International Journal of Economics, Business and Management Research

Vol. 10, No.11; 2026

ISSN: 2456-7760

Hedging Effectiveness of a Canary Option Calendar Spread Strategy on ELSA.JK Stock Using Least Squares Monte Carlo Simulation

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doi.org/10.51505/IJEBMR.2026.11123 URL: https://doi.org/10.51505/IJEBMR.2026.11123

Received: Jun 20, 2026 Accepted: July 01, 2026 Online Published: Nov 25, 2026

Abstract

PT Elnusa Tbk (ELSA.JK) is characterized by the high volatility of the Indonesian energy stock. This study comprehensively evaluates the hedging effectiveness of Canary option calendar spread strategies to mitigate downside risk while preserving profit potential. Using weekly stock price data from May 21, 2021, to May 28, 2025, the stock price movements are modeled using Geometric Brownian Motion (GBM) and the Least Squares Monte Carlo (LSMC) method to price Canary options and determine optimal exercise strategies. The study constructs 292,825 call and put calendar spread combinations by pairing short near-term options with long longer-term options. Hedging performance is evaluated by comparing the hedged and unhedged portfolios baseline using Profit and Loss (P&L), Value at Risk (VaR), and Conditional Value at Risk (CVaR). Results show that the highest performing put calendar spread strategies, selected based on Hedging Effectiveness (HE), demonstrate superior risk reduction performance, achieving VaR reductions ranging from 13.74% to 15.10% and CVaR reductions ranging from 12.64% to 15.13%. In contrast, call calendar spreads indicating ineffectiveness for hedging purposes. Consequently, Canary put calendar spreads provide viable risk management solution for volatile energy sector stocks, effectively protect against downside risk while maintaining upside potential.

Keywords: canary option, calendar spread, least squares monte carlo, high volatility, hedging effectiveness, value at risk, conditional value at risk

1. Introduction

The stock market is a key component of the modern financial system, serving as both an investment vehicle and a source of funding for companies. However, stock price movements are influenced by various economic and political factors, as well as market sentiment, leading to high volatility and increased investment risk. Global economic uncertainty, fluctuations in energy commodity prices, inflation, exchange rates, and international geopolitical dynamics can trigger significant changes in stock prices within a short period of time. Energy sector stocks are among the sectors most sensitive to changes in global economic conditions due to their closely

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tied to energy price fluctuations and developments in the oil and gas industry. Consequently, volatility in energy sector stocks tends to be higher than in other sectors, thereby increasing the risk for investors when making investment decisions (Amaldi & Herusetya, 2025).

In financial theory, investment risk is categorized into systematic risk and unsystematic risk. Unsystematic risk can be minimized through diversification because it is specific to a particular company or sector, whereas systematic risk cannot be eliminated solely through diversification because it is influenced by broader market conditions (Bodie et al., 2021). Thus, systematic risk management is generally carried out through hedging, which is a strategy to reduce potential losses resulting from unfavorable price movements in the underlying assets (Hull, 2022). In the context of energy sector stocks, hedging becomes increasingly important because price volatility can change rapidly and is influenced by various external shocks.

One of the energy sector stocks in Indonesia characterized by relatively high volatility is the stocks of PT Elnusa Tbk, with the stock code ELSA.JK. As a company engaged in energy services and support for the oil and gas industry, the price movements of ELSA.JK are influenced by global energy price dynamics, conditions in the national oil and gas industry, investor sentiment, and Indonesia's macroeconomic conditions. This high volatility creates significant profit opportunities for investors, but on the other hand, it also increases the risk of losses due to stock price changes that are difficult to predict with certainty. Therefore, a hedging strategy is needed that can provide protection against the risk of falling stock prices without eliminating the potential for profit when prices move positively.

Derivative instruments play a crucial role in the implementation of hedging strategies because their value depends on underlying assets such as stocks, commodities, indices, and other financial instruments. Commonly used derivatives include options, futures, forwards, swaps, and warrants, each of which serves a distinct function in risk management and speculation (Lesmana et al., 2024). Among these various instruments, options are often chosen because they provide market participants with the flexibility to obtain protection against price declines without eliminating the opportunity for profit when prices move positively (Hull, 2022). On that basis, options are a relevant instrument to examine in a hedging strategy for ELSA.JK stock.

This study focuses on the use of calendar spread and canary option strategies as hedging instruments for ELSA.JK stock. A calendar spread is a strategy that involves taking positions in contracts with different expiration dates to capitalize on inter-period price differences while managing the risk of price changes (Frau et al., 2025). Meanwhile, a canary option is a more complex option structure designed to respond to specific price movements with specific payoff characteristics. The combination of these two strategies has the potential to provide more effective protection than the use of a single instrument, particularly in highly volatile markets.

To assess the effectiveness of this strategy, an approach is needed that can realistically capture the uncertainty of price movements. Because price volatility is a key determinant of investment risk, relying on a single price scenario may lead to an incomplete assessment of risk exposure

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(Yan & Li, 2024). Therefore, this study employs a Monte Carlo simulation approach to generate various possible price movements for ELSA.JK stock, allowing the performance of the hedging strategy to be evaluated across a range of different market scenarios (Muhtarulloh et al., 2025). This approach is suitable for evaluating the payoff of derivative strategies that exhibit non-linear characteristics and are sensitive to changes in volatility.

Although there has been extensive research on hedging with derivative instruments, studies specifically evaluating the effectiveness of the calendar spread strategy using call options on stocks remain limited. Most previous studies have focused more on general option strategies such as the straddle, strangle, butterfly, or bull spread, while more specific and complex strategies have not been extensively evaluated empirically (Hull, 2022; Lesmana et al., 2024). These limitations indicate a significant research gap that needs to be filled, especially considering that the energy sector stock market is heavily influenced by global dynamics and is characterized by high volatility. Thus, this study is expected to provide both academic and practical contributions to the development of hedging strategies in the energy sector stock market.

1.1 Geometric Brownian Motion

Geometric Brownian Motion (GBM) is one of the most widely used stochastic processes for modeling asset prices because it ensures positive simulated prices and provides a parsimonious framework for option valuation. Under the GBM framework, continuously compounded returns over non-overlapping intervals are assumed to be normally distributed, serially independent, and characterized by constant volatility. These properties facilitate risk-neutral simulation and make GBM a transparent benchmark for evaluating derivative-based hedging strategies.

Nevertheless, empirical stock returns may exhibit departures from these assumptions, including skewness, excess kurtosis, volatility clustering, and discontinuous price movements. Therefore, the empirical adequacy of the GBM assumptions should be examined before the model is employed to generate the underlying stock-price paths. In this study, the suitability of GBM is evaluated through tests of normality, serial independence, stationarity, and conditional heteroskedasticity.

GBM extends the standard Brownian motion process by incorporating both a constant drift rate and volatility parameter. The mathematical derivation is based on solving the following stochastic differential equation:

$$dS(t) = \mu S(t)\, dt + \sigma S(t)\, dW(t) \qquad (1)$$

where $S(t)$ represents the value of the process at time t, μ is the drift rate, σ is the volatility parameter, and $dW(t)$ is the increment of a Wiener process with $W(t) = \varepsilon\sqrt{\Delta t}$ and $\varepsilon \sim N(0,1)$ is a standard normal distributed random variable.

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Let T denote the maturity time and the interval $[0, T]$ is partitioned into M equidistant sub-intervals. Each sub-interval possesses a uniform step size of $\Delta t = \frac{T}{M}$. Consequently, the continuous stochastic asset path can be discretized into the following equation:

$$S(t + \Delta t) - S(t) = \mu S(t)\Delta t + \sigma S(t)\varepsilon\sqrt{\Delta t} \quad (2)$$

A logarithmic transformation $\ln S$ is applied to solve the stochastic differential equation. By applying Itô's lemma under the assumption of a GBM log-normal distribution, the generalized Wiener process followed by $\ln S$ is as follows (Lesmana et al., 2024):

$$d \ln S(t) = \left(\mu - \frac{\sigma^2}{2}\right) dt + \sigma dW(t) \quad (3)$$

for well-known the expression $S(t)$:

$$S(t + \Delta t) = S(t) \exp\left[\left(\mu - \frac{\sigma^2}{2}\right)\Delta t + \sigma\varepsilon\sqrt{\Delta t}\right] \quad (4)$$

In this framework, GBM is characterized as a Markovian process, meaning its future state is independent of its history given the current state. Due to the stochastic component introduced by the Wiener process, GBM allows for the stochastic simulation of multiple future paths by using the drift rate (μ) and volatility parameter (σ). These simulated trajectories can subsequently be utilized to estimate the expected value of the averaged future movement over all realizations.

1.2 Call and Put Option

An option is a right granted to its holder to buy or sell a specific asset under agreed terms, without any obligation to exercise it. A call option provides the holder with the right, but not the obligation, to buy an asset at a predetermined price, known as the strike or exercise price, up to or on a specified expiration date. In contrast, a put option gives the holder the right, to sell an asset at the predetermined exercise price within the same specified period (Hull, 2022).

A European call option is a contract that grants the buyer the right to purchase a specific stock at a predetermined price and quantity on the expiration date of the contract. The payoff of a European call option can be calculated as:

$$C = \max(S_T - K, 0) \quad (5)$$

Meanwhile, a European put option is a contract that gives the buyer the right to sell a specific stock at a predetermined price and quantity on the contract's expiration date. The payoff of a European put option can be expressed as:

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$$P = \max(0, K - S_T) \tag{6}$$

where:
$S_T =$ underlying asset market price at maturity time.
$K =$ strike price.

1.3 Canary Option

Canary options are a type of Bermudan option that grant the holder the right, but not the obligation, to exercise the option on two predetermined exercise dates before maturity. Because the holder has more than one opportunity to exercise, Canary options provide greater flexibility than European options while remaining less complex than standard Bermudan options with multiple exercise dates. The value of a Canary option depends on the optimal exercise strategy, which is determined by comparing the immediate exercise value with the continuation value at the first exercise date.

For a Canary option, let t_1 and t_2 denote the two exercise dates with $t_1 < t_2$. The exercise payoff functions at each exercise date are given by:

$$e_i(S_{t_i}) = \max(S_{t_i} - K, 0), \; i = 1,2 \tag{7}$$

for call option, and

$$e_i(S_{t_i}) = \max(K - S_{t_i}, 0), \; i = 1,2 \tag{8}$$

for put option,
where:
$e_i(S_{t_i}) =$ payoff of the Canary option at exercise date (t_i).

$S_{t_i} =$ stock price at exercise date (t_i).

$K =$ strike price.

$t_i =$ the i-th exercise date, where $i = 1$ refers to the first exercise date and $i = 2$ refers to the second exercise date.

The value of the Canary option is determined by choosing the maximum between exercising the option at the first exercise date and continuing to hold the option until the second exercise date. Therefore, the Canary option value can be expressed as:

$$V_{cnr} = E^Q[max\{e_1(S_{t_1}), E^Q[e_2(S_{t_2}) \mid S_{t_1}]\}] \tag{9}$$

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where:
V_{cnr} = value of the Canary option.

$E^{Q}[.]$ = expectation under the risk-neutral probability measure Q.

$e_1(S_{t_1})$ = payoff obtained from exercising the option at the first exercise date.

$e_2(S_{t_2})$ = payoff obtained from exercising the option at the second exercise date.

S_{t_1} = stock price at the first exercise date.

S_{t_2} = stock price at the second exercise date.

The first term represents the immediate exercise value obtained if the option is exercised at the first exercise date, while the second term represents the continuation value, which is the expected payoff from postponing the exercise decision until the second exercise date. Therefore, the holder will exercise the option at (t_1) if the immediate exercise value exceeds the continuation

value. Otherwise, the option will be held until the next exercise opportunity (Piterbarg, 2025). Since the continuation value cannot be observed directly, it must be estimated numerically. In this study, the Least Squares Monte Carlo (LSMC) method is employed to estimate the continuation value based on simulated stock price paths and determine the optimal exercise strategy.

1.4 Least Square Monte Carlo Simulation

Least Squares Monte Carlo (LSMC) introduced by Longstaff and Schwartz is a numerical simulation method in financial mathematics used to price Bermudan and American style option by estimating the continuation value through least squares regression on simulated asset price paths. The method combines Monte Carlo simulation and regression analysis to determine the optimal exercise strategy for options with early exercise features (Jiang, 2012).

The LSMC method assumes that the underlying asset price follows a stochastic process under the risk neutral measure. In this study, the underlying asset price is modeled using GBM. Using the analytical solution of GBM, the simulated asset price paths are generated using Equation (4). After generating many simulated assets price paths, the payoff at maturity is calculated. For a Canary call option, the payoff function is defined as:

$$\max(S_T - K, 0) \tag{10}$$

while for a put option the payoff function is:

$$\max(K - S_T, 0) \tag{11}$$

where:
S_T = underlying asset market price at time T.

K = strike price.

The valuation process is performed using backward induction starting from the maturity time. At maturity, the option value equals its intrinsic payoff because no continuation opportunity remains. Moving backwards to earlier exercise dates, the continuation value is estimated using least squares regression on the discounted future cash flows obtained from the simulated paths. The continuation value approximation is expressed as:

$$C(S_t) = \sum_{j=1}^{R} a_j \phi_j(S_t) \qquad (12)$$

where $C(S_t)$ denotes the continuation value, a_j are regression coefficients, R are number of basis functions, and $\phi_j(S_t)$ are selected basis functions of the asset price such as polynomial functions (Longstaff & Schwartz, 2001).

In practical implementation, the regression step is usually applied only to in-the-money paths because early exercise decisions are relevant only when the option has positive intrinsic value. The estimated continuation value is then compared with the immediate exercise payoff. If the exercise payoff is greater than the continuation value, the option is exercised immediately. Otherwise, the option holder will continue holding the option until evaluate the next exercise opportunity.

The discounted cash flow at each exercise date is computed using:

$$CF_t = e^{-r\Delta t}(CF_{t+\Delta t}) \qquad (13)$$

where CF_t is a cash flows at t, and $CF_{t+\Delta t}$ is a cash flow at $(t + \Delta t)$.

Finally, the option price is estimated as the average discounted payoff from all simulated paths:

$$V_0 = \frac{1}{N}\sum_{i=1}^{N} CF_i \qquad (14)$$

where V_0 denotes the estimated option price at the initial time, N is the total number of Monte Carlo simulation paths, and CF_i represents the discounted cash flow from the i-th simulated path (Morisi, 2021).

The general procedure of the LSMC algorithm can be summarized as follows:

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1. Generate simulated asset price paths under the risk neutral measure using Monte Carlo simulation.
2. Compute the option payoff at maturity for each simulated path.
3. Move backward from maturity to the first exercise date.
4. Identify all in-the-money paths at each exercise date.
5. Regress discounted future cash flows on selected basis functions to estimate the continuation value.
6. Compare the immediate exercise payoff with the estimated continuation value.
7. Determine the optimal exercise decision for each path.
8. Discount all resulting cash flows back to the initial time.
9. Compute the option price as the average discounted payoff over all simulated paths.

1.5 Calendar Spread Strategy

A Calendar spread is an options strategy that involves simultaneously buying and selling options on the same underlying asset with the same strike price (K) but different expiration dates ($t_1 < t_2$), aiming to profit from time decay differences between the two contracts (TradeStation, 2024). In this study, two types of calendars spread strategies are constructed using Canary options, namely the call calendar spread and the put calendar spread (Frau et al., 2025).

In a long call calendar spread, a shorter-term Canary call option with expiration date t_1 is sold and a longer-term Canary call option with expiration date t_2 is bought at the same strike price K, with $t_1 < t_2$. Similarly, in a long-put calendar spread, a shorter-term Canary put option with expiration date t_1 is sold and a longer-term Canary put option with expiration date t_2 is bought at the same strike price K.

The net cost required to establish each strategy is given by:

$$\mathrm{ND}_c = C(S_0, K, t_2) - C(S_0, K, t_1) \quad (15)$$

$$\mathrm{ND}_p = P(S_0, K, t_2) - P(S_0, K, t_1) \quad (16)$$

where $C(S_0, K, t_i)$ and $P(S_0, K, t_i)$ denote the price of the Canary call and put option, respectively, with initial stock price S_0, strike price K, and expiration date t_i, for $i = 1, 2$.

1.6 Hedging

Hedging is a financial risk management strategy used to reduce exposure to unfavorable price movements in financial markets. In futures and derivatives trading, hedging plays an important economic role by enabling market participants to transfer and manage risk arising from market uncertainty. Through hedging activities, investors and producers can protect the value of their assets or portfolios against fluctuations in underlying asset prices. One of the most widely used instruments for hedging purposes is financial derivatives, particularly options, because they

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provide flexibility in managing downside risk while maintaining potential gains from favorable market movements (Muftiasa et al., 2023).

1.7 Value at Risk (VaR)

VaR is a method to estimate the potential loss of a portfolio that consists of various financial assets, including stocks and options. It indicates the maximum expected loss that may occur over a specific time horizon at a given confidence level.

At the confidence level of $(1-\alpha)$, VaR is determined based on a certain quantile of the return distribution. The calculation of VaR can be carried out using the probability density function of return f_R, which represents the possible future return of an asset, where R may refer to either a single asset or a portfolio. The VaR for period t at the confidence level $(1-\alpha)$ can be expressed as (Fransiska et al., 2025):

$$VaR(1-\alpha) = V_0 \times R^* \times \sqrt{t} \tag{17}$$

where:

R^* = the critical value or cut-off point of the return distribution at a predetermined probability level.

V_0 = represents the initial investment value.

t = refers to the investment period.

1.8 Conditional Value at Risk (CVaR)

Conditional Value at Risk (CVaR) is a risk measure that calculates the average loss that may occur if the risk in an investment portfolio exceeds the VaR level at a certain confidence level. The integral approximation formula can be obtained where z is the loss value and f_X is the probability density function of the loss, as follows (Indarwati & Kusumawati, 2021):

$$CVaR(1-\alpha) = E\left[X^{(1-\alpha)}\right] \tag{18}$$

$$CVaR(1-\alpha) = \frac{1}{\alpha}\int_{VaR_{(1-\alpha)}}^{\infty} z f_X(z)\, dz \tag{19}$$

1.9 Profit and Loss (P&L)

The structural reformulation of the Black–Scholes model carries significant practical utility for the profit and loss (P&L) attribution of option trades. P&L decomposition framework relies on a Taylor series expansion of the pricing function $H(t) = H(t, T, S(t), K, \sigma)$, which denotes the option price at time t given maturity T, $S(t)$ is underlying spot price, K is strike price, and σ is

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volatility. P&L attribution segregates risk by first-order partial derivatives: Θ (theta) represent effect of time decay, Δ (delta) is impact of underlying asset price movement, and v (vega) is sensitivity to volatility movement. The concept of the P&L attribution is based on the Taylor expansion (Blake & Thompson, 2024):

$$\Delta P \approx (\Delta \times \Delta S) + (\Theta \times \Delta t) + (v \times \Delta \sigma) \quad (20)$$

where ΔP represents total net P&L or the overall change in the options value between two reporting dates.

The analysis of profit and loss (P&L) between two reporting dates is a fundamental task in risk management. The framework relies on at least two basic benchmarks. First, the P&L attribution must fully explain the net P&L to eliminate any unexplained variance. Second, a comprehensive change analysis must identify all relevant risk factors. Because P&L attribution purpose to allocate changes in option prices to specific risk factors, such as underlying asset price movements, time to maturity, interest rate fluctuations, dividend yields, and other relevant variables. In a sideways market condition, a call option loses value due to temporal decay, which is counterbalanced by gains from hedging operation, reflecting a buy low and sell high. Beyond risk tracking, P&L attribution is used to evaluate for model, a high-quality model should be capable of accurately explaining variations in option prices through changes in risk factors and corresponding sensitivity measures.

1.10 Variance

Each investment instrument basically has a varying risk profile and level. In this context, risk is often understood as a form of deviation between the actual return received and the expected return. This measure of deviation is generally known as standard deviation, which is a statistical metric that calculates the absolute value of the difference between real results and the average expected value. Variance is the square of the standard deviation. The variant formula can be explained as follows (Wulandari, 2021):

$$\sigma^2 = \frac{\sum_{i=1}^{n}(X_i - \bar{X})^2}{n-1} \quad (21)$$

where σ^2 is the variance of the stock, X_i is the return of the stock in period i, $\bar{X}$ is the average return of the stock, and n is the number of observations.

1.11 Hedging Effectiveness (HE)

Hedging effectiveness (HE) is commonly evaluated using the variance reduction approach, which measures the proportion of portfolio risk eliminated through hedging. This approach

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compares the variance of the hedged portfolio with that of the corresponding unhedged portfolio and is expressed as:

$$HE = 1 - \frac{Var(P\&L_{hedged})}{Var(P\&L_{unhedged})} \quad (22)$$

where $\mathrm{Var}(\mathrm{P\&L_{hedged}})$ denotes the variance of the hedged portfolio and $\mathrm{Var}(\mathrm{P\&L_{unhedged}})$ denotes the variance of the unhedged portfolio. The resulting value represents the proportion of risk reduction achieved by the hedging strategy. An HE value of one indicates complete risk elimination, whereas an HE value of zero implies that the hedging strategy provides no improvement relative to the unhedged position. Negative values indicate that the hedged portfolio exhibits greater variability than the unhedged portfolio, suggesting that the hedging strategy increases portfolio risk rather than reducing it (Sharma, 2023).

2. Method

This study uses weekly stock price data of PT Elnusa Tbk (ELSA.JK) covering the period from May 21, 2021, to May 28, 2025. The data were collected from Yahoo Finance (https://finance.yahoo.com) and were used to estimate the parameters required for the option pricing model. Furthermore, the risk-free interest rate used in this study is set at 5.75% per annum, based on the Bank Indonesia (BI) Rate adopted as the risk-free benchmark for the option valuation.

The selection and validation of the stock-price model were conducted in two stages. First, the historical weekly log-return series was examined under the physical probability measure. The Jarque–Bera test was used to assess whether the return distribution departed significantly from normality. The Ljung–Box test was employed to detect serial dependence in the return series, while the Augmented Dickey–Fuller test was used to examine return stationarity. In addition, the ARCH-LM test was conducted to determine whether the return series exhibited significant conditional heteroskedasticity or volatility clustering. At the 5% significance level, p-values greater than 0.05 for the Jarque–Bera, Ljung–Box, and ARCH-LM tests indicate insufficient evidence to reject the corresponding GBM assumptions, whereas a p-value below 0.05 for the ADF test indicates rejection of the unit-root hypothesis.

Second, after the historical volatility parameter had been estimated, the stock-price paths used for option valuation were generated under the risk-neutral probability measure. Accordingly, the expected return of the stock was replaced by the risk-free interest rate in the simulation process, while volatility was estimated from the historical weekly returns. This distinction ensures that the historical-data diagnostics are used to assess the empirical adequacy of the GBM assumptions, whereas the Canary option prices are obtained using risk-neutral valuation.

The research procedures performed in this study using RStudio software are described as follows:

1. Retrieve the weekly closing price data of ELSA.JK stock from May 21, 2021, to May 28, 2025.
2. Calculate the returns of the ELSA.JK stock using the following formula:

$$R_t = \ln\left(\frac{S_t}{S_{t-1}}\right) \quad (23)$$

S_t = stock price at time t,

S_{t-1} = stock price at time $t-1$.

3. Evaluate the suitability of the Geometric Brownian Motion (GBM) model for the stock returns through:

a. Jarque-Bera normality test.
b. Ljung-Box independence test.
c. Augmented Dickey-Fuller (ADF) stationarity test.
d. ARCH-LM constant volatility test.

4. Determine the model parameter values, namely the initial stock price (S_0), strike price (K), risk-free interest rate ($r = 5.75\%$) per annum based on the Bank Indonesia (BI) Rate used as the valuation benchmark, time to maturity (T), stock price volatility (σ), time steps (M), and number of simulations performed (N). The strike price is assumed to be equal to the initial stock price $K = S_0$, representing an at-the-money (ATM) Canary option.

5. Calculate the annual volatility (σ) using the following equation:

$$\sigma = \frac{s}{\sqrt{\Delta t}} \quad (24)$$

where:

$s =$ standard deviation

$\Delta t = \frac{1}{52}$, represents the number of trading periods in a year. Since the data is weekly, the trading period is also weekly.

6. Generate the stock price paths under the risk-neutral measure using the GBM model presented in Equation (1).
7. Calculate the canary option payoff at each exercise date.
8. Estimate the continuation value at each exercise date using the LSMC method, where polynomial regression is employed to approximate the conditional expected payoff.

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9. Calculate the Canary call and put option prices.
10. Construct the calendar spread strategy by combining Canary options with different maturities.
11. Each calendar spread consists of a short position in a shorter-maturity Canary option and a long position in a longer-maturity Canary option. All feasible calendars spread combinations are generated by pairing a short Canary option with maturity $(t_{1,\text{short}}, t_{2,\text{short}})$ and a long Canary option with maturity $(t_{1,\text{long}}, t_{2,\text{long}})$ subject to the condition $t_{2,\text{long}} > t_{2,\text{short}}$.
12. Transaction costs, taxes, and liquidity effects are ignored.
13. Calculate the profit and loss of the calendar spread strategy as the difference between the values of the long and short Canary option positions after accounting for the initial spread cost.
14. Evaluate the calendar spread position and the underlying stock position at the maturity date of the short leg $(t_{2,\text{short}})$, assuming all positions are closed at that date.
15. Analyzing the hedging effectiveness of the calendar spread strategy using Canary options. The analysis is conducted by comparing the results of P&L, VaR, CVaR, variance, and hedging effectiveness (HE) between the unhedged and hedged portfolios.

3. Result and Discussion

3.1 ELSA.JK Stock Price and Return Data

ELSA.JK stock prices used in the study are given in Figure 1.

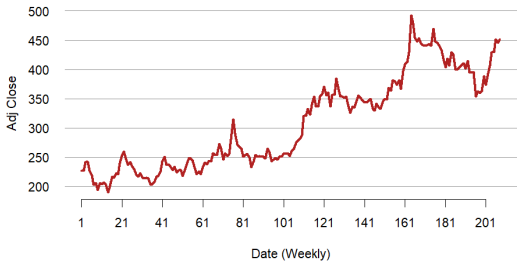


Figure 1. ELSA.JK stock price movement

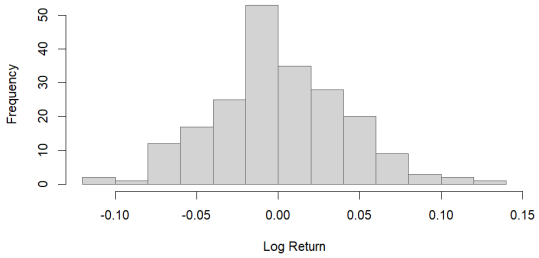


Figure 2. ELSA.JK stock price return histogram

Figure 1 displays the weekly ELSA.JK stock price data employed in this study, covering a total of 208 weeks, while Figure 2 shows the histogram of the weekly log returns obtained using Equation (23).

Prior to performing the LSMC simulation, the suitability of the GBM model for ELSA.JK stock returns was evaluated through a series of statistical tests. Under the GBM framework, log returns are assumed to be normally distributed, independent over time, and characterized by constant volatility.

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Table 1. Summary of GBM Assumption Tests

Test	Statistic	*p*-value
Jarque-Bera	1.61	0.45
Ljung-Box	5.64	0.84
ADF	-6.26	0.01
ARCH-LM	10.17	0.97

At the 5% significance level, the Jarque–Bera test produces a p-value of 0.45, indicating insufficient evidence to reject the normality assumption for the weekly log returns. The Ljung–Box test yields a p-value of 0.84, suggesting that no statistically significant serial dependence is detected in the return series. The ADF test produces a p-value of 0.01, allowing the unit-root null hypothesis to be rejected and supporting the stationarity of the weekly returns. Furthermore, the ARCH-LM test yields a p-value of 0.97, indicating no statistically significant evidence of conditional heteroskedasticity during the observation period.

Taken together, these diagnostic results indicate that the weekly ELSA.JK return series does not exhibit material violations of the distributional, independence, stationarity, and constant-volatility assumptions required for the application of GBM in this study. Therefore, GBM is retained as a parsimonious baseline model for generating stock-price paths in the LSMC valuation framework. Nevertheless, the statistical results should not be interpreted as proof that GBM perfectly represents the stock-price dynamics. The findings are conditional on the selected observation period and weekly data frequency, and the model may not fully capture abrupt price jumps or changes in volatility outside the sample period.

After validating the GBM assumptions, the volatility parameter was estimated from the historical weekly log returns. The annualized volatility obtained using Equation (24) was 29.52% per year, which was subsequently used as an input in the risk-neutral stock-price simulation.

3.2 Canary Option Price Calculation

Using RStudio software, Canary option prices are calculated using LSMC simulation with the following input:

Initial stock price (S_0)	= Rp490
The strike price for the option (K)	= Rp490
Expiration date (T)	= 1 year
Risk-free rate (r)	= 5.75%
Volatility (σ)	= 29.52%
Time steps (M)	= 52

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Table 2. Summary Statistics of Option Prices

Number of simulations (N) = 100000

Option Types	Min.	Max.	Mean	Stdev.
Call	11.92	70.48	55.45	12.12
Put	10.74	44.96	37.60	6.11

A total of 1326 Canary call and put options were generated for all feasible combinations satisfying $t_1 < t_2$. The standard deviations indicate that option prices varied considerably across different exercise and maturity date combinations. This variation is expected because the continuation value estimated through the LSMC method depends on both the exercise date (t_1) and maturity date (t_2).

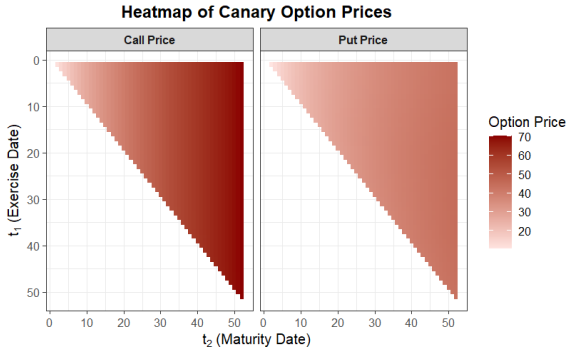


Figure 3. Heatmap of Canary Option Prices

Figure 3 presents the heatmaps of Canary call and put option prices for all feasible combinations of exercise dates (t_1) and maturity dates (t_2). The triangular structure of the heatmaps reflects the constraint that the exercise date must occur before the maturity date ($t_1 < t_2$).

For both call and put options, darker colour intensities are generally observed as the maturity date (t_2) increases, indicating higher option prices for longer maturities. This behaviour is consistent with option pricing theory, as a longer maturity provides greater opportunities for favourable stock price movements before expiration.

Furthermore, the variation in option prices across different combinations of t_1 and t_2 demonstrates that the continuation value estimated using the LSMC method depends on both the exercise date and the maturity date. Consequently, Canary options with later exercise and maturity dates tend to exhibit higher prices than those with shorter durations.

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3.3 Calendar Spread Construction

The Canary option prices obtained from the LSMC simulation were subsequently used to construct calendar spread strategies. A calendar spread consists of a short position in a shorter-maturity Canary option and a long position in a longer-maturity Canary option of the same type. In this study, separate calendar spread portfolios were formed for call options and put options. To ensure consistency with the definition of a calendar spread, only combinations satisfying $t_{2,\text{long}} > t_{2,\text{short}}$ were considered. This condition guarantees that the long position has a longer maturity than the short position, allowing the strategy to benefit from differences in time value between the two options.

The initial costs of the call and put calendar spreads were calculated using Equations (15) and (16), respectively. Since longer-maturity Canary options generally have higher values than shorter-maturity Canary options, most calendar spread strategies resulted in positive initial costs and were therefore classified as debit spreads.

A positive value of the initial cost indicates that the premium paid for the long position exceeds the premium received from the short position, resulting in a net debit. Since longer-maturity Canary options generally possess greater time value than shorter-maturity Canary options, most calendar spread strategies constructed in this study are expected to require a net premium payment.

3.4 Calendar Spread Result

From the 1,326 generated Canary options, feasible calendar spread strategies were constructed by pairing options that satisfied the maturity constraint $t_{2,\text{long}} > t_{2,\text{short}}$. This filtering process produced 292,825 call calendar spread combinations and 292,825 put calendar spread combinations. These strategies were subsequently analyzed to evaluate their profit and loss characteristics and their effectiveness in reducing portfolio risk.

Table 3. Examples of Constructed Call Calendar Spread Strategies

Short t_1 (week)	**Short t_2 (week)**	**Long t_1 (week)**	**Long t_2 (week)**	**Initial Cost**
1	2	1	3	2.79
1	2	1	4	5.18
1	2	1	5	7.27
1	2	1	6	9.30
1	2	1	7	11.10

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Table 4. Examples of Constructed Put Calendar Spread Strategies

Short t_1 (week)	Short t_2 (week)	Long t_1 (week)	Long t_2 (week)	Initial Cost
1	2	1	3	2.26
1	2	1	4	4.08
1	2	1	5	5.75
1	2	1	6	7.13
1	2	1	7	8.46

Table 5. Summary Statistics of Calendar Spread Initial Costs

Strategy	Min.	Max.	Mean	Stdev.
Call Calendar Spread	0.67	58.56	15.45	11.21
Put Calendar Spread	-1.01	34.21	7.75	6.01

Tables 3 and 4 present several examples of the constructed call and put calendar spread strategies. In each strategy, a short position is established in a shorter-maturity Canary option and a long position is taken in a longer-maturity Canary option, satisfying the maturity requirement $t_{2,\text{long}} > t_{2,\text{short}}$. As the maturity of the long position increases, the initial cost of both call and put calendar spreads also increases. This pattern reflects the higher premiums associated with longer-maturity Canary options, which generally possess greater time value than shorter-maturity contracts.

The overall distribution of initial costs across all constructed strategies is summarized in Table 5. The results indicate that call calendar spreads require a higher average initial cost than put calendar spreads. Similarly, the standard deviation of call calendar spread costs exceeds that of put calendar spreads, suggesting greater variation in premium differences among call spread combinations. These findings imply that the additional time value obtained from extending the maturity of a call Canary option is generally larger than that of a put Canary option.

The minimum initial cost for call calendar spreads is positive, indicating that all call spread examples are established as net debit positions. In contrast, put calendar spreads exhibit a minimum initial cost of -1.01, implying that certain combinations can be initiated as net credit spreads, where the premium received from the short position exceeds the premium paid for the long position. Nevertheless, the positive average costs observed for both spread types suggest that most calendar spread strategies constructed in this study require an initial net premium payment.

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While the initial cost provides useful information regarding the capital required to establish a calendar spread position, it does not indicate the strategy's ability to reduce portfolio risk. Therefore, all constructed calendars spread combinations are subsequently evaluated within a hedged portfolio framework using profit and loss distributions, Value at Risk (VaR), Conditional Value at Risk (CVaR), variance, and hedging effectiveness measures.

3.5 Hedged Portfolio Construction

To evaluate the effectiveness of the constructed calendar spread strategies, each spread was combined with a stock position in ELSA.JK. Consistent with the calendar spread framework, the evaluation horizon was set equal to the maturity date of the short leg ($t_{2,\text{short}}$). Therefore, the profit and loss of the stock position (unhedged) is given by:

$$\pi_{\text{unhedged}} = S_{t_{2,\text{short}}} - S_0 \tag{25}$$

The profit and loss of the calendar spread was calculated as the difference between the values of the long and short Canary option positions after accounting for the initial spread cost. For each simulated path, the resulting calendar spread profit and loss is represented by:

$$\pi_{CS} = \left(V_{\text{long},t_2,\text{short}} - V_{\text{short},t_2,\text{short}}\right) - C \tag{26}$$

The profit and loss of the hedged portfolio was then calculated by combining the stock position with the corresponding calendar spread position.

$$\pi_{\text{hedged}} = \pi_{\text{unhedged}} + \pi_{CS} \tag{27}$$

where:

π_{unhedged} = stock profit and loss.

π_{CS} = calendar spread profit and loss.

π_{hedged} = hedged portfolio profit and loss.

$S_{t_2,\text{short}}$ = stock price at the maturity date of the short Canary option.

S_0 = initial stock price.

$V_{\text{long},t_2,\text{short}}$ = value of the long Canary option at the maturity date of the short leg.

$V_{\text{short},t_2,\text{short}}$ = value of the short Canary option at the maturity date of the short leg.

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C = initial cost of the calendar spread.

3.6 Hedging Effective Analysis

In this study, only the put calendar spread strategy is used to hedge ELSA.JK stock. This is because the call calendar spread is not relevant as the main hedging strategy for a long stock portfolio, as it is unable to reduce VaR and CVaR. Instead, this strategy increases the risk of loss

Table 6. Performance Summary of the Top 10 Put Calendar Spread Hedging Strategies

compared to the unhedged position.

Strategy	Mean P&L (unhedged)	Mean P&L (hedged)	VaR Reduction (%)	CVaR Reduction (%)
Short ($t_1 = 16, t_2 = 51$) Long ($t_1 = 51, t_2 = 52$)	27.95	29.70	14.73	14.49
Short ($t_1 = 13, t_2 = 51$) Long ($t_1 = 51, t_2 = 52$)	27.95	29.85	13.74	12.64
Short ($t_1 = 16, t_2 = 50$) Long ($t_1 = 50, t_2 = 51$)	27.35	29.04	14.75	14.56
Short ($t_1 = 15, t_2 = 51$) Long ($t_1 = 51, t_2 = 52$)	27.95	29.75	14.50	13.94
Short ($t_1 = 17, t_2 = 51$) Long ($t_1 = 51, t_2 = 52$)	27.95	29.64	15.10	15.07
Short ($t_1 = 15, t_2 = 50$) Long ($t_1 = 50, t_2 = 51$)	27.35	29.09	14.44	13.99
Short ($t_1 = 13, t_2 = 50$) Long ($t_1 = 50, t_2 = 51$)	27.35	29.19	13.79	12.66
Short ($t_1 = 17, t_2 = 50$) Long ($t_1 = 50, t_2 = 51$)	27.35	28.98	15.04	15.13
Short ($t_1 = 16, t_2 = 49$) Long ($t_1 = 49, t_2 = 50$)	26.85	28.47	14.57	14.54
Short ($t_1 = 14, t_2 = 51$) Long ($t_1 = 51, t_2 = 52$)	27.95	29.80	14.07	13.27

Table 6 presents the performance measures of the top 10 put calendar spread strategies selected based on the highest hedging effectiveness (HE) values. Since hedging effectiveness measures the proportion of portfolio variance reduced relative to the unhedged position, higher HE values indicate greater risk reduction. Therefore, the selected strategies represent the most effective put calendar spread combinations in terms of variance minimization among all constructed strategies. Across all top 10 strategies, the Mean P&L for the hedged portfolio consistently range

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from 28.467 to 29.847, while the unhedged portfolio range of 26.846 to 27.952. The results show that the Mean P&L of the hedged portfolio is higher than that of the unhedged portfolio. For example, in the first row, the Mean P&L increases from 27.952 for the unhedged portfolio to 29.695 for the hedged portfolio. This suggests that the hedged portfolio delivers a more favorable return profile than the unhedged portfolio. This finding is particularly noteworthy because hedging strategies often involve a trade-off between risk reduction and expected return. In contrast, the selected put calendar spread strategies not only reduce portfolio risk but also improve expected profitability, indicating that the benefits obtained from downside protection outweigh the cost of establishing the hedge.

The VaR reduction percentages for the top 10 put calendar spread strategies are all positive, ranging from approximately 13.74% to 15.10%. A positive VaR reduction means that the Value at Risk of the hedged portfolio is lower than that of the unhedged portfolio. In other words, after applying the put calendar spread, the potential loss at the chosen confidence level decreases. For instance, a VaR reduction of 15.10% means that the hedged portfolio reduces potential loss by about 15.10% relative to the unhedged portfolio. This is a strong indication that the put calendar spread is effective in reducing downside risk. The consistency of positive VaR reduction across all top 10 strategies confirms that the put calendar spread provides stable protection against unfavorable market movements.

The CVaR reduction percentages are also all positive, ranging from approximately 12.64% to 15.13%. A positive CVaR reduction indicates that the extreme loss risk, measured by Conditional Value at Risk, is lower in the hedged portfolio than in the unhedged portfolio. Since CVaR captures the average loss beyond the VaR threshold, this result is especially important because it shows that the put calendar spread is effective not only in reducing ordinary downside risk, but also in mitigating tail risk. For example, a CVaR reduction of 15.13% implies that the expected loss in the worst-case tail of the distribution is reduced by approximately 15.13% after hedging. Therefore, the put calendar spread provides meaningful protection against severe loss scenarios, which is valuable for risk-averse investors and portfolio managers who must protect against extreme losses. This result is particularly relevant for ELSA.JK, whose stock price is exposed to fluctuations in energy markets and other external shocks. The reduction in CVaR indicates that the put calendar spread is effective in mitigating losses during extreme market conditions, which are often of greatest concern to risk managers.

An additional observation from Table 6 is that the top 10 strategies exhibit highly similar maturity structures. Most of the selected strategies involve short Canary put options with maturities around $t_2 = 49$, 50, and 51 weeks and long Canary put options with maturities extending $t_2 = 50$, 51, and 52 weeks. This pattern suggests that calendar spreads constructed near the end of the investment horizon provide superior hedging performance. Longer-maturity Canary options retain greater time value and offer stronger protection against adverse price movements, while the shorter-maturity positions generate premium income that partially offsets the cost of establishing the hedge. Consequently, the maturity configuration observed in the top-ranked strategies appears to balance risk protection and premium efficiency effectively. The

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concentration of top-performing strategies near the end of the investment horizon also suggests that maturity selection is a critical determinant of hedging effectiveness, as small differences in maturity structure can materially influence the balance between protection and premium cost.
Furthermore, the variance analysis provides further evidence of the strategy's effectiveness. The hedged portfolios exhibit lower return variance compared to the unhedged position, showing more stable and predictable performance. Since the strategies were selected based on hedging effectiveness, which is defined as the proportion of variance reduction relative to the unhedged portfolio, lower variance is expected among the top-ranked strategies. The results therefore confirm that the hedging effectiveness measure successfully identifies calendar spread structures capable of stabilizing portfolio performance. This reduction in volatility is particularly crucial for investors seeking consistent returns with minimized fluctuations. The combination of higher mean returns, lower VaR, lower CVaR, and reduced variance demonstrates that the put calendar spread strategy enhances portfolio performance while simultaneously reducing multiple dimensions of risk.

Overall, the results indicate that put calendar spreads constitute an effective hedging instrument for ELSA.JK stock, by combining downside protection with favorable return characteristics, the strategy improves the portfolio risk-return profile and demonstrates its potential as a practical risk management tool for investors exposed to volatile energy-sector equities.

4. Conclusion

This study evaluates the use of the put calendar spread strategy as a hedging instrument for ELSA.JK stock. The strategy was constructed using Canary options priced through the LSMC simulation method and then compared with the unhedged stock position to assess its hedging performance.

Based on the simulation results, the put calendar spread strategy shows a better risk-return profile than the unhedged position. The hedged portfolio produces a higher Mean P&L, indicating that the strategy can improve the average portfolio performance. In addition, the positive VaR and CVaR reduction percentages show that the strategy successfully reduces both potential losses and extreme losses. This means that the put calendar spread not only improves profitability but also provides protection against downside risk.

Specifically, the empirical results from the top 10 strategies reveal that the Mean P&L of the hedged portfolio consistently outperforms the unhedged baseline, improving from approximately 27.35–27.95 to 28.46–29.85. Furthermore, the risk mitigation is highly significant, as evidenced by VaR and CVaR reductions of 13.74%–15.10% and 12.64%–15.13%, respectively.

Overall, the findings indicate that the put calendar spread strategy is effective in hedging ELSA.JK stock. By reducing VaR and CVaR while increasing the Mean P&L, this strategy provides a more stable and favorable portfolio performance. Therefore, the put calendar spread can be considered a suitable alternative hedging strategy to manage downside risk in ELSA.JK stock under uncertain market conditions.

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