

Comparison of black scholes and garch models using collar strategy as a hedging efforts in the telecommunication industry (Telkomsel, XL, Indosat)

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Abstract

Purpose: This study aims to examine the influence of the internal control system and human resource competence on the quality of financial reports within the Nabire Regency Government.

Research/methodology: A quantitative approach was employed using primary data collected through questionnaires distributed to 30 respondents working in financial administration across various regional apparatus organizations (OPD) in Nabire. The data were analyzed using multiple linear regression with SPSS to test the hypotheses regarding the direct effects of internal control and HR competence on report quality.

Results: The results indicate that both the internal control system and the competence of human resources have significant positive effects on the quality of financial reporting. The better the internal control mechanisms and the higher the HR competence, the more reliable, accurate, and transparent the financial reports produced by the local government.

Conclusions: Strengthening internal controls and enhancing HR competence are essential strategies for improving the quality of local government financial reports, ensuring better public accountability and compliance with reporting standards.

Limitations: The study is limited by its small sample size and focus on a single regency, which may restrict the generalizability of findings to other regions or government levels.

Contribution: This research contributes to public sector accounting literature by empirically demonstrating how governance and human capital factors influence financial reporting quality in local governments, offering insights for policymakers and practitioners aiming to enhance financial transparency.

Keywords: *Financial Reporting Quality, Human Resource Competence, Internal Control System, Local Government, Nabire Regency*

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1. Introduction

This research analyzes the comparison between the Black-Scholes model with historical volatility and GARCH volatility, utilizing the collar strategy as a hedging effort on the stocks of TLKM, EXCL, and ISAT. TLKM, EXCL, and ISAT are companies operating in the infrastructure and telecommunications sectors (Karagozoglu, 2022). The Black-Scholes model is one of the theories for calculating option

prices, which requires five variables: strike price, current stock price, time to expiration, volatility, and interest rate (Shahvaroughi Farahani, Babaei, & Esfahani, 2024). GARCH is a model used to predict the volatility of returns on financial assets (Naimy & Hayek, 2018). PT Telkom Indonesia (Persero) Tbk is a state-owned enterprise (SOE) in Indonesia, focusing on information technology and communication (infrastructure and telecommunications), headquartered in Jakarta with an office in Bandung (Widiarma & Yulianto, 2023). PT Telkom has several subsidiaries, including PT Telekomunikasi Selular, PT Telkom Satelit Indonesia, PT Telekomunikasi Indonesia International, PT Metra-Net, PT Infrastruktur Telekomunikasi Indonesia, PT Dayamitra Telekomunikasi Tbk, PT Graha Sarana Duta, PT Telkom Akses, and PT Sigma Cipta Caraka.

PT Indosat Ooredoo Hutchison Tbk is a telecommunications company (mobile operator) in Indonesia, providing cellular and data communication services. PT Indosat merged with PT Hutchison 3 Indonesia/H3I, which also operates in the cellular and data communication sector. PT XL Axiata Tbk is another telecommunications company in Indonesia, providing mobile and data communication services. In 2014, PT XL Axiata Tbk acquired PT AXIS Telekom Indonesia (PT Natrindo Telepon Seluler). Indonesia is the fourth most populous country in the world, with a current population of approximately 277,373,151 people. The infrastructure sector, particularly telecommunications companies, plays a significant role in the country's economic, educational, and business advancement (Mahmood, Misra, Sun, Luqman, & Papa, 2024). With the growing demand for digital services, especially for data and voice services, there is a significant business development opportunity in the telecommunications infrastructure sector (Sacco, 2020). This business development could involve transforming a traditional telecommunications company into a digital telecom company (Bist, Agarwal, Aini, & Khofifah, 2022).

Indonesia's economy has experienced two major crises between 2000 and 2020. The first was the 2008 subprime mortgage crisis, which originated from housing loan defaults in the USA, leading to a global stock market downturn, including in Indonesia (Fitrah, Alhamdi, Majid, & Handayani, 2022). The second was the economic impact of the COVID-19 pandemic during 2019-2020, which caused a significant decline in Indonesia's economy (Tambunan, 2021). Based on Table 1.3, the 2008 crisis shows a volatility range for TLKM.JK returns between -11.2% and 9.09%, with the highest closing value of TLKM in 2008 reaching 2,050 on January 8, 2008, and the lowest closing value recorded on October 28, 2008, at 1,000. The COVID-19 pandemic led to TLKM's highest closing value of 4,030 on January 13, 2020, and the lowest value of 2,560 on September 30, 2020, resulting in a return volatility range for TLKM between -7.48% and 12.08% in 2020.

The rapid fluctuations in returns are referred to as volatility, which measures the statistical change in the price of a security over a given period. Volatility movement can result in profits for investors or pose risks leading to significant losses (Yang & Yang, 2021). Return fluctuations indicate that the volatility in this data is extremely high (Ridho, 2024). One way to anticipate stock price volatility and minimize the risk of loss is through derivative instruments. A derivative is an investment instrument whose value depends on the underlying asset (Vasista, 2022). Types of derivatives include futures contracts, forward contracts, options contracts, and swap contracts. A futures contract is an agreement between two parties to buy or exchange assets at a predetermined price, time, and quantity in the future (Injadat, 2014). A forward contract is an agreement between two parties to buy or exchange assets at an agreed-upon price, time, and quantity (Hasanudin & Haryati, 2023). A swap contract involves exchanging assets at a predetermined price, time, and quantity. An options contract provides the right (but not the obligation) to exchange assets at a future time for an agreed-upon price, time, and quantity.

The use of options as a derivative instrument in this research is chosen because options have unique characteristics compared to other instruments. An option is a contract that grants the holder the right (but not the obligation) to buy (call option) or sell (put option) a specific asset at a specific price (strike price/exercise price) within a certain period. In other words, an option is a type of contract between two parties in which one party grants the other the right to buy or sell a specific asset at an agreed price and period in the future. Options have no value if the contract is not exercised on the expiration date. There are four positions in options: First, a Long Call Option, where the buyer has the right to purchase the

stock at a specific price in the future. Second, a Short Call Option, where the investor sells the stock, anticipating a price drop in the future. Third, a Long Put Option, where the investor buys the stock, expecting the price to decline. Fourth, a Short Put Option is where the investor sells the stock, anticipating the price will rise.

According to (Akin & Akin, 2024) a sharp and unexpected rise in indices may result in significant investment losses. For example, following the 2008-2009 global financial crisis, the volatility of the S&P/ASX 200 index from September 4, 2009, to October 1, 2009, was 6% (70% annually). According to Isyuardhana and Surur (2018) one of the ways to perform risk management is through hedging the assets owned. Several options strategies can be chosen for speculation or hedging purposes. According to Isyuardhana and Surur (2018) strategi *long straddle* the long straddle strategy yields high profits when the market price rises or falls drastically. According to Nichols, (2023) collar strategies involve creating capped returns, often by combining short call options with long put positions. Among derivative-based risk management strategies, collar strategies are of particular interest to investors.

Hendrawan and Arifin (2023) studied the implementation of options contracts using the Black-Scholes and GARCH models on the Jakarta Islamic Index with a collar strategy. GARCH was used to find the variance of volatility in the Black-Scholes calculation, which was then compared with the Black-Scholes calculation using historical volatility. During times of crisis, options with GARCH and collar strategies resulted in an average profit of 3.07% for 1-month options and 7.01% for 3-month options. During non-crisis periods, options with GARCH volatility and the collar strategy yielded an average profit of 0.16% for 1-month options but a loss of 1.45% for 3-month options. The collar strategy produced a maximum volatility of 12.71%, 15.18%, and 17.14%. It was also found that the GARCH model outperformed Black-Scholes based on the AMSE value for both 1-month and 3-month options during the crisis and non-crisis periods.

Hendrawan, Laksana, and Aminah (2020) studied the volatility of the Jakarta Composite Index (IHSG) from 2009 to 2018 using the Long Straddle strategy and tested its accuracy with AMSE using both historical volatility models and the Black-Scholes model as well as the GARCH volatility model based on ARIMA lag models. The study found that the GARCH model was more accurate than Black-Scholes for call options with durations of 1 and 2 months, with accuracy rates of 0.26% and 0.92%, respectively, while for put options with durations of 1 and 2 months, Black-Scholes was more accurate with accuracy rates of 0.18% and 0.26%. For a 3-month duration, Black-Scholes was more accurate for both put and call options, with accuracy rates of 2% and 0.31%, respectively.

According to Basson, Van den Berg, and Van Vuuren (2018) and long butterfly (LB) strategies provide the best returns for indices with moderate volatility and perform well. According to Eun Sinclair, the collar strategy is a combination of the covered call option and the protective put option. The collar strategy offers limited profits but provides hedging with minimal cost or even at no cost if the price of the put option is equal to the price of the call option sold. Black-Scholes is a pricing model used to determine the fair price or value for call and put options based on six variables, such as volatility, type of option, stock price, time, strike price, and risk-free interest rate (Hull, 2022:270)

Volatility is a measure of the statistical change in the price of a security over a certain period (Zournatzidou & Floros, 2023). Volatility is a key variable in option pricing models. In the Black-Scholes model, volatility is one of the calculation variables (He & Lin, 2021). Therefore, before calculating the value of a call or put option, the volatility value must first be determined (Nafia, Agmour, Foutayeni, & Achtaich, 2023). Volatility can be calculated using Implied Volatility and Historical Volatility (Moghaddam, Liu, & Serota, 2021). Implied Volatility reflects the anticipated volatility of a stock in the future as perceived by traders. On the other hand, Historical Volatility is calculated based on the historical fluctuations in stock returns. GARCH (Generalized Autoregressive Conditional Heteroscedasticity) 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 Bollerslev (1986), which aims for parsimony or choosing simpler models that ensure positive

variance. The ARCH/GARCH model is used to model time-varying risks and provides a more flexible framework for capturing the dynamic structure of conditional variance. Based on the phenomena outlined above and previous research, this study aims to conduct a “comparison of the black scholes model with historical volatility and garch volatility using the collar strategy as a hedging effort on tlkm, excl, and isat stocks.”

2. Literature Review

2.1. Investment and Investment Risk

Investment refers to the activity of allocating capital over a specified period to generate profit. Some forms of investment include gold, deposits, stocks, property, mutual funds, and real estate. Stocks represent an investment in a company, serving as a stake in the company’s ownership. Bonds are debt securities issued by the government and are listed on exchanges. Gold is a form of investment with minimal risk, and it is always in demand due to its stable value and the potential for price increases each year. Mutual funds are vehicles for collecting funds from investors, which are then invested in a portfolio of securities. Deposits are a form of investment where funds are saved for a specific period before they can be withdrawn.

Investment risk refers to the potential for loss experienced by investors when actual returns differ from expected returns. Broadly, investment risks are categorized into two types: systematic risk and unsystematic risk. Systematic risk refers to risks that cannot be controlled or avoided, such as interest rate risk, inflation risk, foreign exchange risk, commodity risk, and country risk. Unsystematic risk refers to risks that can be controlled or mitigated, such as liquidity risk, reinvestment risk, financial risk, and business risk.

2.2. Option Theory

An option is a contract that gives the holder the right to buy or sell an asset at a predetermined price before or after a specified date. In financial risk management, hedging strategies can be employed using derivative instruments. Derivatives are financial instruments whose value depends on or is derived from another, more fundamental variable. Frequently, the underlying variable of a derivative is the price of a traded asset. For example, stock options are derivatives that derive their value from the price of the underlying stock. Some types of derivative products include futures, forwards, swaps, and options. Futures, forwards, and swaps are obligatory contracts, meaning the transaction must be executed at maturity. In contrast, options are mandatory for the seller but optional for the buyer. The option buyer has the choice to execute the contract or not at maturity, with a premium paid to the seller.

2.3. Option Pricing Theory

Option Pricing Theory is a theory that explains how options are valued. This theory is used to calculate the fair price of an option. One of the methods for calculating the fair price of an option is the Black-Scholes model, which was introduced in 1973 by Fisher Black and Myron Scholes.

2.4. The Black-Scholes Model

The Black-Scholes method is one of the methods for determining the price of an option. The assumptions used in this model include the payment of dividends. The model assumes that stock prices follow a stochastic process, meaning they change randomly over time. The Black-Scholes model, developed in 1973 by Fischer Black and Myron Scholes, serves as the foundation for determining the fair price of both call and put options. The Black-Scholes model uses six variables: time, risk-free interest rate, volatility, type of option, stock price, and strike price (Hull, 2009:277).

According to Hull, (2009) the Black-Scholes formula for a call option is as follows:

$$C = SN(d1) - e^{-RfT} XN(d2).....(2.1)$$

While the formula for a put option is:

$$P = Xe^{-RfT} N(-d2) - SN(d1).....(2.2)$$

Where:

$$d1 = \left(\ln \frac{[S/X] + [Rf - \frac{\sigma^2}{2}]}{\sigma\sqrt{T}} T \right) \dots\dots\dots (2.3)$$

$$d2 = d1 - \sigma\sqrt{T} \dots\dots\dots (2.4)$$

Where:

- S = Current stock price
- X = Strike/exercise price
- T = Time to maturity
- Rf = Risk-free interest rate
- σ = Stock price variance/volatility
- N = Cumulative standard normal distribution

2.5. Volatility

In the Black-Scholes calculation, volatility is one of the key variables. Volatility is the degree of fluctuation in the price of a stock or security over time. Volatility can be used to assess the potential opportunities or risks associated with a stock. Higher volatility indicates higher risk, while lower volatility indicates lower risk. Historical Volatility and Implied Volatility are types of volatility. Implied Volatility reflects the anticipated future volatility of a stock based on the views of investors, observing demand and supply dynamics, which is used to predict the future price movement of the stock. Historical Volatility, on the other hand, refers to the variance in the price of an asset over a specific period. To calculate Historical Volatility, the daily price changes in the stock exchange are considered, where R_t represents the natural logarithm of today's stock price (S_t) divided by the price from the previous day (S_{t-1}). The results of this calculation are expressed as the percentage change in the stock price. According to Jain (2001:3):

$$R_t = LN \left(\frac{S_t}{S_{t-1}} \right) \dots\dots\dots (2.5)$$

Where:

- R_t = The natural logarithm of today's stock price (S_t) divided by the previous day's stock price (S_{t-1})
- S_t = Stock price today
- S_{t-1} = Stock price the previous day

Next, calculate the average daily price change (R_m) over a certain period (n).

$$R_m = \frac{\sum n R_t}{n} \dots\dots\dots (2.6)$$

Where:

- R_m = Average daily price change
- R_t = The natural logarithm of today's stock price (S_t) divided by the previous day's stock price (S_{t-1})
- n = Observation period

Then, calculate the standard deviation of the daily price change (historical volatility):

$$HV = \sqrt{\frac{\sum (R_t - R_m)^2}{n-1}} \dots\dots\dots (2.7)$$

Where:

- HV = Historical Volatility
- R_m = Average daily price change
- R_t = The natural logarithm of today's stock price (S_t) divided by the previous day's stock price (S_{t-1})
- n = Observation period

Finally, calculate the annual historical volatility by multiplying by the square root of 252 (the average number of trading days per year).

$$\text{annual HV} = \sqrt{252} * HV \dots\dots\dots (2.8)$$

2.6. GARCH Theory

The Black-Scholes method is one of the methods used to determine the price of options. The assumptions used in this model include the payment of dividends, which are paid in a constant market condition. The stock price, which changes randomly over time, is assumed to follow a stochastic process. The Black-Scholes model, developed in 1973 by Fischer Black and Myron Scholes, serves as the foundation for determining the fair price of both call and put options. The Black-Scholes model uses six variables: time, risk-free interest rate, volatility, type of option, stock price, and strike price. The GARCH model (Generalized Autoregressive Conditional Heteroscedasticity) is a model used in forecasting data with heteroscedasticity problems. This model was developed by Bollerslev (1986) from the ARCH model introduced by Robert F. Engle (1982). The steps involved in the GARCH model are as follows:

The first step in the GARCH method is to calculate the realized return for each company's stock. Next, the return of the company is statistically described to understand the characteristics of the return data. Then, the stationarity of the return data is tested using the Dickey-Fuller test.

The GARCH (Generalized Autoregressive Conditional Heteroscedasticity) model was first developed from the ARCH (Autoregressive Conditional Heteroscedasticity) model introduced by Robert Engle. The GARCH model was developed by Bollerslev (1986) to improve the ARCH model. The Autoregressive (AR) condition has certain requirements, such as the data being stationary, meaning it should be around the mean or have a constant variance of observations. Stationarity can be tested using the Augmented Dickey-Fuller Test (ADF). In this model, conditional variance is influenced by past residuals and lagged conditional variances (Hardianti & Widarjono, 2017). The GARCH model can be expressed as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1 e_{t-1}^2 + \dots + \alpha_p e_{t-p}^2 + \lambda_1 \sigma_{t-1}^2 + \dots + \lambda_q \sigma_{t-q}^2 \dots\dots\dots (2.9)$$

Where:

p = indicates ARCH component

q = indicates GARCH component

e_{t-p} = variable from the previous x periods.

The time period that affects the model can be limited within the GARCH model.

Bollerslev (1986) proposed the GARCH (1,1) model in volatility modeling, with σ_n^2 calculated from the long-run average variance level, V_L , as well as σ_{n-1} and u_{n-1} . According to Hull (2009), the GARCH (1,1) equation is as follows:

$$\sigma_n^2 = \gamma V_L + \alpha u_{n-1}^2 + \beta \sigma_{n-1}^2 \dots\dots\dots (2.10)$$

Where γ represents V_L , α represents u_{n-1}^2 , dan β represents σ_{n-1}^2 , The total constant should satisfy the following equation:

$$\gamma + \alpha + \beta = 1 \dots\dots\dots (2.11)$$

In GARCH (1,1) it shows that σ_n^2 depends on the most recent observations of u^2 and the latest estimate of variance levels. The more general GARCH (p,q) model calculates σ_n^2 from p observations of u^2 and q lagged variance estimates. If $\omega = \gamma V_L$, the GARCH (1,1) model can be written as:

$$\sigma^2 = \omega + \alpha u_{n-1}^2 + \beta \sigma_{n-1}^2 \dots\dots\dots (2.12)$$

Once ω , α , and β are estimated, γ can be calculated as $1 - \alpha - \beta$. The long variance V_L can be calculated as ω/γ . For a stable GARCH process, the condition $\alpha + \beta < 1$ must hold.

2.7. Collar Strategy

The collar strategy is a combination of buying the underlying stock/index, a covered call option, and a protective put option. The collar option addresses the volatility of the highest price by obtaining a more stable price through the simultaneous purchase of a put option and the sale of a call option for the same stock. The payoff diagram of the collar option can be seen in Figure 2.1. A put option provides a profit when the stock price in the capital market is lower than the strike price of the put option (K_P), as the stock price is protected from significant declines. The stock price gain is capped at the strike price of the call option (K_C), as the call option will be executed if the market price exceeds K_C . The collar strategy provides limited profits but offers hedging at a low cost or even no cost if the price of the put option is equal to the price of the call option.

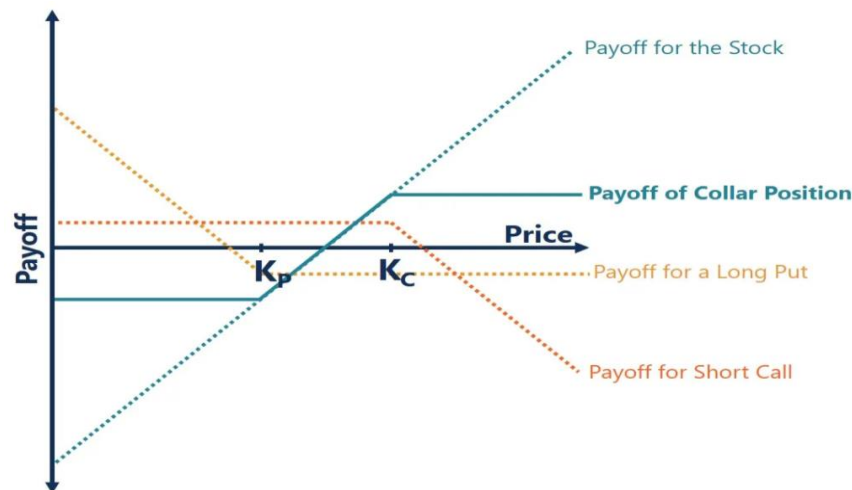


Figure 1. Collar strategy payoff diagram
Source: www.corporatefinanceinstitute.com

A put option offers a profit when the stock price in the capital market is lower than the strike price of the put option (K_P) because the stock price is protected from significant declines. The stock profit is limited to the strike price of the call option (K_C), as the call option will be executed if the market price exceeds K_C . The collar strategy offers limited profit but provides hedging with minimal or no cost if the price of the put option equals the price of the call option sold.

2.8. Framework

The research framework of this study involves the application of options using the Black-Scholes model (with GARCH Volatility and Historical Volatility) on the Infrastructure sector, specifically the Telecommunications sub-sector (Telkom, Indosat, EXCL), as a risk calculation method. This is then applied using the collar strategy.

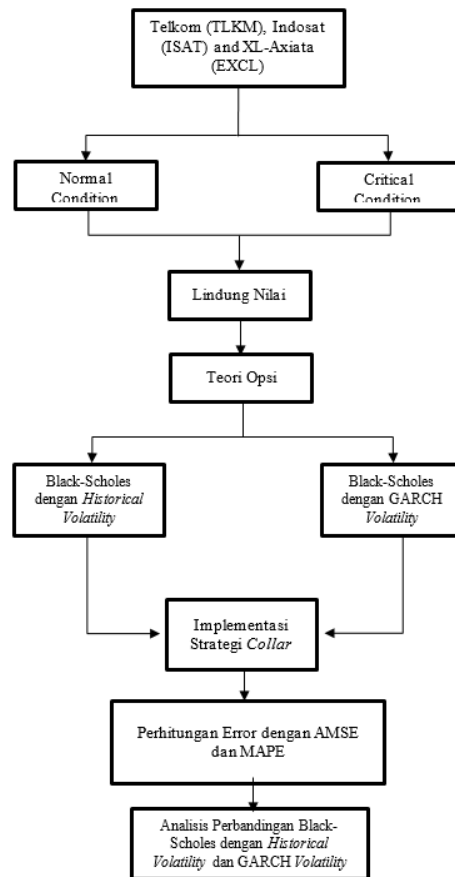


Figure 2. Framework

3. Research Methodology

3.1. Type of Research

This study will utilize option theory with the Black-Scholes and GARCH models using the collar strategy, making this a quantitative research study. Quantitative research is characterized by the use of numerical data from the data collection process to interpretation. Quantitative research is systematic, structured, and objective. Quantitative research is a research method used to study a specific sample or population, where data is collected using research instruments, and data analysis is statistical with the purpose of testing hypotheses.

3.2. Operationalization of Variables

Research variables are attributes or properties or values of an object or subject that vary and are defined by the researcher for studying their variations. The following operational variables are used to understand the application of options on the Indonesian Stock Exchange Index:

Table 1. Operational Variables

Measured Variable	Variable Concept	Indicator	Scale
Call Option Price	The price paid by the buyer to the seller of the call option	Call Option Premium (Black-Scholes) $C = S_0N(d_1) - e^{-RfT}XN(d_2)$	Ratio
Put Option Price	The price paid by the buyer to the seller of the put option	Put Option Premium (Black-Scholes) $P = Xe^{-RfT}N(-d_2) - S_0N(-d_1)$	Ratio

Collar Strategy Return	Return is the profit obtained by the company, individual, or institution from investment policies using the collar strategy	Return in Collar Strategy: Return= S – (P-C), jika $0 < S < X$ dan Imbal hasil= X – S – (P-C), jika $S < X$	Ratio
GARCH (1,1) Model Variance	Variance is a measure of how far a set of numbers is spread	σ^2 $= \omega + \alpha u_{n-1}^2$ $+ \beta \sigma_{n-1}^2$	Ratio
Error Rate Calculation using AMSE and MAPE	Analytical method used to evaluate a model, with smaller values indicating better model performance	$AMSE = \frac{1}{N} \sum_{t=1}^N \left(\frac{AP_t - SP_t}{AP_t} \right)^2$	Ratio

3.3. Population and Sample

a) Population

The population refers to the generalization area defined in a study, consisting of subjects/objects with certain characteristics and qualities that have been determined by the researcher for analysis, study, and drawing conclusions. On the Indonesia Stock Exchange (Bursa Efek Indonesia), there are several indices that contain stocks based on specific criteria. In this study, the selected population consists of companies in the infrastructure sector, specifically telecommunications companies, that are listed on the Indonesia Stock Exchange (BEI) as of 2007.

b) Sample

A sample is a portion of the population selected through specific procedures to represent the characteristics of the population. A sample includes members of the population chosen for involvement in the study, either for observation, treatment, or providing opinions about the research topic. There are two types of sampling methods: probability sampling and non-probability sampling. One type of non-probability sampling is purposive sampling. The criteria for sample selection in this study are stocks listed on the Indonesia Stock Exchange since 2007. The selected stocks are those operating in non-building infrastructure, primarily in telecommunications. Therefore, based on these criteria, the stocks selected are TLKM, EXCL, and ISAT. The purposive sampling criteria for this study are based on the telecommunications subsector index data (Telkom, Indosat, XL Axiata) from 2007 to 2022

3.4. Data Collection and Data Sources

This study uses secondary data collected from the Yahoo Finance website (<https://www.finance.yahoo.com/>) in the form of daily closing prices of the Infrastructure sector, specifically the Telecommunications subsector (Telkom, Indosat, XL Axiata), listed on the Indonesia Stock Exchange.

P For the 1-month option duration:

Observation period: January 1, 2007 – December 31, 2021, with the testing data from February 1, 2007 – January 31, 2022.

For the 3-month option duration:

Observation period: January 1, 2007 – December 31, 2021, with the testing data from April 4, 2007 – March 31, 2022

3.5. Data Analysis Techniques

Data analysis techniques refer to the methods used to systematically search and organize the collected data. The following steps outline the data analysis process for this study:

a) Black-Scholes Model Calculation

Black & Scholes, (1973) laid an important foundation in derivative securities theory by developing the Black-Scholes Option Pricing Model (OPM) and publishing the journal *The Pricing of Options and Corporate Liabilities*. (Merton, (1973) refined this model by relaxing some of the unrealistic assumptions, publishing the journal *Theory of Rational Option Pricing*. According to the Black-Scholes OPM, the value of an option is a function of the current price of the underlying asset, exercise price, time to expiration, risk-free interest rate, and the variance of the underlying asset's returns. To calculate the value of a call option, the equation (2.1) is used, while the value of a put option can be calculated using equation (2.2). Iqrami et al., (2021) state that the Asian option price is determined using the geometric average, which is approximated to the Black-Scholes framework, using stock movement data from HMS Holdings Corp from November 1, 2019, to November 1, 2020, with exercise prices (K) of \$25.00, \$30.00, and \$35.00 for Asian call options at \$1.790927, \$0.066597, and \$0.000235, respectively, and for Asian put options at \$0.301904, \$3.575965, and \$8.507994. The price differences can serve as a guide for investors when making decisions to buy or sell options. (Pratiwi, 2015) states that simulation results indicate that the Adomian decomposition method closely matches the calculation from the diffusion equation, concluding that Adomian decomposition is suitable for solving the Black-Scholes equation.

b) Historical Volatility Calculation

Volatility is the degree of fluctuation in the price of a stock or security over time. It is often referred to as market mood because it reflects the rise and fall of securities over a specific period. Volatility levels can be used to measure the risk of an investment. High volatility implies higher risk. However, high volatility does not necessarily mean that a stock is unattractive. The movement or volatility in stock prices reflects market conditions, which may be unstable.

Volatility is crucial for predicting stock price movements. According to Jain, (2011), understanding volatility behavior and its relationship with the market can provide an advantage compared to merely analyzing stock prices. High volatility reflects unusual supply and demand characteristics and can create uncertainty in the expected return. Research by (Keown et al., 2020) shows that the higher the level of volatility, the higher the uncertainty in the returns from stocks.

Historical volatility refers to the total volatility of a security over the past year. The calculation of Historical Volatility from daily stock price changes on the stock exchange can be broken down into four steps :

The first step is determining the parameters. Three parameters must be defined:

The time period, which serves as the reference to calculate returns (rewards) at the initial stage.

The number of periods in a month, usually 20 or 21 days, used in the calculation of returns.

The number of days in a year used to calculate volatility in annual percentage terms, usually 1 day (daily returns), 21 days (monthly returns), 63 days (quarterly returns), or 252 days (annual returns)

The second step is calculating Historical Volatility from daily price changes on the stock exchange using the following equation:

$$R_t = LN \left(\frac{S_t}{S_{t-1}} \right) \dots \dots \dots (3.1)$$

Where:

R_t = daily return

LN = natural logarithm

S_t = today's closing price

S_{t-1} = previous day's closing price

The third step is calculating the average variation in daily price changes (R_m) over a specific period (n) using the following equation:

$$R_m = \frac{\sum n R_t}{n} \dots\dots\dots (3.2)$$

Next, calculate the squared deviation (R_s) from the average return (R_m) using the following equation:

$$R_s = (R_t - R_m)^2 \dots\dots\dots (3.3)$$

Next, calculate the average variation in daily price changes, $(R_v)^2$ as the variance in returns using the following equation:

$$(R_v)^2 = \frac{\sum n (R_t - R_m)^2}{n-1} \dots\dots\dots (3.4)$$

Volatility is the standard deviation, not variance, so to determine Historical Volatility (HV), the variance is placed under a square root, as follows;

$$HV = \sqrt{\frac{\sum n (R_t - R_m)^2}{n-1}} \dots\dots\dots (3.5)$$

The fourth step is calculating the annual historical volatility (HV) by multiplying by the square root of 252 (the average number of trading days per year).

$$HV = \sqrt{\frac{\sum R_t^2}{n}} \dots\dots\dots (3.6)$$

$$HV = \sqrt{T} \sqrt{\frac{\sum (R_t - R_m)^2}{n-1}} \text{ or equivalently } HV = \sqrt{\frac{T}{n-1} \sum n (R_t - R_m)^2} \quad (3.7)$$

Yang & Zhang, (2000), found that the volatility estimation model based on HLOC prices provides more accurate and efficient results than variance estimators based only on closing prices (VCC).. Buescu et al., (2011), stated that the volatility estimation model (VZ) developed provided more efficient results compared to the VYZ model. The advantage of these models is that they provide estimates that are not overblown. These models use the method of moments to explain random stock price movements, assuming that the variance of stock price movements is not constant. The research indicates that these volatility models provide the minimum variance, meaning there is only slight deviation from the actual volatility estimates.

3.6. GARCH Volatility Calculation

Many studies have explored volatility estimation models. (Hwang & Satchell, (2001) mentioned several models for volatility estimation, including Autoregressive Conditional Heteroskedasticity developed by (Engle, 1982), Generalized Autoregressive Conditional Heteroskedasticity (GARCH) by Bollerslev, (1986) and Stochastic Volatility (SV) by Jacquier et al, (1994). These volatility estimation models are based on closing prices (close-to-close).

The equation for calculating GARCH Model is as follows:

$$\sigma^2 = \omega + \alpha u_{n-1}^2 + \beta \sigma_{n-1}^2 \dots\dots\dots (3.8)$$

Where:

u_{n-1} = return at period $n-1$ obtained from the formula $u_{n-1} = LN \left(\frac{S_{n-1}}{S_{n-2}} \right)$

σ_{n-1} = volatility at period $n-1$

Once ω , α , and β are estimated, γ can be calculated as $1 - \alpha - \beta$. Long variance V_L be calculated as ω/γ . For a stable GARCH process, the condition $\alpha + \beta < 1$ must hold.

(Kim & Shephard, 1998) stated that the SV model is superior to the GARCH model. Matei, (2009) stated that the predictive ability of the GARCH model is superior compared to other models like ARCH and ARMA. Li & Hong, (2011) found that the volatility estimation model based on HLOC prices

provides more efficient results compared to the model based solely on closing price estimators (GARCH).

3.7. *Uji AMSE*

Forecasting models are then validated using various indicators. Common indicators used include the Mean Absolute Deviation (MAD) and Mean Square Error (MSE). To analyze a model, a mathematical function for the average percentage mean squared error (AMSE) method is required. Mean Squared Error (MSE) is the average squared error between the actual values and forecasted values. The MSE method is commonly used to check the estimation error in forecasting. A low MSE value or an MSE close to zero indicates that the forecasted results align well with actual data and can be used for forecasting in future periods. MSE is typically used to evaluate regression or forecasting models such as Moving Average, Weighted Moving Average, and Trendline Analysis.

The formula for calculating MSE is as follows:

$$AMSE = \frac{1}{N} \sum_{t=1}^N \left(\frac{AP_t - SP_t}{AP_t} \right)^2 \dots\dots\dots(3.9)$$

Where:

AP_t = Actual option premium value

SP_t = Option premium value from model calculation

N = Number of experiments conducted

A small AMSE value means a small error value, with a direct relationship between AMSE and error values. Wan method is relatively better as it yields smaller values compared to MSE Prasad and Rao, where the variance of random effects causes larger MSE values.

3.8. *MAPE Test*

The Mean Absolute Percentage Error (MAPE) method is used to obtain the deviation between predicted values and actual values, providing information on how significant the forecasting error is compared to the actual value of the series. The percentage error value in MAPE impacts the accuracy of the forecast. The measurement using MAPE can be used by the general public because it is easy to understand and apply in predicting forecasting accuracy. The smaller the MAPE value, the more accurate a model is in making predictions.

$$MAPE = \frac{1}{N} \sum_{t=1}^N \left(\frac{Ai - Fi}{Ai} \right) \times 100\% \dots\dots\dots(3.10)$$

Where:

n = Sample size

A_i = Actual data value

F_i = Forecasted data value

In this formula, the difference between the actual data and the forecast is divided by the actual data, and then the absolute value (magnitude) is taken. This means MAPE will always yield a positive value. MAPE is one of the most commonly used accuracy measures for forecasting models compared to MAD, MAE, RMSE, or others.

Table 2. Interpretation of MAPE Values

MAPE Value	Interpretation
≤ 10%	Very accurate forecast results
10 – 20%	Good forecast results
20 – 50%	Fair forecast results (acceptable)
> 50%	Inaccurate forecast results

From these values, it can be understood that MAPE values up to 50% are still usable. When the MAPE exceeds 50%, the forecasting model is no longer valid.

According to Nabillah & Ranggadara, (2020), MAPE provides a benchmark for how large the prediction error is compared to the realized values of the calculations. Subsequently, if the production outcome is predicted to be 70% and the MAPE is 30%, it can be concluded that the linear regression results possess a valid forecasting model.

3.9. Collar Strategy Types

Hendrawan et al. (2020) used a strangle strategy with X_p 5% lower than S_o and X_c 5% higher than S_o in their research. The authors refer to this research when determining the collar strategy with the type $X_p = 95\% * S_o$, $X_c = 105\% * S_o$. In this study, additional types were included to examine the effects of changes in X_c values on volatility and average profits obtained from the collar strategy, as well as to identify the best type of collar strategy. The types used in this study are:

$$\begin{aligned} X_p &= 95\% * S_o, X_c = 105\% * S_o \\ X_p &= 95\% * S_o, X_c = 107.5\% * S_o \\ X_p &= 95\% * S_o, X_c = 110\% * S_o \end{aligned}$$

According to Jang and Koo (2024), the results of the research concluded that the option strategy depends on market conditions. The zero-cost collar strategy, with a 2% strike price difference from the index price for both the call and put options and a six-month contract duration, is profitable.

4. Results and Discussion

4.1. Calculation of Historical Volatility

The data used in this study are the closing stock prices of TLKM and ISAT from 2007 to 2022. These data will be used to calculate the historical volatility for the Black-Scholes model as follows:

1) Calculating Historical Volatility for TLKM Stock (1-month period)

The calculation of Historical Volatility from daily price changes on the stock exchange, where R_t represents the natural logarithm of the current stock price (S_t) divided by the previous day's stock price (S_{t-1}). The data used for the 1-month period calculation is from January 2, 2007, to December 30, 2022. For instance, on January 4, 2007, (S_t) was 2030 and the previous day's stock price

(S_{t-1}) was 2070. Using the formula $R_t = \ln(S_t / S_{t-1})$

$$R_t = \ln\left(\frac{2030}{2070}\right) = -1.95\%. \quad R = \ln\left(\frac{S_t}{S_{t-1}}\right) \text{ found } t-1$$

Next, the average daily price change (R_m) for a specific period (n) $R_m = (\sum_{t=1}^n R_t) / n$ with n is the sum of values R_t on data used. where n is the number of active trading days in the stock exchange each month

$$R_m = \frac{\sum_{t=1}^{21} R_t}{21} = -0.0043$$

By knowing the value of R_m then the HV value can be found with formula

$HV = \sqrt{\frac{\sum_{t=1}^n (R_t - R_m)^2}{n-1}}$. This calculation involves summing the squared differences between R_t and R_m . The sum is then divided by the number of data points minus one, yielding an HV value of 0.0010. The annual HV is obtained by multiplying $\sqrt{252} * HV$, where 252 is the average number of trading days per year. $annual HV = \sqrt{252} * HV = 0.0154$.

Table 3. Historical Volatility Calculation for TLKM Stock (1-month period)

Date	Close Price	Rt	Rm	(Rt - Rm)	(Rt - Rm) ²	HV	Annual HV
1/2/2007	2070	0	- 0.0043319 89	0.0043319 89	1.87661E- 05	0.000968 662	0.015377 037
1/3/2007	2030	- 0.0195128 14	- 0.0043319 89	- 0.0151808 25	0.000230 457	0.003394 536	0.053886 582
1/4/2007	2030	0	- 0.0043319 89	0.0043319 89	1.87661E- 05	0.000968 662	0.015377 037
1/5/2007	2000	- 0.0148886 12	- 0.0043319 89	- 0.0105566 23	0.000111 442	0.002360 533	0.037472 295
1/8/2007	1990	- 0.0050125 42	- 0.0043319 89	- 0.0006805 52	4.63152E- 07	0.000152 176	0.002415 721
1/9/2007	1940	- 0.0254466 66	- 0.0043319 89	- 0.0211146 76	0.000445 83	0.004721 385	0.074949 665
1/10/2007	1930	- 0.0051679 7	- 0.0043319 89	- 0.0008359 81	6.98864E- 07	0.000186 931	0.002967 437
1/11/2007	1920	- 0.0051948 17	- 0.0043319 89	- 0.0008628 27	7.44471E- 07	0.000192 934	0.003062 734
1/12/2007	1970	0.0257083 57	- 0.0043319 89	0.0300403 46	0.000902 422	0.006717 226	0.106632 651

Source: Processed Data

2) Calculating Historical Volatility for TLKM Stock (3-month period)

For the 3-month period, the data used is from January 2, 2007, to December 30, 2022. The calculations follow the same method as for the 1-month period, yielding the following results:

Table 4. Historical Volatility Calculation for TLKM Stock (3-month period)

Date	Close Price	Rt	Rm	(Rt - Rm)	(Rt - Rm) ²	HV	Annual HV
1/2/2007	2070						
1/3/2007	2070	0.00%	-0.0008	0.0008	0.0000	0.02%	0.28%
1/4/2007	2030	-1.95%	-0.0008	-0.0187	0.0004	0.42%	6.64%
1/5/2007	2030	0.00%	-0.0008	0.0008	0.0000	0.02%	0.28%
1/8/2007	2000	-1.49%	-0.0008	-0.0141	0.0002	0.32%	5.00%
1/9/2007	1990	-0.50%	-0.0008	-0.0042	0.0000	0.09%	1.50%
1/10/2007	1940	-2.54%	-0.0008	-0.0246	0.0006	0.55%	8.75%
1/11/2007	1930	-0.52%	-0.0008	-0.0044	0.0000	0.10%	1.55%
1/12/2007	1920	-0.52%	-0.0008	-0.0044	0.0000	0.10%	1.56%

Source: Processed Data

3) Calculating Historical Volatility for ISAT Stock (1-month period)

For the 1-month period, the data used is from January 2, 2007, to December 30, 2022. The calculations for ISAT stock follow the same process as for TLKM stock and yield the following results:

Table 5. Historical Volatility Calculation for ISAT Stock (1-month period)

Date	Close Price	Rt	Rm	(Rt - Rm)	(Rt - Rm)^2	HV	Annual HV
1/2/2007	6750						
1/3/2007	6700	-0.0074	-0.0056	-0.0018	3.33523E-06	0.00041	0.00648
1/4/2007	6650	-0.0075	-0.0056	-0.0019	3.54176E-06	0.00042	0.00668
1/5/2007	6600	-0.0075	-0.0056	-0.0019	3.75774E-06	0.00043	0.00688
1/8/2007	6550	-0.0076	-0.0056	-0.0020	3.98355E-06	0.00045	0.00708
1/9/2007	6400	-0.0232	-0.0056	-0.0176	0.00031	0.00393	0.06233
1/10/2007	5900	-0.0813	-0.0056	-0.0757	0.00574	0.01694	0.26884
1/11/2007	6000	0.0168	-0.0056	0.0224	0.00050	0.00501	0.07957
1/12/2007	5850	-0.0253	-0.0056	-0.0197	0.00039	0.00441	0.06996

Source: Processed Data

4) Calculating Historical Volatility for ISAT Stock (3-month period)

For the 3-month period, the data used is from January 2, 2007, to December 30, 2022. The calculations follow the same procedure as for TLKM stock and yield the following results:

Tabel 6. Tabel Perhitungan Historical Volatility Saham ISAT Periode 3 bulan

Date	Close Price	Rt	Rm	(Rt - Rm)	(Rt - Rm)^2	HV	Annual HV
1/2/2007	6750						
1/3/2007	6700	-0.74%	-0.0012	-0.0062	0.00%	0.00138	0.02200
1/4/2007	6650	-0.75%	-0.0012	-0.0063	0.00%	0.00140	0.02218
1/5/2007	6600	-0.75%	-0.0012	-0.0063	0.00%	0.00141	0.02238
1/8/2007	6550	-0.76%	-0.0012	-0.0064	0.00%	0.00142	0.02259
1/9/2007	6400	-2.32%	-0.0012	-0.0219	0.05%	0.00490	0.07783
1/10/2007	5900	-8.13%	-0.0012	-0.0801	0.64%	0.01791	0.28434
1/11/2007	6000	1.68%	-0.0012	0.0180	0.03%	0.00404	0.06407
1/12/2007	5850	-2.53%	-0.0012	-0.0241	0.06%	0.00538	0.08546

Source: Processed Data

4.2. GARCH Volatility Calculation Results

In calculating the volatility using GARCH, it is necessary to first conduct stationarity and heteroscedasticity tests on the data used. The following steps outline the process for calculating volatility using GARCH:

1) Stationarity Test

The stationarity test is conducted to determine whether the data used has a stable distribution. The test is performed using the Augmented Dickey-Fuller (ADF) test. Data is considered stationary if the ADF value is $< 5\%$.

Table 7. Stationarity Test of TLKM Stock Closing Price

Test Unit Root	ADF (<i>Augmented Dicky Fuller</i>)
Level	0.6166
1st Difference	0

Based on Table 4.9, the data stationarity test using the ADF Unit Root Test at the level stage shows that the data is not stationary because the value is 0.6166, which is above 0.05. Therefore, it is necessary to conduct an ADF test using the first difference. After conducting the first difference test, the ADF value is 0.0000, which is below the significance level of 0.05. Thus, the data used is stationary.

2) Mean Model Estimation

The identification of AR, MA, and ARMA models can be determined from their *Autocorrelation* (ACF) and *Partial Autocorrelation* (PACF). The best possible model is identified based on the highest spikes in the ACF and PACF charts, which are used to determine the maximum order of $AR(p)$ and $MA(q)$.

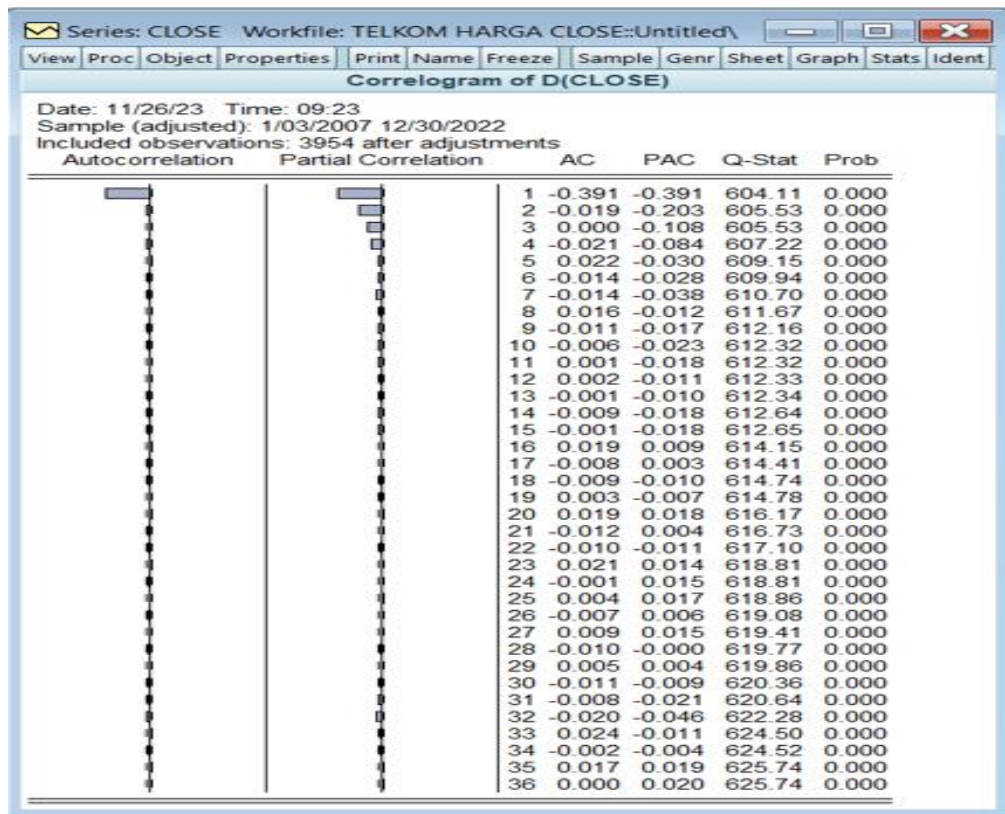


Figure 3. Correlogram of TLKM Data

The correlogram in Figure 4.1 shows that the ARMA model used is AR(1) and MA(1). The AR and MA orders are determined from the highest spikes in the ACF and PACF. The model is then tested using AR(1) and MA(1) as follows:

Table 8. GARCH Model AIC Results

AR Partial Correlation (p)	IC (d)	MA Auto Correlation (q)	ARIMA	Akaike info criterion
1	1	0	AR(1)	11.27558
0	1	1	MA(1)	10.78607
1	1	1	AR(1) MA(1)	10.78444

From Table 4.10, the results from each model estimation are presented. The best model is determined by comparing the Akaike Information Criterion (AIC) value, where the smallest AIC value is preferred. The smallest AIC value of 10.78444 is obtained for the ARIMA(1,1,1) model, which will be used in the next GARCH calculations.

3) Heteroscedasticity Effect Test

After estimating the mean model, the best model identified was ARIMA(1,1,1). Next, the heteroscedasticity effect in the residuals of the best model is tested.

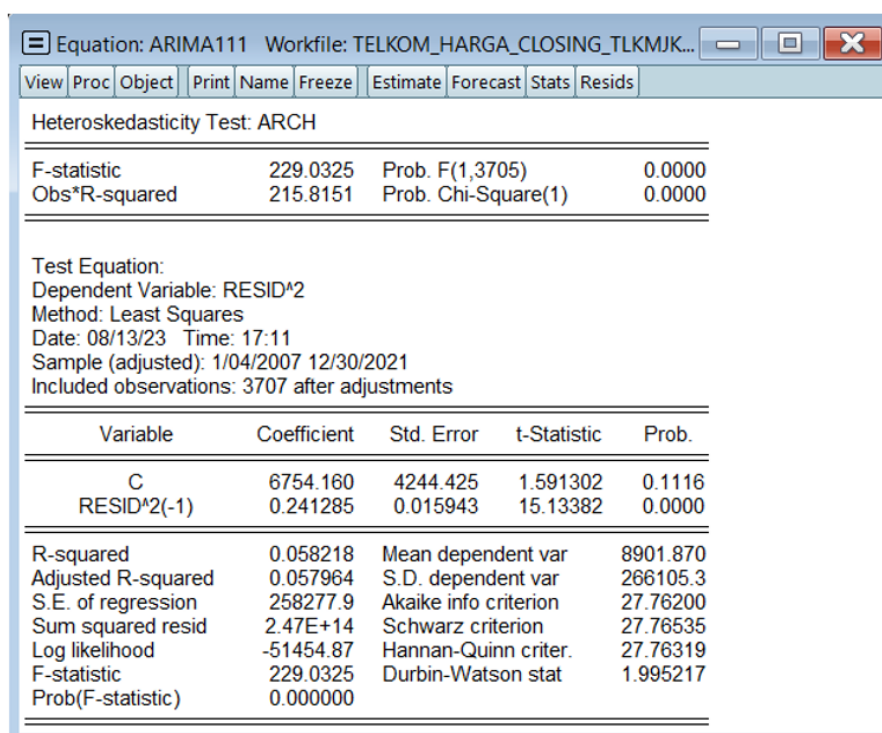


Figure 4. Heteroscedasticity Effect Test

The heteroscedasticity effect test is conducted using the ARCH LM test with a significance level of 0.05. Based on Figure 4.3, the LM value is 0.0000, indicating that there is an ARCH effect in the data from the ARIMA(1,1,1) model, as the probability value is < 0.05 . Figure 4.2 shows that the ARIMA(1,1,1) model has a GARCH effect. Therefore, we proceed to verify the GARCH model used. The best GARCH(1,1) model is then used to forecast volatility.

4.3. Bank Indonesia Interest Rate/BI Rate/7-Day Repo Rate

The Bank Indonesia Interest Rate/BI Rate/7-Day Repo Rate is a monetary policy rate set by Bank Indonesia and announced to the public. The following table presents the Bank Indonesia interest rates for the period 2007-2022.

Table 9. Bank Indonesia Interest Rates from 2007 to 2022

Year	BI-7Day-RR %
2007	8.604166667
2008	8.666666667
2009	7.145833333
2010	6.5
2011	6.583333333
2012	5.770833333
2013	6.479166667
2014	7.541666667
2015	7.520833333
2016	6
2017	4.5625
2018	5.104166667
2019	5.625
2020	4.25
2021	3.520833333
2022	4

Source: Processed data

The Bank Indonesia interest rate fluctuated according to government policies from 2007 to 2022. In the Black-Scholes calculations with Historical Volatility and GARCH Volatility, the researcher used the annual average BI rate applicable during the specified period.

4.4. Black-Scholes Model Calculation with Historical Volatility

To calculate the volatility using the Black-Scholes model with Historical Volatility for both 1-month and 3-month periods, data on stock spot prices, exercise prices, and the BI Rate/7-Day Repo Rate are required. This study uses the Collar strategy, with exercise prices set 5% lower and 5% higher as boundaries. The steps for performing the Black-Scholes calculation for 1-month and 3-month periods are as follows.

1) Identifying Black-Scholes *Historical Volatility Variables*

Table 10. Black-Scholes Variable Values

Variable	Value	Unit	Description
S	1980	Rupiah	Stock closing price
Xp	1881	Rupiah	Put exercise price (-5% of S)
Xc	2079	Rupiah	Call exercise price (+5% of S)
	2128.5	Rupiah	Call exercise price (+7.5% of S)
	2178	Rupiah	Call exercise price (+10% of S)
T	0.083333333	1 Month	Maturity time (1-month period)
	0.25	3 Months	Maturity time (3-month period)
Rf	0.086041667	%	Applicable interest rate (BI Rate)
σ	0.305576976	%	Historical volatility (1 month)
	0.261025201	%	Historical volatility (3 months)

Source: Processed data

2) Calculating Normal Distribution Values

After identifying the variables for the Black-Scholes calculation, the next step is to calculate the normal distribution to find the call and put values using the following formulas:

$$d1 = \left(\ln \frac{[S/X] + \frac{[Rf - \sigma^2]}{2}}{\sigma \sqrt{T}} \right) \dots \dots \dots (4.2)$$

$$d2 = d1 - \sigma \sqrt{T} \dots \dots \dots (4.3)$$

Where:

S : Stock closing price

X : Put/Call exercise price

Rf : risk-free rate

σ : Volatility variance

$$d1p = \left(\ln \frac{[1980/1881] + \frac{[0.0860 - 0.305^2]}{2}}{0.3055 \sqrt{0.0833}} \right) \dots \dots \dots (4.4)$$

$$d1p = 0.706863 \dots \dots \dots (4.5)$$

$$d2p = 0.706863 - 0.3055 \sqrt{0.0833} \dots \dots \dots (4.6)$$

$$d2p = 0.618651 \dots \dots \dots (4.7)$$

$$d1c = \frac{[\ln(1980/2709) + (0.0860 - 0.305^2)/2] + 0.305\sqrt{0.0833}}{0.0833} \dots\dots\dots(4.8)$$

$$d1c = -4.2771 \dots\dots\dots(4.9)$$

$$d2c = -4.2771 - 0.305\sqrt{0.0833} \dots\dots\dots(4.10)$$

$$d2c = -0.51592 \dots\dots\dots(4.11)$$

Source: Processed data

3) Calculating Normal Distribution Values

After identifying the variables for the Black-Scholes calculation, the next step is to calculate the normal distribution to find the call and put values using the following formulas:

$$C = SN(d1c) - e^{-RfT} XcN(d2c) \dots\dots\dots(4.12)$$

$$C = 1980N(-4.2771) - e^{-0.0860 \cdot 0.0833} 2079N(-0.51592)$$

$$C = 36.8316$$

The formula for a put option is as follows:

$$P = Xpe^{-RfT} N(-d2p) - SN(d1p) \dots\dots\dots(4.13)$$

$$P = 1881e^{-0.0860 \cdot 0.0833} N(0.618651) - 1980N(0.706863) \dots\dots\dots(4.14)$$

$$P = 25.7882 \dots\dots\dots(4.15)$$

Once the call and put values are obtained, the next step is to find the BEP (Break-Even Point) for the options using the following formulas:

$$\text{BEP Call} = Xc + P - C \dots\dots\dots(4.16)$$

$$\text{BEP Put} = Xp + P - C \dots\dots\dots(4.17)$$

Using these formulas, the BEP Call value is obtained as 2090.043403 and the BEP Put value as 1892.043403. These BEP values are then compared to the strike price (Xc) of the call option on the same day, which is 2079. The capital required for this option is calculated as S + P - C, resulting in 1968.9565. If the option is executed on that day, the profit will be 2081.043403 - 1968.9565 = 101.043403.

4) Black-Scholes Value Using *Historical Volatility*

Using the calculations above, the Black-Scholes value with Historical Volatility for TLKM, ISAT, and EXCL stocks is obtained as follows:

Tabel 11. Nilai Opsi TLKM Black Scholes dengan *Historical Volatility*

Stoc k	Scenario	Xp	Xc	C	P	BEP Call	BEP Put	Time Maturity
TLK M	Xp = 95%*So	188	2079	36.83160	25.78820	2090.043	1892.043	1 month
	Xc = 105%*So	1		391	093	403	403	
		188	2079	79.33522	44.93531	2113.399	1915.399	3 months
		1		496	873	906	906	
	Xp = 95%*So	188	2128	24.12602	25.78820	2126.837	1879.337	1 month
		1	.5	752	093	827	827	

	Xc = 107.5%*So							
		188 1	2128 .5	61.99989 994	44.93531 873	2145.564 581	1898.064 581	3 months
	Xp = 95%*So, Xc = 110%*So	188 1	2178	15.22197 963	25.78820 093	2167.433 779	1870.433 779	1 month
		188 1	2178	47.76566 12	44.93531 873	2180.830 342	1883.830 342	3 months
EXCL	Xp = 95%*So Xc = 105%*So	206 2	2278 .6	45.02637 422	32.26752 426	2291.321 398	2074.315 441	1 month
		206 2	2278 .6	119.1593 298	76.86505 395	2320.856 824	2103.850 867	3 months
	Xp = 95%*So Xc = 107.5%*So	206 2	2332 .8	30.49419 724	32.26752 426	2331.040 711	2059.783 264	1 month
		206 2	2332 .8	99.20436 385	76.86505 395	2355.153 348	2083.895 901	3 months
	Xp = 95%*So, Xc = 110%*So	206 2	2387 .1	19.99843 12	32.26752 426	2374.796 434	2049.287 498	1 month
		206 2	2387 .1	81.96888 013	76.86505 395	2392.169 353	2066.660 418	3 months
ISAT	Xp = 95%*So Xc = 105%*So	603 3	6667 .5	131.5750 284	94.26467 749	6704.810 351	6069.810 351	1 month
		603 3	6667 .5	366.3689 556	240.4896 43	6793.379 313	6158.379 313	3 months
	Xp = 95%*So Xc = 107.5%*So	603 3	6826 .3	89.07322 16	94.26467 749	6821.058 544	6027.308 544	1 month
		603 3	6826 .3	307.6353 799	240.4896 43	6893.395 737	6099.645 737	3 months
	Xp = 95%*So, Xc = 110%*So	603 3	6985	58.38778 498	94.26467 749	6949.123 107	5996.623 107	1 month
		603 3	6985	256.5668 539	240.4896 43	7001.077 211	6048.577 211	3 months

Source: Processed data

a) Profit/Loss Calculation in Collar Strategy

Based on the calculations of call and put option values using Black-Scholes with historical volatility and GARCH volatility, and a 1-month maturity time, the profit and loss probabilities are calculated based on the criteria below Xp, between Xp and Xc, or above Xc. Losses occur when X is below Xp and X is between Xp and So. X represents the strike price, Xp is the put exercise price, and So is the stock closing price. Profits are obtained when X is above Xc and X is between So and Xc.

b) Profit/Loss Comparison between Collar Strategy and Without

The collar strategy calculations performed using the Black-Scholes model with Historical Volatility and GARCH Volatility are compared with the calculations for options without a collar strategy. This comparison displays the minimum, maximum, and average profits or losses.

Table 12. Profit Comparison for TLKM Stock using Black-Scholes Historical Volatility and GARCH Volatility in Collar and Non-Collar Options

Kondisi	Waktu kontrak	Data	Saham TLKMJK											
			HV Black Scholes dengan Strategi Collar				GARCH Black Scholes dengan Strategi Collar				tanpa strategi collar			
			rata-rata	min	max	range	rata-rata	min	max	range	rata-rata	min	max	range
Non Krisis (2007)	1 bulan	$X_p = 95\% * So, X_c = 105\% * So$	0.76%	-4.64%	5.79%	10.44%	3.31%	-1.92%	8.11%	10.02%	0.38%	-23.29%	18.04%	41.33%
		$X_p = 95\% * So, X_c = 107.5\% * So$	0.83%	-5.08%	7.47%	12.56%	6.03%	-0.06%	12.82%	12.88%				
		$X_p = 95\% * So, X_c = 110\% * So$	0.89%	-5.70%	9.87%	15.58%	3.28%	-3.13%	11.91%	15.04%				
	3 bulan	$X_p = 95\% * So, X_c = 105\% * So$	1.97%	-3.02%	6.89%	9.91%	12.24%	6.84%	17.44%	10.60%				
		$X_p = 95\% * So, X_c = 107.5\% * So$	1.89%	-3.94%	8.41%	12.35%	12.40%	6.17%	19.37%	13.21%	-0.63%	-33.60%	19.05%	52.64%
		$X_p = 95\% * So, X_c = 110\% * So$	1.78%	-4.75%	10.17%	14.91%	12.42%	5.50%	21.30%	15.80%				
Krisis (2008-2009)	1 Bulan	$X_p = 95\% * So, X_c = 105\% * So$	0.64%	-4.61%	6.15%	10.76%	3.07%	-2.02%	8.13%	10.15%	0.45%	-27.54%	26.96%	54.49%
		$X_p = 95\% * So, X_c = 107.5\% * So$	0.58%	-5.14%	7.73%	12.87%	5.66%	-0.27%	12.89%	13.15%				
		$X_p = 95\% * So, X_c = 110\% * So$	0.49%	-5.80%	9.79%	15.60%	2.93%	-3.23%	11.94%	15.17%				
	3 bulan	$X_p = 95\% * So, X_c = 105\% * So$	2.25%	-3.72%	7.66%	11.38%	12.10%	6.08%	17.54%	11.46%				
		$X_p = 95\% * So, X_c = 107.5\% * So$	2.35%	-4.50%	9.21%	13.72%	12.48%	5.40%	19.48%	14.08%	-0.10%	-34.64%	32.48%	67.12%
		$X_p = 95\% * So, X_c = 110\% * So$	2.38%	-5.09%	10.83%	15.92%	12.67%	4.74%	21.42%	16.68%				
Non Krisis (210 - 2019)	1 bulan	$X_p = 95\% * So, X_c = 105\% * So$	0.87%	-4.99%	5.81%	10.80%	3.40%	-2.23%	8.02%	10.25%	0.82%	-20.08%	21.43%	41.51%
		$X_p = 95\% * So, X_c = 107.5\% * So$	0.79%	-5.24%	7.46%	12.69%	5.66%	-0.71%	12.62%	13.33%				
		$X_p = 95\% * So, X_c = 110\% * So$	0.69%	-5.85%	9.93%	15.78%	2.87%	-3.44%	11.81%	15.26%				
	3 bulan	$X_p = 95\% * So, X_c = 105\% * So$	1.91%	-4.48%	6.78%	11.26%	11.48%	4.76%	16.88%	12.12%	2.28%	-34.83%	28.57%	63.40%
		$X_p = 95\% * So, X_c = 107.5\% * So$	1.90%	-4.95%	8.35%	13.30%	11.65%	4.08%	18.81%	14.72%				
		$X_p = 95\% * So, X_c = 110\% * So$	1.88%	-5.44%	10.07%	15.51%	11.66%	3.43%	20.73%	17.30%				
Krisis (2020-2022)	1 Bulan	$X_p = 95\% * So, X_c = 105\% * So$	0.46%	-4.86%	5.77%	10.63%	2.86%	-2.31%	7.78%	10.09%	0.66%	-29.00%	31.56%	60.56%
		$X_p = 95\% * So, X_c = 107.5\% * So$	0.43%	-5.32%	7.37%	12.69%	5.02%	-0.85%	12.11%	12.97%				
		$X_p = 95\% * So, X_c = 110\% * So$	0.37%	-5.95%	9.73%	15.68%	2.53%	-3.51%	11.59%	15.10%				
	3 bulan	$X_p = 95\% * So, X_c = 105\% * So$	1.38%	-4.14%	6.28%	10.43%	0.00%	0.00%	0.00%	0.00%	1.90%	-22.08%	34.33%	56.41%
		$X_p = 95\% * So, X_c = 107.5\% * So$	1.50%	-4.90%	7.87%	12.78%	0.00%	0.00%	0.00%	0.00%				
		$X_p = 95\% * So, X_c = 110\% * So$	1.61%	-5.61%	9.56%	15.17%	10.56%	2.94%	18.96%	16.02%				

Table 13. Profit Comparison for EXCL Stock using Black-Scholes Historical Volatility and GARCH Volatility in Collar and Non-Collar Options

Kondisi	Waktu kontrak	Data	Saham EXCLK											
			HV Black Scholes dengan Strategi Collar				GARCH Black Scholes dengan Strategi Collar				tanpa strategi collar			
			rata-rata	min	max	range	rata-rata	min	max	range	rata-rata	min	max	range
Non Krisis (2007)	1 bulan	$X_p = 95\% * So, X_c = 105\% * So$	-0.21%	-4.82%	5.98%	10.80%	4.83%	0.68%	10.68%	10.00%	-1.23%	-34.81%	38.46%	73.28%
		$X_p = 95\% * So, X_c = 107.5\% * So$	-0.44%	-5.08%	7.59%	12.68%	11.61%	6.74%	19.99%	13.25%				
		$X_p = 95\% * So, X_c = 110\% * So$	-0.64%	-5.72%	9.66%	15.38%	5.58%	0.68%	15.68%	15.00%				
	3 bulan	$X_p = 95\% * So, X_c = 105\% * So$	-0.80%	-3.29%	7.42%	10.71%	11.96%	9.73%	20.48%	10.76%				
		$X_p = 95\% * So, X_c = 107.5\% * So$	-1.57%	-4.16%	8.97%	13.13%	12.14%	9.73%	23.17%	13.44%	-3.06%	-25.93%	33.33%	59.26%
		$X_p = 95\% * So, X_c = 110\% * So$	-2.27%	-4.86%	10.59%	15.45%	12.27%	9.73%	25.86%	16.13%				
Krisis (2008-2009)	1 Bulan	$X_p = 95\% * So, X_c = 105\% * So$	2.00%	-4.51%	6.32%	10.83%	6.83%	0.56%	10.68%	10.12%	3.03%	-63.18%	55.04%	118.22%
		$X_p = 95\% * So, X_c = 107.5\% * So$	2.13%	-5.13%	7.89%	13.02%	14.17%	6.49%	20.00%	13.52%				
		$X_p = 95\% * So, X_c = 110\% * So$	2.20%	-5.80%	9.86%	15.67%	8.50%	0.56%	15.68%	15.12%				
	3 bulan	$X_p = 95\% * So, X_c = 105\% * So$	4.68%	-3.09%	7.70%	10.79%	17.30%	8.96%	20.52%	11.55%	13.02%	-66.67%	92.11%	158.77%
		$X_p = 95\% * So, X_c = 107.5\% * So$	5.32%	-4.00%	9.27%	13.27%	19.00%	8.96%	23.21%	14.24%				
		$X_p = 95\% * So, X_c = 110\% * So$	5.91%	-4.78%	10.88%	15.66%	20.56%	8.96%	25.89%	16.93%				
Non Krisis (210 - 2019)	1 bulan	$X_p = 95\% * So, X_c = 105\% * So$	0.69%	-4.76%	6.31%	11.07%	5.63%	0.34%	10.60%	10.26%	0.77%	-33.21%	51.35%	84.56%
		$X_p = 95\% * So, X_c = 107.5\% * So$	0.70%	-5.28%	7.90%	13.17%	12.52%	5.99%	19.80%	13.81%				
		$X_p = 95\% * So, X_c = 110\% * So$	0.68%	-5.93%	9.75%	15.67%	6.88%	0.34%	15.60%	15.26%				
	3 bulan	$X_p = 95\% * So, X_c = 105\% * So$	1.82%	-3.97%	7.60%	11.57%	13.98%	7.46%	19.90%	12.44%	1.45%	-57.53%	86.49%	144.02%
		$X_p = 95\% * So, X_c = 107.5\% * So$	1.94%	-4.80%	9.22%	14.02%	15.08%	7.46%	22.58%	15.12%				
		$X_p = 95\% * So, X_c = 110\% * So$	2.04%	-5.49%	10.87%	16.36%	16.06%	7.46%	25.26%	17.80%				
Krisis (2020-2022)	1 Bulan	$X_p = 95\% * So, X_c = 105\% * So$	0.29%	-4.77%	6.05%	10.82%	5.16%	0.28%	10.34%	10.06%	0.24%	-48.16%	81.56%	129.72%
		$X_p = 95\% * So, X_c = 107.5\% * So$	0.32%	-5.32%	7.64%	12.96%	11.83%	5.87%	19.20%	13.33%				
		$X_p = 95\% * So, X_c = 110\% * So$	0.36%	-6.00%	9.62%	15.61%	6.48%	0.28%	15.34%	15.06%				
	3 bulan	$X_p = 95\% * So, X_c = 105\% * So$	1.05%	-4.12%	6.86%	10.97%	0.00%	0.00%	0.00%	0.00%	1.09%	-91.68%	95.04%	186.71%
		$X_p = 95\% * So, X_c = 107.5\% * So$	1.06%	-4.93%	8.44%	13.37%	0.00%	0.00%	0.00%	0.00%				
		$X_p = 95\% * So, X_c = 110\% * So$	1.06%	-5.61%	10.07%	15.68%	14.21%	7.08%	23.41%	16.34%				

Table 14. Profit Comparison for ISAT Stock using Black-Scholes Historical Volatility and GARCH Volatility in Collar and Non-Collar Options

Kondisi	Waktu kontrak	Data	Saham ISAT.JK											
			HV Black Scholes dengan Strategi Collar				GARCH Black Scholes dengan Strategi Collar				tanpa strategi collar			
			rata-rata	min	max	range	rata-rata	min	max	range	rata-rata	min	max	range
Non Krisis (2007)	1 bulan	Xp = 95%*So, Xc = 105%*So	2.26%	-4.60%	5.96%	10.56%	7.29%	0.68%	10.68%	10.00%	2.71%	-35.71%	24.29%	60.00%
		Xp = 95%*So, Xc = 107.5%*So	2.48%	-5.08%	7.57%	12.66%	14.72%	6.74%	19.99%	13.25%				
		Xp = 95%*So, Xc = 110%*So	2.58%	-5.71%	9.62%	15.34%	8.83%	0.68%	15.68%	15.00%				
	3 bulan	Xp = 95%*So, Xc = 105%*So	3.55%	-3.25%	7.10%	10.35%	16.76%	9.73%	20.48%	10.76%				
		Xp = 95%*So, Xc = 107.5%*So	3.96%	-4.13%	8.66%	12.79%	18.19%	9.73%	23.17%	13.44%	5.52%	-33.33%	39.44%	72.77%
		Xp = 95%*So, Xc = 110%*So	4.28%	-4.85%	10.32%	15.18%	19.39%	9.73%	25.66%	16.13%				
Krisis (2008-2009)	1 Bulan	Xp = 95%*So, Xc = 105%*So	-0.06%	-4.73%	6.16%	10.96%	4.88%	0.56%	10.68%	10.12%				
		Xp = 95%*So, Xc = 107.5%*So	-0.27%	-5.14%	7.74%	12.89%	11.67%	6.49%	20.00%	13.52%	-0.84%	-37.80%	40.83%	78.62%
		Xp = 95%*So, Xc = 110%*So	-0.43%	-5.80%	9.63%	15.43%	5.81%	0.56%	15.68%	15.12%				
	3 bulan	Xp = 95%*So, Xc = 105%*So	1.15%	-3.37%	7.76%	11.13%	13.68%	8.96%	20.52%	11.55%				
		Xp = 95%*So, Xc = 107.5%*So	0.78%	-4.27%	9.31%	13.58%	14.28%	8.96%	23.21%	14.24%	-2.65%	-40.15%	45.57%	85.72%
		Xp = 95%*So, Xc = 110%*So	0.38%	-5.03%	10.93%	15.95%	14.75%	8.96%	25.89%	16.93%				
Non Krisis (210 - 2019)	1 bulan	Xp = 95%*So, Xc = 105%*So	0.14%	-4.89%	6.15%	11.04%	5.16%	0.36%	10.59%	10.23%				
		Xp = 95%*So, Xc = 107.5%*So	0.13%	-5.25%	7.74%	12.99%	11.91%	6.04%	19.80%	13.75%	0.22%	-36.90%	93.35%	130.25%
		Xp = 95%*So, Xc = 110%*So	0.15%	-5.92%	9.95%	15.87%	6.22%	0.36%	15.59%	15.23%				
	3 bulan	Xp = 95%*So, Xc = 105%*So	0.96%	-4.22%	7.24%	11.46%	13.22%	7.62%	19.90%	12.28%				
		Xp = 95%*So, Xc = 107.5%*So	0.81%	-4.89%	8.84%	13.72%	14.00%	7.62%	22.58%	14.96%	-0.15%	-58.76%	118.71%	177.48%
		Xp = 95%*So, Xc = 110%*So	0.68%	-5.44%	10.48%	15.92%	14.66%	7.62%	25.26%	17.64%				
Krisis (2020-2022)	1 Bulan	Xp = 95%*So, Xc = 105%*So	0.80%	-4.77%	6.12%	10.88%	5.60%	0.28%	10.34%	10.06%				
		Xp = 95%*So, Xc = 107.5%*So	0.90%	-5.32%	7.56%	12.88%	12.42%	5.87%	19.20%	13.33%	5.49%	-45.45%	164.57%	210.03%
		Xp = 95%*So, Xc = 110%*So	0.98%	-6.02%	9.49%	15.50%	7.15%	0.28%	15.34%	15.06%				
	3 bulan	Xp = 95%*So, Xc = 105%*So	2.02%	-3.97%	6.89%	10.86%	0.00%	0.00%	0.00%	0.00%				
		Xp = 95%*So, Xc = 107.5%*So	2.26%	-4.84%	8.48%	13.33%	0.00%	0.00%	0.00%	0.00%	17.72%	-45.99%	212.50%	258.49%
		Xp = 95%*So, Xc = 110%*So	2.51%	-5.60%	10.12%	15.73%	15.66%	7.08%	23.41%	16.34%				

c) MSE Comparison for Collar Strategy using Historical Volatility and GARCH Volatility

The calculations are performed by comparing the error in the BEP Option Collar price with the price at maturity. The best model is determined by the smallest MSE compared to other models. The error is calculated as follows:

$$MSE = \frac{1}{N} \sum_{t=1}^N (\hat{x} - x)^2$$

$$MSE = \frac{\sum (\text{Strike Price} - \text{BEP Put})^2 \text{ all data points}}{N}$$

Table 15. MSE Comparison for TLKM Stock using Black-Scholes with Historical Volatility and GARCH Volatility in Collar and Non-Collar Options

Kondisi	Maturity	Tipe Strategi Collar	Saham TLKM.JK		Hasil
			MSE HV Black Scholes	MSE GARCH Volatility Black Scholes	
Non Krisis (2007)	1 Bulan	Xp = 95%*So, Xc = 105%*So	0.008546255	0.006780236	Model GARCH lebih baik dibandingkan dengan Model HV
		Xp = 95%*So, Xc = 107.5%*So	0.009113471	0.007075596	
		Xp = 95%*So, Xc = 110%*So	0.009545413	0.007434898	
	3 bulan	Xp = 95%*So, Xc = 105%*So	0.015738173	0.017252857	Model HV lebih baik dibandingkan dengan model GARCH
		Xp = 95%*So, Xc = 107.5%*So	0.015669343	0.016986489	
		Xp = 95%*So, Xc = 110%*So	0.015685521	0.016744437	
Krisis (2008-2009)	1 Bulan	Xp = 95%*So, Xc = 105%*So	0.009915634	0.00900241	Model HV lebih baik dibandingkan dengan model GARCH
		Xp = 95%*So, Xc = 107.5%*So	0.010341207	0.009113381	
		Xp = 95%*So, Xc = 110%*So	0.010717121	0.009294404	
	3 bulan	Xp = 95%*So, Xc = 105%*So	0.022669022	0.02551719	Model HV lebih baik dibandingkan dengan model GARCH
		Xp = 95%*So, Xc = 107.5%*So	0.022489306	0.025189762	
		Xp = 95%*So, Xc = 110%*So	0.022510362	0.024887852	
Non Krisis (210 - 2019)	1 Bulan	Xp = 95%*So, Xc = 105%*So	0.006120981	0.004714753	Model HV lebih baik dibandingkan dengan model GARCH
		Xp = 95%*So, Xc = 107.5%*So	0.006647415	0.005008443	
		Xp = 95%*So, Xc = 110%*So	0.007034509	0.005366661	
	3 bulan	Xp = 95%*So, Xc = 105%*So	0.010867786	0.017252857	Model HV lebih baik dibandingkan dengan model GARCH
		Xp = 95%*So, Xc = 107.5%*So	0.011611966	0.025189762	
		Xp = 95%*So, Xc = 110%*So	0.012318753	0.009253555	
Krisis (2020-2022)	1 Bulan	Xp = 95%*So, Xc = 105%*So	0.0073571	0.007077257	Model GARCH lebih baik dibandingkan dengan Model HV
		Xp = 95%*So, Xc = 107.5%*So	0.007838367	0.007328324	
		Xp = 95%*So, Xc = 110%*So	0.008222462	0.007645181	
	3 bulan	Xp = 95%*So, Xc = 105%*So	0.014859124	0.014231351	Model GARCH lebih baik dibandingkan dengan Model HV
		Xp = 95%*So, Xc = 107.5%*So	0.0153866	0.014182502	
		Xp = 95%*So, Xc = 110%*So	0.01593527	0.014153595	

Table 16. MSE Comparison for EXCL Stock using Black-Scholes with Historical Volatility and GARCH Volatility in Collar and Non-Collar Options

Kondisi	Maturity	Tipe Strategi Collar	Saham EXCLJK		Hasil
			MSE HV Black Scholes	MSE GARCH Volatility Black Scholes	
Non Krisis (2007)	1 Bulan	$X_p = 95\%*So, X_c = 105\%*So$	0.005566213	0.005392494	Model GARCH lebih baik dibandingkan dengan Model HV
		$X_p = 95\%*So, X_c = 107.5\%*So$	0.006009944	0.005392494	
		$X_p = 95\%*So, X_c = 110\%*So$	0.006415451	0.005392494	
	3 bulan	$X_p = 95\%*So, X_c = 105\%*So$	0.007096266	0.013533277	Model HV lebih baik dibandingkan dengan model GARCH
		$X_p = 95\%*So, X_c = 107.5\%*So$	0.006462403	0.013533277	
		$X_p = 95\%*So, X_c = 110\%*So$	0.00607073	0.013533277	
Krisis (2008-2009)	1 Bulan	$X_p = 95\%*So, X_c = 105\%*So$	0.058219015	0.064073808	Model HV lebih baik dibandingkan dengan model GARCH
		$X_p = 95\%*So, X_c = 107.5\%*So$	0.057889941	0.064073808	
		$X_p = 95\%*So, X_c = 110\%*So$	0.057794949	0.064073808	
	3 bulan	$X_p = 95\%*So, X_c = 105\%*So$	0.278724018	0.313393768	Model HV lebih baik dibandingkan dengan model GARCH
		$X_p = 95\%*So, X_c = 107.5\%*So$	0.273206612	0.313393768	
		$X_p = 95\%*So, X_c = 110\%*So$	0.268687841	0.313393768	
Non Krisis (210 - 2019)	1 Bulan	$X_p = 95\%*So, X_c = 105\%*So$	0.049014471	0.014198688	Model HV lebih baik dibandingkan dengan model GARCH
		$X_p = 95\%*So, X_c = 107.5\%*So$	0.04900062	0.014198688	
		$X_p = 95\%*So, X_c = 110\%*So$	0.049134608	0.014198688	
	3 bulan	$X_p = 95\%*So, X_c = 105\%*So$	0.043748636	0.013533277	Model HV lebih baik dibandingkan dengan model GARCH
		$X_p = 95\%*So, X_c = 107.5\%*So$	0.043256708	0.313393768	
		$X_p = 95\%*So, X_c = 110\%*So$	0.043009017	0.046053447	
Krisis (2020-2022)	1 Bulan	$X_p = 95\%*So, X_c = 105\%*So$	0.169533779	0.020160155	Model GARCH lebih baik dibandingkan dengan Model HV
		$X_p = 95\%*So, X_c = 107.5\%*So$	0.167765116	0.020160155	
		$X_p = 95\%*So, X_c = 110\%*So$	0.166726891	0.020160155	
	3 bulan	$X_p = 95\%*So, X_c = 105\%*So$	0.244776258	0.0334532	Model GARCH lebih baik dibandingkan dengan Model HV
		$X_p = 95\%*So, X_c = 107.5\%*So$	0.229657259	0.0334532	
		$X_p = 95\%*So, X_c = 110\%*So$	0.22577398	0.0334532	

Table 17. MSE Comparison for ISAT Stock using Black-Scholes with Historical Volatility and GARCH Volatility in Collar and Non-Collar Options

Kondisi	Waktu kontrak	Data	Saham ISATJK											
			HV Black Scholes dengan Strategi Collar				GARCH Black Scholes dengan Strategi Collar				tanpa strategi collar			
			rata-rata	min	max	range	rata-rata	min	max	range	rata-rata	min	max	range
Non Krisis (2007)	1bulan	$X_p = 95\%*So, X_c = 105\%*So$	2.26%	-4.60%	5.96%	10.56%	7.23%	0.68%	10.68%	10.00%	2.71%	-35.71%	24.29%	60.00%
		$X_p = 95\%*So, X_c = 107.5\%*So$	2.48%	-5.08%	7.57%	12.66%	14.72%	6.74%	19.99%	13.25%				
		$X_p = 95\%*So, X_c = 110\%*So$	2.58%	-5.71%	9.62%	15.34%	8.83%	0.68%	15.68%	15.00%				
	3 bulan	$X_p = 95\%*So, X_c = 105\%*So$	3.55%	-3.25%	7.10%	10.35%	16.76%	9.73%	20.48%	10.76%				
		$X_p = 95\%*So, X_c = 107.5\%*So$	3.96%	-4.13%	8.66%	12.79%	18.19%	9.73%	23.17%	13.44%	5.52%	-33.33%	39.44%	72.77%
		$X_p = 95\%*So, X_c = 110\%*So$	4.28%	-4.85%	10.32%	15.18%	19.39%	9.73%	25.86%	16.13%				
Krisis (2008-2009)	1Bulan	$X_p = 95\%*So, X_c = 105\%*So$	-0.06%	-4.79%	6.16%	10.96%	4.88%	0.56%	10.68%	10.12%				
		$X_p = 95\%*So, X_c = 107.5\%*So$	-0.27%	-5.14%	7.74%	12.89%	11.67%	6.49%	20.00%	13.52%	-0.84%	-37.80%	40.83%	78.62%
		$X_p = 95\%*So, X_c = 110\%*So$	-0.43%	-5.80%	9.63%	15.43%	5.81%	0.56%	15.68%	15.12%				
	3 bulan	$X_p = 95\%*So, X_c = 105\%*So$	1.16%	-3.37%	7.76%	11.13%	13.68%	8.96%	20.52%	11.55%				
		$X_p = 95\%*So, X_c = 107.5\%*So$	0.78%	-4.27%	9.31%	13.58%	14.28%	8.96%	23.21%	14.24%	-2.65%	-40.15%	45.57%	85.72%
		$X_p = 95\%*So, X_c = 110\%*So$	0.38%	-5.03%	10.93%	15.95%	14.75%	8.96%	25.89%	16.93%				
Non Krisis (210 - 2019)	1bulan	$X_p = 95\%*So, X_c = 105\%*So$	0.14%	-4.89%	6.15%	11.04%	5.16%	0.36%	10.59%	10.23%				
		$X_p = 95\%*So, X_c = 107.5\%*So$	0.13%	-5.25%	7.74%	12.99%	11.91%	6.04%	19.80%	13.75%	0.22%	-36.90%	93.35%	130.25%
		$X_p = 95\%*So, X_c = 110\%*So$	0.15%	-5.92%	9.95%	15.87%	6.22%	0.36%	15.59%	15.23%				
	3 bulan	$X_p = 95\%*So, X_c = 105\%*So$	0.96%	-4.22%	7.24%	11.46%	13.22%	7.62%	19.90%	12.28%				
		$X_p = 95\%*So, X_c = 107.5\%*So$	0.81%	-4.89%	8.84%	13.72%	14.00%	7.62%	22.58%	14.96%	-0.15%	-58.76%	118.71%	177.48%
		$X_p = 95\%*So, X_c = 110\%*So$	0.68%	-5.44%	10.48%	15.92%	14.66%	7.62%	25.26%	17.64%				
Krisis (2020-2022)	1Bulan	$X_p = 95\%*So, X_c = 105\%*So$	0.80%	-4.77%	6.12%	10.88%	5.60%	0.28%	10.34%	10.06%				
		$X_p = 95\%*So, X_c = 107.5\%*So$	0.90%	-5.32%	7.56%	12.88%	12.42%	5.87%	19.20%	13.33%	5.49%	-45.45%	164.57%	210.03%
		$X_p = 95\%*So, X_c = 110\%*So$	0.98%	-6.02%	9.49%	15.50%	7.15%	0.28%	15.34%	15.06%				
	3 bulan	$X_p = 95\%*So, X_c = 105\%*So$	2.02%	-3.97%	6.89%	10.86%	0.00%	0.00%	0.00%	0.00%				
		$X_p = 95\%*So, X_c = 107.5\%*So$	2.26%	-4.84%	8.48%	13.33%	0.00%	0.00%	0.00%	0.00%	17.72%	-45.99%	212.50%	258.49%
		$X_p = 95\%*So, X_c = 110\%*So$	2.51%	-5.60%	10.12%	15.73%	15.66%	7.08%	23.41%	16.34%				

From the tables above, it is evident that for TLKM, ISAT, and EXCL stocks during both crisis and non-crisis periods with a 3-month maturity, the GARCH model outperforms the *Historical Volatility* model when using scenarios with X_c 5%, 7.5%, and 10%.

5. Conclusion

Based on the analysis of the results of this study, the following conclusions are drawn:

For TLKM, ISAT, and EXCL stocks under normal conditions with 1-month and 3-month maturity, the Black-Scholes model with GARCH Volatility provides more profit compared to the Black-Scholes

model with Historical Volatility. The Black-Scholes model with GARCH Volatility also provides better value protection compared to the Black-Scholes model with Historical Volatility. For TLKM, ISAT, and EXCL stocks, the collar strategy results in lower volatility compared to not using the collar strategy. This strategy is very suitable for investors who desire relatively stable asset values. The GARCH model produces smaller AMSE and MAPE values under crisis conditions for 1-month and 3-month option contracts. In non-crisis conditions, GARCH performs better for the 1-month option contract. Using GARCH Volatility during both crisis and non-crisis conditions with a 1-month maturity results in a maximum profit of 10%.

Suggestions

For investors looking to invest in ISAT and TLKM stocks, to achieve higher profits, they may opt for a 3-month contract period. Investors can use the Black-Scholes model with GARCH volatility for a 3-month contract. For investors aiming for a maximum profit of 10% on ISAT and TLKM stocks with a 1-month contract period, the Black-Scholes model using historical volatility can be applied. For academics who wish to continue this research, it is suggested to include MAD (Mean Absolute Deviation) and MAPE (Mean Absolute Percentage Error) as additional comparison metrics for the best model, alongside MSE (Mean Square Error). Academics can also explore other options strategies besides the collar strategy, such as long straddle, short straddle, long strangle, and short strangle. A comparison of which strategy provides better profit and loss protection can also be conducted..

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