1) model is employed to forecast volatility, with parameter values as follows:

Table 8 Parameter GARCH (1,1)

Model	Nilai		
	α	β	Ω
GARCH(1,1)	0.063912	0.942221	0.808739

Source: Processed data

Table 9. GARCH Modeling

	Data Stasioner	Mean Model	Efek Heterokedastisitas	Model GARCH
TOWR periode 1 bulan	√	ARIMA(2,1,1)	√	GARCH(1,1)
TOWR periode 3 bulan	√	ARIMA(2,1,1)	√	GARCH(1,1)
TBIG periode 1 bulan	√	ARIMA(2,1,1)	√	GARCH(1,1)
TBIG periode 3 bulan	√	ARIMA(2,1,1)	√	GARCH(1,1)

Source: Processed data

Table 10. Calculation Model GARCH

	Ω	α	β
TOWR periode 1 bulan	0.808739	0.063912	0.942221
TOWR periode 3 bulan	0.870079	0.045386	0.955876
TBIG periode 1 bulan	0.807681	0.063991	0.942174
TBIG periode 3 bulan	0.818926	0.064768	0.941534

Source: Processed data

Table 11. Calculation *Historical Volatility* TOWR Stock over 1 month period

Date	Closing Price	Rt (return)	Rm	Rt - Rm	HV	annual HV
03/01/2011	259					
04/01/2011	255	-0.0156	-0,0007	-0,0148	0.0129	0.2051
05/01/2011	259	0.0156	-0,0007	0.0163	0.0129	0.2051
06/01/2011	258	-0.0039	-0,0007	-0.0031	0.0129	0.2051
07/01/2011	260	0.0077	-0,0007	0.0085	0.0129	0.2051
10/01/2011	257	-0.0116	-0,0007	-0.0109	0.0129	0.2051
11/01/2011	258	0.0039	-0,0007	0.0046	0.0129	0.2051

Source: Processed data

The variables obtained from Tables 10 and 11 will yield the GARCH(1,1) equation as follows:

$$\sigma^2 = 0.808739 + 0.063912\, u_{n-1}^2 + 0.942221\, \sigma_{n-1}^2 \ldots\ldots\ldots\ldots\ldots\ldots\ldots (13)$$

From the above equation, the value of σ^2 can be determined by substituting the values of return u_(n-1)^2 and its volatility σ_(n-1)^2. The return and volatility values are obtained from the historical volatility calculations.

$$\sigma^2 = 0.8087 + 0.0639 * -0.0156 + 0.9422 * 0.0129$$

$$\sigma^2 = 0.8199$$

$$\sigma = 0.9054$$

4.7 Bank Indonesia Interest Rate/BI Rate/7 Days Rate Repo

The Bank Indonesia Interest Rate, also known as the BI Rate or 7 Days Rate Repo, is the policy interest rate set by the monetary policy stance established by Bank Indonesia and announced to the public. The table below illustrates the interest rates set by Bank Indonesia during the period 2011-2022.

Table 12. Bank Indonesia Interest Rates during the period 2011-2022

Year	**BI-7Day-RR**
2011	6,58
2012	5,77
2013	6,48
2014	7,54
2015	7,52

2016	6,00
2017	4,56
2018	5,10
2019	5,63
2020	4,25
2021	3,52
2022	4,00

Source: Processed data

Bank Indonesia's interest rates fluctuate in accordance with government policies from 2011 to 2022. In the calculation of Black-Scholes with Historical Volatility and GARCH Volatility, researchers use the prevailing interest rates set by Bank Indonesia during specified periods.

4.8 Calculation of Black-Scholes Model with Historical Volatility

To calculate the Black-Scholes volatility with historical volatility for the 1-month and 3-month periods, data on the stock spot price, exercise price, and BI Rate/7 Days Rate Repo are required. This study adopts the collar strategy, setting the exercise price to less than 5% and more than 5%. The following are the steps for calculating Black-Scholes for the 1-month and 3-month periods.

Table 13. Black-Scholes Variable Values

Variable	Value	note
S	254	Closing stock
Xp	241.3	Strike price put (asumsi -5% dari S)
Xc	266.7	Strike price call (asumsi +5% dari S)
	273.05	Strike price call (asumsi +7.5% dari S)
	279.4	Strike price call (asumsi +10% dari S)
T	0.083	1 month period maturity time
	0.25	3 month period maturity time
Rf	6.58%	suku bunga yang berlaku
σ	0.7771	1 month period maturity time
	0.9577	3 month period maturity time

Source: Processed data

After identifying the variables for Black-Scholes calculations, the next step involves computing the normal distribution to determine the values of call and put options in Black-Scholes, using the following formula:

$$d1 = \left(\ln\frac{[S/X]+\left[Rf-\frac{\sigma^2}{2}\right]}{\sigma\sqrt{T}}\ T\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (14)$$

$$d2 = d1 - \sigma\sqrt{T} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (15)$$

Where:

S : stock closing price
X : put/call strike price
Rf : risk-free rate
σ : volatility variance

$$d1p = \left(\ln\frac{[254/241.3]+\left[0.0658-\frac{0,0075385^2}{2}\right]}{0.7771\sqrt{0.08333}}\ 0.08333\right) \ldots\ldots\ldots\ldots\ldots (16)$$

$$d1p = 0.3652 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (17)$$

$$d2p = 0.3652 - 0.7771\sqrt{0.08333} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (18)$$

$$d2p = 0.1409 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (19)$$

$$d1c = \left(\ln\frac{[254/266.7]+\left[0.0658-\frac{0,0075385^2}{2}\right]}{0.7771\sqrt{0.08333}}\ 0.08333\right) \ldots\ldots\ldots\ldots\ldots (20)$$

$$d1c = -0.0808 \ldots\ldots(21)$$
$$d2c = -0.0808 - 0.0075385\sqrt{0.08333} \ldots\ldots(22)$$
$$d2c = -0.3052 \ldots\ldots(23)$$

After calculating the normal distribution value, the next step is to find the call and put values using the Black-Scholes model. The formula for a call option is as follows:

$$C = SN(d1c) - e^{-RfT} X_c N(d2c) \ldots\ldots(24)$$
$$C = 254N(-0.0808) - e^{-0.0658*0.08333}\, 266.7N(-0.3052) \ldots\ldots(25)$$
$$C = 17.9961 \ldots\ldots(26)$$

Meanwhile, the formula for a put option is as follows

$$P = X_p e^{-RfT} N(-d2p) - SN(d1p) \ldots\ldots(27)$$
$$P = 241.3e^{-0.0658*0.0833} N(0.1409) - 254N(0.3652) \ldots\ldots(28)$$
$$P = 15.7492 \ldots\ldots(29)$$

After obtaining the values for the call and put, the next step is to find the BEP (Break-Even Point) or breakeven point in the option using the following formula:

BEP Call = X_c + P – C ……………………………………………...(30)

BEP Put = X_p + P – C …………………………………………………(31)

Thus, using the formula, the values obtained were BEP Call = 268.9469 and BEP Put = 243.5469. The values of BEP Call and BEP Put are then compared with the Strike Price Call on the same day, which is 279.4. The capital required when executing this option was calculated as S + P - C, resulting in 251.7530. If the option is executed on that day, a loss of -8.2061 will be incurred, calculated as 256.0637 – 243.5469. Using the above calculations, the Black-Scholes values with Historical Volatility for TOWR and TBIG stocks are determined.

Table 14. TOWR Stock Values in Black-Scholes with Historical Volatility

Scenario	Xp	Xc	C	P	BEP Call	BEP Put	Time Maturity
Xp = 95% * S Xc = 105% * S	241.3	266.7	17.99	15.74	268.94	243.54	1 Month
	241.3	266.7	21.91	17.18	271.42	246.02	3 Month
Xp = 95% * S Xc = 107.5% * S	241.3	273.05	15.72	15.74	273.02	241.27	1 Month
	241.3	273.05	19.52	17.18	275.39	243.64	3 Month
Xp = 95% * S Xc = 110% * S	241.3	279.4	13.68	15.74	277.32	239.23	1 Month
	241.3	279.4	17.35	17.18	279.57	241.47	3 Month

Source: Processed data

Table 15. TBIG Stock Values in Black-Scholes with Historical Volatility

Scenario	Xp	Xc	C	P	BEP Call	BEP Put	Time Maturity
Xp = 95% * S	479.75	530.25	14.38	11.47	533.15	482.65	1 Month
Xc = 105% * S	479.75	530.25	7.76	5.61	532.39	481.89	3 Month
Xp = 95% * S	479.75	542.87	10.64	11.47	542.04	478.92	1 Month
Xc = 107.5% * S	479.75	542.87	4.80	5.61	542.06	478.94	3 Month
Xp = 95% * S	479.75	555.50	7.72	11.47	551.75	476.00	1 Month
Xc = 110% * S	479.75	555.50	2.84	5.611	552.72	476.97	3 Month

Source: Processed data

4.9 Calculation of the Black-Scholes Model with GARCH Volatility

To calculate the Black-Scholes volatility with GARCH volatility over periods of one and three months, data on stock spot prices, exercise prices, and the BI Rate/7 Days Rate Repo are required. This study employs the collar strategy, using exercise prices of less than 5% and greater than 5% as limits. The following are the steps in calculating Black-Scholes over the 1-month and 3-month periods.

Table 16. Values of Black-Scholes Variables

Variable	Value	Note
S	254	Closing stock
Xp	241.3	Strike Price put (asumsi -5% dari S)
Xc	266.7	Strike Price call (asumsi +5% dari S)
	273.05	Strike Price call (asumsi +7.5% dari S)
	279.4	Strike Price call (asumsi +10% dari S)
T	0.08	1 month period maturity time
	0.25	3 month period maturity time
Rf	6.58%	suku bunga yang berlaku
σ	0.89	1 month period maturity time
	0.93	3 month period maturity time

Source: Processed data

After identifying the variables for the Black-Scholes calculation, the next step is to perform the normal distribution calculation to find the values of call and put options in the Black-Scholes model.

$$d1p = \left(\ln \frac{[254/241.3] + \left[0.06 - \frac{0.89^2}{2}\right]}{0.89\sqrt{0.08}}\ 0.08\right) \ldots\ldots (32)$$

$$d1p = 0.34 \ldots\ldots (33)$$

$$d2p = 0.34 - 0.89\sqrt{0.08} \ldots\ldots (34)$$

$$d2p = 0.08 \ldots\ldots (35)$$

$$d1c = \left(\ln \frac{[254/266.7] + \left[0.06 - \frac{0.89^2}{2}\right]}{0.89\sqrt{0.08}}\ 0.08\right) \ldots\ldots (36)$$

$$d1c = -0.03 \ldots\ldots (37)$$

$$d2c = -0.03 - 0.89\sqrt{0.08} \ldots\ldots (38)$$

$$d2c = -0.29 \ldots\ldots (39)$$

After calculating the normal distribution value, the next step is to find the call and put values using the Black-Scholes model. The formula for a call option is as follows:

$$C = SN(d1c) - e^{-RfT} X_c N(d2c) \ldots\ldots (40)$$

$$C = 254N(-0.03) - e^{-0.06*0.08}\, 266.7N(-0.29) \ldots\ldots (41)$$

$$C = 21.57 \ldots\ldots (42)$$

Meanwhile, the formula for a put option is as follows

$$P = X_p e^{-RfT} N(-d2p) - SN(d1p) \ldots\ldots (43)$$

$$P = 241.3e^{-0.06*0.08} N(0.08) - 254N(0.34) \ldots\ldots (44)$$

$$P = 19.11 \ldots\ldots (45)$$

After obtaining the values for the call and put, the next step is to find the BEP (Break-Even Point) or breakeven point in the option using the following formula:

BEP Call = X_c + P – C ……(46)

BEP Put = X_p + P – C ……(47)

Using this formula, the values obtained are BEP Call = 269.2033 and BEP Put = 243.8033. The values of BEP Call and BEP Put are then compared with the Strike Price Call on the same day, which is 266.7. The capital required when executing this option was calculated as S + P − C, resulting in 251.4966. If the option is executed on that day, a loss of -7.6932 is incurred, calculated as 251.4966 – 243.8033. Using the above calculations, the Black-Scholes values with Historical Volatility for TOWR and TBIG stocks are determined.

Table 17. TOWR Stock Values in Black-Scholes with GARCH Volatility

Scenario	Xp	Xc	C	P	BEP Call	BEP Put	Time Maturity
Xp = 95% * S	241.30	266.70	22.30	19.80	269.20	243.80	1 Month
Xc = 105% * S	241.30	266.70	44.78	38.62	272.86	247.46	3 Month
Xp = 95% * S	241.30	273.05	19.99	19.80	273.23	241.48	1 Month
Xc = 107.5% * S	241.3	273.05	42.47	38.62	276.90	245.15	3 Month
Xp = 95% * S	241.3	279.4	17.16	19.11	277.44	239.34	1 Month
Xc = 110% * S	241.3	279.4	40.27	38.62	281.05	242.95	3 Month

Source: Processed data

Table 18. TBIG Stock Values in Black-Scholes with GARCH Volatility

Scenario	Xp	Xc	C	P	BEP Call	BEP Put	Time Maturity
Xp = 95% * S	241.3	266.7	21.54	19.08	269.15	243.75	1 Month
Xc = 105% * S	241.3	266.7	43.20	37.13	272.77	247.37	3 Month
Xp = 95% * S	241.3	273.05	19.23	19.08	273.19	241.44	1 Month
Xc = 107.5% * S	241.3	273.05	40.88	37.13	276.80	245.05	3 Month
Xp = 95% * S	241.3	279.4	17.12	19.08	277.44	239.34	1 Month
Xc = 110% * S	241.3	279.4	38.67	37.13	280.94	242.84	3 Month

Source: Processed data

Based on the calculation of call and put option values using Black Scholes with historical volatility and GARCH, as well as maturity times of one and three months, the next step involves calculating the probability of profit and loss with criteria below Xp, between Xp and Xc, or above Xc.

Table 19. Comparison of Profit Opportunities between Black Scholes Historical Volatility and GARCH Models in the 1-Month Collar Options for TOWR Stock

Kondisi	Data	SAHAM TOWR							
		HV Black Scholes dengan Strategi Collar				GARCH Volatility Black Scholes dengan Strategi Collar			
		X < Xp	Xp < X < So	So < X < Xc	X > Xc	X < Xp	Xp < X < So	So < X < Xc	X > Xc
Krisis	Xp = 95%*So, Xc = 105%*So	21.7586%	31.5946%	21.3115%	28.3159%	21.7586%	31.5946%	21.3115%	28.3159%
	Xp = 95%*So, Xc = 107.5%*So	21.7586%	31.5946%	28.6140%	21.0134%	21.7586%	31.5946%	28.6140%	21.0134%
	Xp = 95%*So, Xc = 110%*So	21.7586%	31.5946%	33.5320%	16.0954%	21.7586%	31.5946%	33.5320%	16.0954%
Non Krisis	Xp = 95%*So, Xc = 105%*So	16.8895%	34.6702%	30.2585%	24.8663%	16.9045%	34.6120%	30.2855%	24.8885%
	Xp = 95%*So, Xc = 107.5%*So	16.8895%	34.6702%	37.2549%	17.8699%	16.9045%	34.6120%	37.2881%	17.8858%
	Xp = 95%*So, Xc = 110%*So	16.8895%	34.6702%	41.2656%	13.8592%	16.9045%	34.6120%	41.3024%	13.8715%

Source: Processed data

Table 20. Comparison of Profit Opportunities between Black Scholes Historical Volatility and GARCH Models in the 1-Month Collar Options for TBIG Stock

Kondisi	Data	SAHAM TBIG							
		HV Black Scholes dengan Strategi Collar				GARCH Volatility Black Scholes dengan Strategi Collar			
		X < Xp	Xp < X < So	So < X < Xc	X > Xc	X < Xp	Xp < X < So	So < X < Xc	X > Xc
Krisis	Xp = 95%*So, Xc = 105%*So	19.6721%	27.4218%	21.4605%	33.5320%	19.6721%	27.4218%	21.4605%	33.5320%
	Xp = 95%*So, Xc = 107.5%*So	19.6721%	27.4218%	29.3592%	25.6334%	19.6721%	27.4218%	29.3592%	25.6334%
	Xp = 95%*So, Xc = 110%*So	19.6721%	27.4218%	34.4262%	20.5663%	19.6721%	27.4218%	34.4262%	20.5663%
Non Krisis	Xp = 95%*So, Xc = 105%*So	24.3316%	24.6435%	23.9305%	29.9020%	24.3087%	24.6209%	23.9518%	29.9286%
	Xp = 95%*So, Xc = 107.5%*So	24.3316%	24.6435%	30.8378%	22.9947%	24.3087%	24.6209%	30.8653%	23.0152%
	Xp = 95%*So, Xc = 110%*So	24.3316%	24.6435%	37.9234%	15.9091%	24.3087%	24.6209%	37.9572%	15.9233%

Source: Processed data

Table 21. Comparison of Profit Opportunities between Black Scholes Historical Volatility and GARCH Models in the 3-Month Collar Options for TOWR Stock

Kondisi	Data	SAHAM TOWR							
		HV Black Scholes dengan Strategi Collar				GARCH Volatility Black Scholes dengan Strategi Collar			
		X < Xp	Xp < X < So	So < X < Xc	X > Xc	X < Xp	Xp < X < So	So < X < Xc	X > Xc
Krisis	Xp = 95%*So, Xc = 105%*So	36.3057%	12.1019%	8.9172%	43.6306%	36.3057%	12.1019%	8.9172%	43.6306%
	Xp = 95%*So, Xc = 107.5%*So	36.3057%	12.1019%	13.5350%	39.0127%	36.3057%	12.1019%	13.5350%	39.0127%
	Xp = 95%*So, Xc = 110%*So	36.3057%	12.1019%	17.9936%	34.5541%	36.3057%	12.1019%	17.9936%	34.5541%
Non Krisis	Xp = 95%*So, Xc = 105%*So	30.6150%	18.4938%	14.2157%	39.6613%	30.5531%	18.5103%	14.2284%	39.6967%
	Xp = 95%*So, Xc = 107.5%*So	30.6150%	18.4938%	19.8752%	34.0018%	30.5531%	18.5103%	19.8930%	34.0321%
	Xp = 95%*So, Xc = 110%*So	30.6150%	18.4938%	23.6185%	30.2585%	30.5531%	18.5103%	23.6396%	30.2855%

Source: Processed data

Table 22. Comparison of Profit Opportunities between Black Scholes Historical Volatility and GARCH Models in the 3-Month Collar Options for TBIG Stock

Kondisi	Data	SAHAM TBIG							
		HV Black Scholes dengan Strategi Collar				GARCH Volatility Black Scholes dengan Strategi Collar			
		X < Xp	Xp < X < So	So < X < Xc	X > Xc	X < Xp	Xp < X < So	So < X < Xc	X > Xc
Krisis	Xp = 95%*So, Xc = 105%*So	17.8344%	15.4459%	18.9490%	48.8854%	17.8344%	15.4459%	18.9490%	48.8854%
	Xp = 95%*So, Xc = 107.5%*So	17.8344%	15.4459%	21.1783%	46.6561%	17.8344%	15.4459%	21.1783%	46.6561%
	Xp = 95%*So, Xc = 110%*So	17.8344%	15.4459%	23.2484%	44.5860%	17.8344%	15.4459%	23.2484%	44.5860%
Non Krisis	Xp = 95%*So, Xc = 105%*So	31.9964%	16.4884%	12.2103%	41.0873%	31.9358%	16.5031%	12.2212%	41.1240%
	Xp = 95%*So, Xc = 107.5%*So	31.9964%	16.4884%	17.2460%	36.0517%	31.9358%	16.5031%	17.2614%	36.0839%
	Xp = 95%*So, Xc = 110%*So	31.9964%	16.4884%	21.3458%	31.9519%	31.9358%	16.5031%	21.3649%	31.9804%

Source: Processed data

4.10 Comparison of MSE for Collar Options Strategy using Historical Volatility and GARCH Volatility

The calculation involves determining the magnitude of the error in the BEP (Break-Even Point) of Collar Options compared to the price at maturity. The extent of the error can be seen in the table below:

Table 23. Comparison of MSE (Mean Squared Error) Model between Black Scholes with Historical Volatility and GARCH Volatility for TOWR Stock

Kondisi	Maturity	Tipe Strategi Collar	Saham TOWR		Hasil
			MSE HV Black Scholes	MSE GARCH Volatility Black Scholes	
Krisis	1 Bulan	Xp = 95%*So, Xc = 105%*So	12099.26389	11593.57307	Model GARCH lebih baik dibandingkan dengan Model HV
		Xp = 95%*So, Xc = 107.5%*So	12924.90293	12729.74708	
		Xp = 95%*So, Xc = 110%*So	13572.82869	13935.03898	Model HV lebih baik dibandingkan dengan model GARCH
	3 bulan	Xp = 95%*So, Xc = 105%*So	28727.69293	27819.83199	Model GARCH lebih baik dibandingkan dengan Model HV
		Xp = 95%*So, Xc = 107.5%*So	30027.8661	28998.78868	
		Xp = 95%*So, Xc = 110%*So	31287.06153	30299.37114	
Non Krisis	1 Bulan	Xp = 95%*So, Xc = 105%*So	3156.427716	2932.41319	Model GARCH lebih baik dibandingkan dengan Model HV
		Xp = 95%*So, Xc = 107.5%*So	3405.679214	3316.922839	
		Xp = 95%*So, Xc = 110%*So	3595.510735	3728.858267	Model HV lebih baik dibandingkan dengan model GARCH
	3 bulan	Xp = 95%*So, Xc = 105%*So	8552.367152	8233.295328	Model GARCH lebih baik dibandingkan dengan Model HV
		Xp = 95%*So, Xc = 107.5%*So	8928.267837	8559.870417	
		Xp = 95%*So, Xc = 110%*So	9293.33454	8936.188913	

Source: Processed data

In Table 23, the results indicate that under crisis conditions with a maturity of one month and three months in the scenario Xp=95%*So, Xc=105%* Therefore, Xp=95%* Therefore, Xc=107.5%* Therefore, the GARCH model performs better than the HV model. However, under crisis conditions with a maturity of one month, in the scenario Xp=95%*So, Xc=110%* Therefore, the HV model is better than the GARCH model. In non-crisis conditions, with a maturity of 1 month and 3 months in the scenario Xp=95%*So, Xc=105%*So, Xp=95%*So, Xc=107.5%*So, the GARCH model is superior to the HV model. Meanwhile, under non-crisis conditions with a maturity of one month in the scenario Xp=95%*So, Xc=110%* Therefore, the HV model is better than the GARCH model. Overall, the Black Scholes model with Historical Volatility is better than the Black Scholes model with GARCH Volatility under both crisis and non-crisis conditions, with a maturity of one and three months when Xp=95%*So, Xc=110%*So. This superiority is attributed to the fact that the parameters with returns above 10% are not as prevalent, making the Historical Volatility model sufficient to provide good results.

Table 24. Comparison of MSE (Mean Squared Error) Model between Black Scholes with Historical Volatility and GARCH Volatility for TBIG Stock

Kondisi	Maturity	Tipe Strategi Collar	Saham TBIG		Hasil
			MSE HV Black Scholes	MSE GARCH Volatility Black Scholes	
Krisis	1 Bulan	Xp = 95%*So, Xc = 105%*So	69946.1528	67831.94857	Model GARCH lebih baik dibandingkan dengan Model HV
		Xp = 95%*So, Xc = 107.5%*So	74628.61365	73477.10907	
		Xp = 95%*So, Xc = 110%*So	78617.77793	79451.28391	Model HV lebih baik dibandingkan dengan model GARCH
	3 bulan	Xp = 95%*So, Xc = 105%*So	195148.789	193448.1249	Model GARCH lebih baik dibandingkan dengan Model HV
		Xp = 95%*So, Xc = 107.5%*So	201907.8174	200514.5061	
		Xp = 95%*So, Xc = 110%*So	207963.2458	207791.3101	
Non Krisis	1 Bulan	Xp = 95%*So, Xc = 105%*So	13387.49709	12777.90083	Model GARCH lebih baik dibandingkan dengan Model HV
		Xp = 95%*So, Xc = 107.5%*So	14179.27611	13880.79672	
		Xp = 95%*So, Xc = 110%*So	14806.15757	15082.86413	Model HV lebih baik dibandingkan dengan model GARCH
	3 bulan	Xp = 95%*So, Xc = 105%*So	34116.2812	33544.90742	Model GARCH lebih baik dibandingkan dengan Model HV
		Xp = 95%*So, Xc = 107.5%*So	34921.70834	34624.74403	
		Xp = 95%*So, Xc = 110%*So	35563.97659	35802.35787	Model HV lebih baik dibandingkan dengan model GARCH

Source: Processed data

In Table 24, the results indicate that under crisis conditions with a maturity of one month and three months in the scenario Xp=95%*So, Xc=105%* Therefore, Xp=95%* Therefore, Xc=107.5%* Therefore, the GARCH volatility model is better than the HV model. However, under crisis conditions with a maturity of one month, in the scenario Xp=95%*So, Xc=110%* Therefore, the HV model is better than the GARCH Volatility model. In non-crisis conditions, with a maturity of one month and three months in the scenario Xp=95%*So, Xc=105%* Therefore, Xp=95%* Therefore, Xc=107.5%* Therefore, the GARCH volatility model is superior to the HV model. Meanwhile, under non-crisis conditions with a maturity of one month in the scenario Xp=95%*So, Xc=110%* Therefore, the HV model is better than the GARCH Volatility model. The Black Scholes model with Historical Volatility is better in this case because under the scenario Xp=95%*So, Xc=110%* Therefore, there are not many returns above 10%, making Historical Volatility sufficient for the modeling process.

5. Conclusions

1. For TOWR stock under normal conditions with a maturity of one and three months, the Black-Scholes model with GARCH Volatility provides more profits than the Black-Scholes model with Historical Volatility. The Black-Scholes model with GARCH Volatility also offers better value protection than the model with Historical Volatility.
2. For TOWR stock under crisis conditions with a maturity of one and three months, the Black-Scholes model with GARCH Volatility yields more profits than the Black-Scholes model with Historical Volatility. The Black-Scholes model with GARCH Volatility also provides better value protection than the model with Historical Volatility.
3. For TBIG stock under normal conditions with a maturity of one and three months, the Black-Scholes model with GARCH Volatility generates more profits than the Black-Scholes model with Historical Volatility. The Black-Scholes model with GARCH Volatility also offers better value protection than the model with Historical Volatility.
4. For TBIG stock under crisis conditions with a maturity of one and three months, the Black-Scholes model with GARCH Volatility yields more profits than the Black-Scholes model with Historical Volatility. The Black-Scholes model with GARCH Volatility also provides better value protection than the model with Historical Volatility.
5. The Black-Scholes model using GARCH Volatility performs better than the model using Historical Volatility for TOWR stock under crisis and non-crisis conditions with a maturity of three months in all scenarios. The Black-Scholes model using Historical Volatility performs better than the model using GARCH Volatility under crisis and non-crisis conditions with a maturity of one and three months in the scenario Xp=95%*So, Xc=110%*So. For TBIG stock, the Black-Scholes model using GARCH Volatility is better than using Historical Volatility under crisis conditions with a maturity of three months in all scenarios, and under crisis and non-crisis conditions with a maturity of one and three months in the scenarios Xp=95%*So, Xc=105%*So, and Xp=95%*So, Xc=107.5%*So.

For TBIG stocks, the Black-Scholes model using Historical Volatility is better than using GARCH Volatility in the scenario Xp=95%*So, Xc=110%* Therefore, under crisis conditions with a maturity of one month and non-crisis conditions with a maturity of one and three months.

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