

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

Victor Bastanta Sitepu¹, Abdul Mukti Soma²

Universitas Telkom, Bandung, Jawa Barat, Indonesia^{1,2}

victorsitepu2018@gmail.com¹



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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 study compares 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 operate 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). The GARCH model is 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 that focuses on information technology and communication (infrastructure and telecommunications). It is 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 that provides cellular and data communication services. PT Indosat merged with PT Hutchison 3 Indonesia/H3I, which also operates in the cellular and data communication sectors. PT XL Axiata Tbk is another telecommunications company in Indonesia that provides 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. 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 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 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 is 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.

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 movements can result in profits for investors or pose risks, leading to significant losses (Yang & Yang, 2021). Return fluctuations indicate that the volatility in the data is extremely high (Ridho, 2024). One way to anticipate stock price volatility and minimize the risk of loss is to use derivative instruments. A derivative is an investment instrument whose value depends on an underlying asset (Vasista, 2022). The 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 the exchange of assets at predetermined prices, times, and quantities. An options contract provides the right (but not the obligation) to exchange assets at a future time for an agreed price, time, and quantity.

The use of options as a derivative instrument in this research was 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/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 its expiration date. There are four positions in the 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

sell 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 that the price will rise.

According to Akin and 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 way to perform risk management is by hedging the assets owned. Several options strategies can be chosen for speculation or hedging. According to Isyuardhana and Surur (2018), 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 (Endi, Fanggida, & Ndoen, 2023).

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 the 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, respectively. 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, respectively. The collar strategy produced maximum volatilities 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%. 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 and protective put options. 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. 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 measures the statistical change in the price of a security over a certain period (Zournatzidou & Floros, 2023). Volatility is a key variable in options 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 be determined (Nafia, Agmour, Foutayeni, & Achtaich, 2023). Volatility can be calculated using implied and historical volatility (Moghaddam, Liu, & Serota, 2021). Implied Volatility reflects the anticipated future volatility of a stock as perceived by traders. In contrast, Historical Volatility is calculated based on the historical fluctuations in stock returns. Generalized Autoregressive Conditional Heteroscedasticity (GARCH) is an extension of the Autoregressive Conditional Heteroscedasticity (ARCH) 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 a 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 the 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 profits. Investment can take various forms, including gold, deposits, stocks, property, mutual funds, and real estate. Stocks represent an investment in a company and serve as a stake in the company’s ownership. Bonds are debt securities issued by the government and listed on exchanges. Gold is a form of investment with minimal risk and is always in demand because of its stable value and potential for price increases each year. Mutual funds are vehicles for collecting funds from investors, which are then invested in portfolios of securities. Deposits are a form of investment in which funds are saved for a specific period before they can be withdrawn.

Investment risk refers to the potential loss experienced by investors when actual returns differ from expected returns. Investment risks are broadly categorized into systematic and unsystematic risks. Systematic risk refers to risks that cannot be controlled or avoided, such as interest rate, inflation, foreign exchange, commodity, and country risks. Unsystematic risk refers to risks that can be controlled or mitigated, such as liquidity, reinvestment, financial, and business risks (Yuliansyah, 2023).

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 derivatives (Irianto et al., 2024). Derivatives are financial instruments whose value depends on or is derived from another fundamental variable (Bashiri, Lindrianasari, & Dharma, 2023). The underlying variable of a derivative is frequently the price of a traded asset. For example, stock options are derivatives that derive their value from the prices of the underlying stocks. Some types of derivative products include futures, forwards, swaps and options. Simbolon, Fadlan, and Jihad (2023) stated that futures, forwards, and swaps are obligatory contracts, meaning that the transaction must be executed at maturity. In contrast, options are mandatory for sellers but optional for buyers. The option buyer has the choice to execute the contract at maturity, with a premium paid to the seller.

2.3. Option Pricing Theory

Option Pricing Theory 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 used to determine the price of an option. The assumptions used in this model include dividend payments. The model assumes that stock prices follow a stochastic process, which means that 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 prices 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

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

The formula for a put option is

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

Where:

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

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

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 a key variable. Volatility is the degree of fluctuation in the price of a stock or security over a given period. Volatility can be used to assess the potential opportunities or risks associated with stocks. Higher volatility indicates a higher risk, whereas lower volatility indicates a 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 stock prices. 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, the average daily price change (R_m) is calculated 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, the standard deviation of the daily price change (historical volatility) is calculated as follows:

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

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

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

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 under constant market conditions. 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 prices of both call and put options. The Black-Scholes model uses six variables: time, risk-free interest rate, volatility, option type, stock price, and strike price. The generalized autoregressive conditional heteroscedasticity (GARCH) model is used to forecast 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 return data. Then, the stationarity of the return data was 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 Engle. The GARCH model was developed by Bollerslev (1986) to improve upon 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 (ADF) test. In this model, the conditional variance is influenced by past residuals and lagged conditional variances (Hardianti & Widarjono, 2017). The GARCH model is 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 to 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), 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 be satisfied.

2.7. Collar Strategy

The collar strategy combines 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 sale of a call option for the same stock. The payoff diagram of the collar option is shown 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 equals the price of the call option.

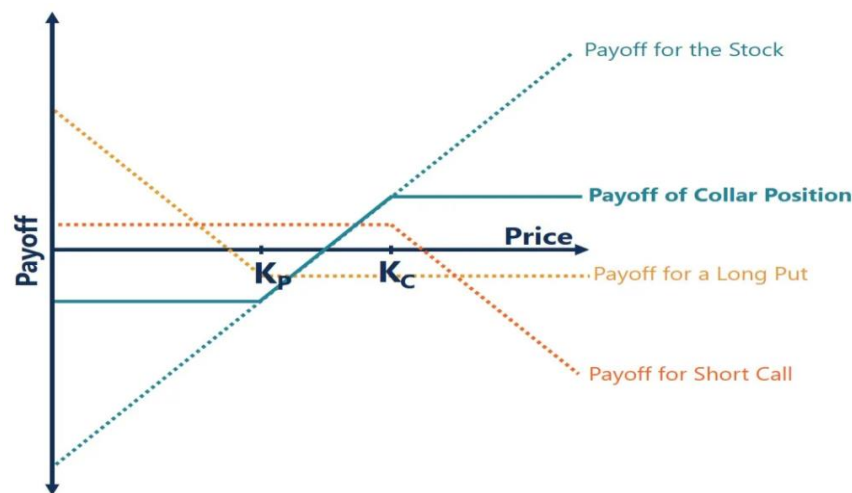


Figure 1. Collar strategy payoff diagram
Source: www.corporatefinanceinstitute.com

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 a significant decline. The stock profit is limited to the strike price of the call option (K_C) because the call option is 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.

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) in the infrastructure sector, specifically the telecommunications sub-sector (Telkom, Indosat, and EXCL), as a risk calculation method. This was then applied using the collar strategy.

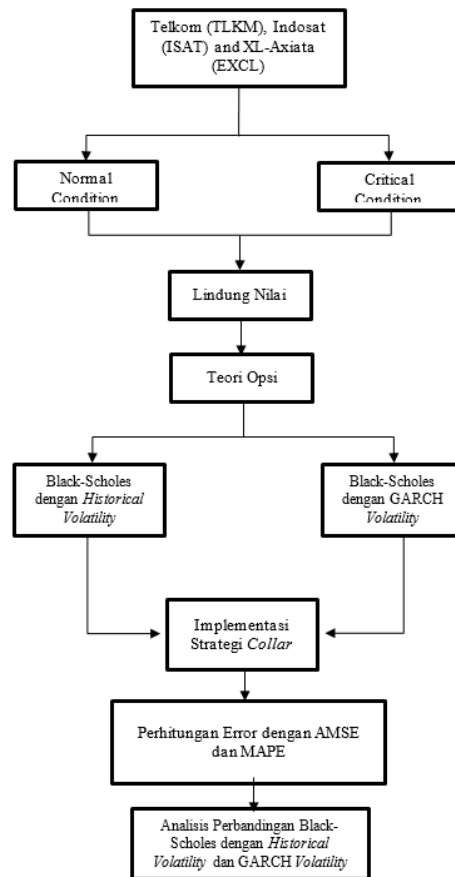


Figure 2. Framework

3. Research Methodology

3.1. Type of Research

This study utilizes 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 for interpretation. Quantitative research is systematic, structured, and objective in nature. Quantitative research is a research method used to study a specific sample or population, where data are collected using research instruments, and data analysis is statistical with the purpose of testing hypotheses.

3.2. Operationalization of Variables

Research variables are attributes, properties, or values of an object or subject that vary and are defined by the researcher to study 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	$\sigma^2 = \omega + \alpha u_{n-1}^2 + \beta \sigma_{n-1}^2$	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 conclusion. The Indonesia Stock Exchange (Bursa Efek Indonesia) has 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, 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 its characteristics. A sample includes members of the population chosen for involvement in the study, either for observation, treatment, or providing opinions on the research topic. There are two types of sampling methods: probability and non-probability sampling. Purposive sampling is a type of non-probability sampling. The criteria for sample selection in this study were stocks listed on the Indonesia Stock Exchange since 2007. The selected stocks are those of companies operating in non-building infrastructure, primarily telecommunications. Therefore, based on these criteria, TLKM, EXCL, and ISAT were selected. 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, to December 31, 2021, with testing data from February 1, 2007, to 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 for and organize the collected data. The following steps outline the data analysis process used in this study:

a) Black-Scholes Model Calculation

(Merton (1973) refined this model by relaxing some of the unrealistic assumptions in 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 variance of the underlying asset's returns. To calculate the value of a call option, 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. Price differences can serve as a guide for investors when deciding 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 a given period. It is often referred to as the 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 investments. High volatility implies a higher risk. However, high volatility does not necessarily mean that a stock is unappealing. The movement or volatility of 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 over merely analyzing stock prices. High volatility reflects unusual supply and demand characteristics and can create uncertainty in expected returns. Keown et al. (2020) show 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 in 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 was to determine the parameters. Three parameters must be defined.

The time period serves as a reference for calculating returns (rewards) at the initial stage.

The number of periods in a month, usually 20 or 21 days, is 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 to calculate 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 involves 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, 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; therefore, 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 involves 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 than the VYZ model. The advantage of these models is that they provide estimates that are not exaggerated. These models use the method of moments to explain random stock price movements, assuming that the variance of stock price movements is constant. The research indicates that these volatility models provide the minimum variance, meaning that there is only a slight deviation from the actual volatility estimates.

3.6. GARCH Volatility Calculation

Many studies have explored volatility estimation. Hwang and Satchell (2001) mentioned several models for volatility estimation, including Autoregressive Conditional Heteroskedasticity (ARCH) 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 the 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 be satisfied.

(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 to that of other models, such as ARCH and ARMA. Li and Hong (2011) found that the volatility estimation model based on HLOC prices provides more efficient results than the model based solely on closing price estimators (GARCH).

3.7. Uji AMSE

The forecasting models were then validated using various indicators. Common indicators 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. The Mean Squared Error (MSE) is the average squared error between the actual 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 the 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 the 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 indicates a small error value, with a direct relationship between the AMSE and error values. The 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 was used to obtain the deviation between the predicted and actual values, providing information on how significant the forecasting error was compared to the actual value of the series. The percentage error value in MAPE affects the accuracy of the forecast. The 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 the 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

Ai = Actual data value

Fi = Forecasted data value

In this formula, the difference between the actual data and the forecast is divided by the actual data, and the absolute value (magnitude) is then taken. This implies that MAPE will always yield a positive value. MAPE is one of the most commonly used accuracy measures for forecasting models compared with MAD, MAE, RMSE, and 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 of up to 50% are still usable. When the MAPE exceeds 50%, the forecasting model is invalid.

According to Nabillah and Ranggadara (2020), MAPE provides a benchmark for the magnitude of the prediction error compared to the realized values of the calculations. Subsequently, if the production outcome is predicted to be 70% and the MAPE 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 $X_p = 95\% * S_o$ and $X_c = 105\% * S_o$. 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 and to identify the best type of collar strategy. The types used in this study were as follows:

$$X_p = 95\% * S_o, X_c = 105\% * S_o$$

$$X_p = 95\% * S_o, X_c = 107.5\% * S_o$$

$$X_p = 95\% * S_o, X_c = 110\% * S_o$$

According to Jang and Koo (2024), the results of their 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 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 TLKM and ISAT closing stock prices 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 were 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

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

Next, the average daily price change (R_m) for a specific period (n) $R_m = \left(\sum_{t=1}^n R_t \right) / n$ 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 was 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 were from January 2, 2007, to December 30, 2022. The calculations followed 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 were from January 2, 2007, to December 30, 2022. The calculations for ISAT stock followed the same process as for TLKM stock and yielded 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 were from January 2, 2007, to December 30, 2022. The calculations followed the same procedure as for the TLKM stock and yielded 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 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 the GARCH model:

1) Stationarity Test

A stationarity test was conducted to determine whether the data used had a stable distribution. The test is performed using the Augmented Dickey-Fuller (ADF) test. Data are 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 are 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 of the variables. After conducting the first difference test, the ADF value was 0.0000, which was below the significance level of 0.05. Thus, the data used were 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 orders of AR(p) and MA(q) models.

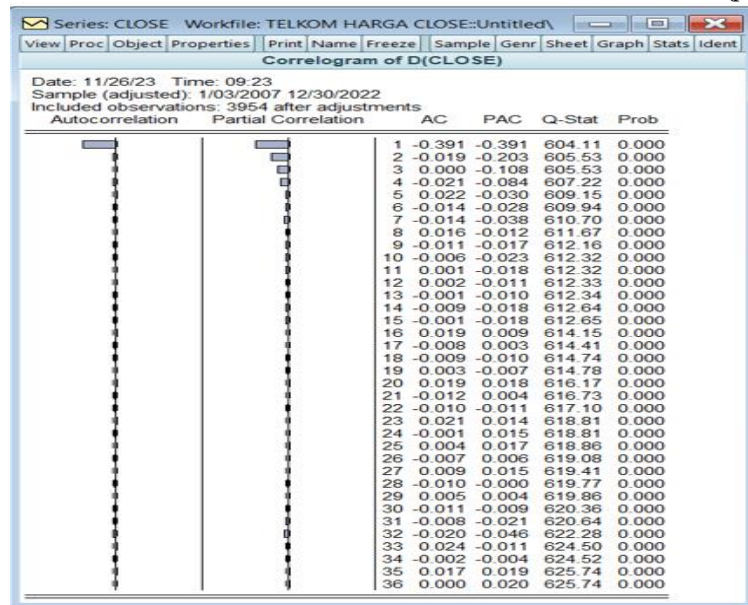


Figure 3. Correlogram of TLKM Data

The correlogram in Figure 4.1 shows that the ARMA model used is AR(1) and MA(1). The AR and MA orders were 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)	I C (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

Table 4.10 presents the results of each model estimation. The best model was determined by comparing the Akaike Information Criterion (AIC) values, where the smallest AIC value was preferred. The smallest AIC value of 10.78444 is obtained for the ARIMA(1,1,1) model, which is 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 was evaluated.

boundariess. 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 was 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

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

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

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

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

$$d1c = \left(\ln \frac{[1980/2079] + \frac{[0.0860 - 0.305^2]}{2}}{0.305 \sqrt{0.0833}} \right) \dots \dots \dots (4.8)$$

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

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

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

Source: Processed data

3) Calculating Normal Distribution Values

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

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

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

$$C = 36.8316$$

The formula for a put option is as follows.

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

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

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

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

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

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

Using these formulas, the BEP Call value is obtained as 2090.043403 and the BEP Put value as 1892.043403, respectively. These BEP values are then compared to the strike price (X_c) of the call option on the same day (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
	Xc = 107.5%*So	1	.5	752	093	827	827	
		188	2128	61.99989	44.93531	2145.564	1898.064	3 months
		1	.5	994	873	581	581	
	Xp = 95%*So,	188	2178	15.22197	25.78820	2167.433	1870.433	1 month
	Xc = 110%*So	1		963	093	779	779	

		188 1	2178	47.76566 12	44.93531 873	2180.830 342	1883.830 342	3 months
EXC L	Xp = 95%*So	206 2	2278 .6	45.02637 422	32.26752 426	2291.321 398	2074.315 441	1 month
	Xc = 105%*So	206 2	2278 .6	119.1593 298	76.86505 395	2320.856 824	2103.850 867	3 months
	Xp = 95%*So	206 2	2332 .8	30.49419 724	32.26752 426	2331.040 711	2059.783 264	1 month
	Xc = 107.5%*So	206 2	2332 .8	99.20436 385	76.86505 395	2355.153 348	2083.895 901	3 months
	Xp = 95%*So, Xc =	206 2	2387 .1	19.99843 12	32.26752 426	2374.796 434	2049.287 498	1 month
	110%*So	206 2	2387 .1	81.96888 013	76.86505 395	2392.169 353	2066.660 418	3 months
ISA T	Xp = 95%*So	603 3	6667 .5	131.5750 284	94.26467 749	6704.810 351	6069.810 351	1 month
	Xc = 105%*So	603 3	6667 .5	366.3689 556	240.4896 43	6793.379 313	6158.379 313	3 months
	Xp = 95%*So	603 3	6826 .3	89.07322 16	94.26467 749	6821.058 544	6027.308 544	1 month
	Xc = 107.5%*So	603 3	6826 .3	307.6353 799	240.4896 43	6893.395 737	6099.645 737	3 months
	Xp = 95%*So, Xc =	603 3	6985	58.38778 498	94.26467 749	6949.123 107	5996.623 107	1 month
	110%*So	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 the put exercise price, and So 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 for each group.

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%				
		$X_p = 95\% * So, X_c = 107.5\% * So$	0.83%	-5.08%	7.47%	12.56%	6.03%	-0.06%	12.82%	12.88%	0.38%	-23.29%	18.04%	41.33%
		$X_p = 95\% * So, X_c = 110\% * So$	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%				
		$X_p = 95\% * So, X_c = 107.5\% * So$	0.58%	-5.14%	7.73%	12.87%	5.66%	-0.27%	12.89%	13.15%	0.45%	-27.54%	26.96%	54.49%
		$X_p = 95\% * So, X_c = 110\% * So$	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%				
		$X_p = 95\% * So, X_c = 107.5\% * So$	0.79%	-5.24%	7.46%	12.69%	5.66%	-0.71%	12.62%	13.33%	0.82%	-20.08%	21.43%	41.51%
		$X_p = 95\% * So, X_c = 110\% * So$	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%				
		$X_p = 95\% * So, X_c = 107.5\% * So$	1.90%	-4.95%	8.35%	13.30%	11.65%	4.08%	18.81%	14.72%	2.28%	-34.83%	28.57%	63.40%
		$X_p = 95\% * So, X_c = 110\% * So$	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%				
		$X_p = 95\% * So, X_c = 107.5\% * So$	0.43%	-5.32%	7.37%	12.69%	5.02%	-0.85%	12.11%	12.97%	0.66%	-29.00%	31.56%	60.56%
		$X_p = 95\% * So, X_c = 110\% * So$	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%				
		$X_p = 95\% * So, X_c = 107.5\% * So$	1.50%	-4.90%	7.87%	12.78%	0.00%	0.00%	0.00%	0.00%	1.90%	-22.08%	34.33%	56.41%
		$X_p = 95\% * So, X_c = 110\% * So$	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 EXCLJK											
			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%				
		$X_p = 95\% * So, X_c = 107.5\% * So$	-0.44%	-5.08%	7.59%	12.68%	11.61%	6.74%	19.99%	13.25%	-1.23%	-34.81%	38.46%	73.28%
		$X_p = 95\% * So, X_c = 110\% * So$	-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%				
		$X_p = 95\% * So, X_c = 107.5\% * So$	2.13%	-5.13%	7.89%	13.02%	14.17%	6.49%	20.00%	13.52%	3.03%	-63.18%	55.04%	118.22%
		$X_p = 95\% * So, X_c = 110\% * So$	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%				
		$X_p = 95\% * So, X_c = 107.5\% * So$	5.32%	-4.00%	9.27%	13.27%	19.00%	8.96%	23.21%	14.24%	13.02%	-66.67%	92.11%	158.77%
		$X_p = 95\% * So, X_c = 110\% * So$	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%				
		$X_p = 95\% * So, X_c = 107.5\% * So$	0.70%	-5.28%	7.90%	13.17%	12.52%	5.99%	19.80%	13.81%	0.77%	-33.21%	51.35%	84.56%
		$X_p = 95\% * So, X_c = 110\% * So$	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%				
		$X_p = 95\% * So, X_c = 107.5\% * So$	1.94%	-4.80%	9.22%	14.02%	15.08%	7.46%	22.58%	15.12%	1.45%	-57.53%	86.49%	144.02%
		$X_p = 95\% * So, X_c = 110\% * So$	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%				
		$X_p = 95\% * So, X_c = 107.5\% * So$	0.32%	-5.32%	7.64%	12.96%	11.83%	5.87%	19.20%	13.33%	0.24%	-48.16%	81.56%	129.72%
		$X_p = 95\% * So, X_c = 110\% * So$	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%				
		$X_p = 95\% * So, X_c = 107.5\% * So$	1.06%	-4.93%	8.44%	13.37%	0.00%	0.00%	0.00%	0.00%	1.09%	-91.68%	95.04%	186.71%
		$X_p = 95\% * So, X_c = 110\% * So$	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%	25.86%	16.13%				
Krisis (2008-2009)	1 Bulan	Xp = 95%*So, Xc = 105%*So	-0.06%	-4.79%	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 were performed by comparing the error in the BEP Option Collar price with the price at maturity. The best model was determined by the smallest MSE compared to the other models. The error was calculated as follows:

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

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

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	0.007838567	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	0.013393768	
		$X_p = 95\%*So, X_c = 110\%*So$	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%	93.36%	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 were drawn:

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

with Historical Volatility. The Black-Scholes model with GARCH Volatility also provides better value protection than the Black-Scholes model with Historical Volatility. For TLKM, ISAT, and EXCL stocks, the collar strategy results in lower volatility compared to the non-use of the collar strategy. This strategy is 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, the GARCH model 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

Investors looking to invest in ISAT and TLKM stocks to achieve higher profits 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 strategies. A comparison of which strategy provides better profit and loss protection can also be conducted in the future.

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