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EVALUATING EFFECTIVENESS OF IRON CONDOR AND SHORT STRANGLE STRATEGIES AS HEDGING INSTRUMENTS FOR NIKKEI 225 INDEX: A STANDARD AND ANTITHETIC MONTE CARLO APPROACH

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ABSTRACT

Global equity markets, including the Nikkei 225 Index, often experience high volatility due to economic and geopolitical factors. Sudden price changes may cause significant losses, making hedging essential for managing extreme risks and preserving portfolio value. This study evaluates the effectiveness of two option strategies, Iron Condor and short Strangle, as hedging tools for the Nikkei 225. The dataset consists of daily closing prices of the Nikkei 225 index, obtained from the Investing.com website (https://id.investing.com). The methodology combines Monte Carlo simulation-based and Antithetic Monte Carlo on the Geometric Brownian Motion model to generate future price paths, and the Black-Scholes-Merton model to value option premiums. The Iron Condor, a hedged strategy, limits both profit and loss, offering stability for conservative investors. The short Strangle, while potentially more profitable, exposes investors to unlimited downside risk. Simulation results show that the short Strangle yields higher average returns but with much greater volatility. In contrast, the Iron Condor provides more stable and controlled outcomes with lower extreme risk. Based on quantitative metrics such as mean profit, standard deviation, Value-at-Risk, and loss probability, the Iron Condor is concluded to be more effective for hedging in low-to-moderate volatility markets. This study offers practical insights for investors and risk managers when choosing risk management strategies based on individual risk tolerance.

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1. INTRODUCTION

The capital market serves as a place where investors buy and sell various investment instruments, such as shares. It is also an important place for companies to raise capital to expand and develop their businesses. In the context of an increasingly integrated global economy, capital market dynamics are strongly influenced by global economic developments. The ongoing global economic crisis has been shown to amplify stock market volatility, thereby increasing risks and uncertainties faced by investors. Heightened volatility tends to weaken investor confidence and reduce their willingness to participate in capital markets. Empirical evidence confirms this phenomenon across both developed and emerging economies, where global shocks trigger volatility spillovers that destabilize investment patterns [1]. This underscores the urgent need for effective mechanisms to safeguard investment portfolios in times of economic turbulence. Therefore, understanding and implementing effective risk management mechanisms has become essential for sustaining investor confidence and maintaining market stability.

In response to such uncertainties, risk management strategies have become increasingly important, one of which is the implementation of hedging mechanisms. Hedging is an action taken to protect the value of assets against future price fluctuations. Numerous studies emphasize the significance of derivatives such as options and futures in hedging portfolios under volatile market conditions [2]. Empirical evidence further suggests that advanced hedging approaches, including dynamic and VaR-based strategies, can improve the effectiveness of risk management in derivatives markets [3]. In the international context, hedging has also been shown to play a critical role in stabilizing corporate performance and mitigating exposure to global financial shocks [4].

In practice, hedging can be implemented through various derivative instruments such as forward contracts, futures contracts, rights issues, swaps, warrants, and stock option contracts. Among the various financial instruments, options offer more flexibility. An option grants its holder the right, but not the obligation, to buy or sell an underlying asset at a specified strike price within a predetermined horizon. The option's premium is commonly decomposed into intrinsic value (the immediate in-the-money payoff) and extrinsic value (time), which reflects uncertainty, volatility, and time to expiration. Recent evidence on exercise behavior shows that market frictions and exercise boundary violations can make early exercise rational, underscoring the practical relevance of intrinsic value in real markets [5]. In parallel, modern pricing research links option values to underlying factor dynamics, reinforcing how market conditions shape the evolution of intrinsic and time value components [6].

Strategies for using options have become more complex as the market has evolved. This study focuses on the Iron Condor and short Strangle strategies because both are effective in markets with low to moderate volatility and prices that tend to stay within a certain range, such as the Nikkei 225 index. The Iron Condor strategy is applied when it is expected that the price of the underlying instrument will be between the exercise prices of options issued in spreads within a specified period [7]. On the other hand, the short Strangle, while riskier as it sells both a call and a put without protection, offers higher premiums and is effective in markets that are expected to remain range-bound but may still see larger price swings [8]. Both strategies are commonly used by traders in the derivatives market to manage risk in uncertain, sideways-moving markets. The purpose of selecting these two strategies is to assess their hedging effectiveness on the Nikkei 225 index and to provide practical insights for investors seeking to manage risk in Asian markets.

The Nikkei 225 Index is a primary benchmark of the Tokyo Stock Exchange and serves as a key indicator of Japan's economic performance, representing 225 large-cap companies across various sectors. Its price-weighted methodology makes the index highly sensitive to high-priced constituents, which can disproportionately influence index movements. Previous research shows that price adjustments between spot and futures markets of the Nikkei 225 exhibit nonlinear dynamics and market microstructure effects [9]. The Japanese stock market is also subject to volatility spillovers during periods of global stress, such as the COVID-19 pandemic, highlighting the vulnerability of the Nikkei 225 to external shocks [10]. Furthermore, policy uncertainty has been found to significantly increase idiosyncratic volatility among Nikkei 225 constituent stocks, amplifying the index's fluctuations [11]. These characteristics make the Nikkei 225 a meaningful underlying index for evaluating option-based hedging strategies. Given Japan's position as one of Indonesia's largest export destinations and a major source of foreign direct investment, fluctuations in the Nikkei 225 may indirectly affect Indonesia's economy through trade volume, capital inflows, and investor sentiment. More broadly, Japan remains a central hub in Asian financial networks, and changes in the Nikkei 225 have been shown to transmit volatility and return spillovers to other regional markets, including ASEAN and East Asia [12], [13]. This highlights the relevance of studying the Nikkei 225 not only for insights into Japan's domestic market but also for understanding broader regional spillovers across Asian economies.

Although option strategies have been widely examined in financial literature, their specific application to the Nikkei 225 index remains limited. Monte Carlo simulation has become an essential method for analyzing risk and asset behavior in uncertain market conditions, particularly for evaluating derivative instruments [14]. Furthermore, methodological innovations continue to enhance its effectiveness, such as optimized diffusion models that integrate Monte Carlo simulations in stock trading research to better capture nonlinear and stochastic dynamics [15]. Therefore, employing Monte Carlo simulation in this study is well justified for forecasting underlying price distributions, estimating expected payoffs, and assessing the hedging effectiveness of option strategies.

In finance, risk-neutral valuation is the cornerstone principle for pricing derivatives via Monte Carlo simulation: under the risk-neutral measure, the expected payoff of an option is discounted at the risk-free rate to obtain its present value. The procedure typically involves simulating many possible future paths of the underlying under the risk-neutral drift, computing payoffs, averaging them, and discounting [16]. Additionally, in the context of spread options, recent work has shown how Monte Carlo simulation under risk-neutral measure can be calibrated precisely via enhanced methods to produce accurate option prices [17]. In this study, we adopt this risk-neutral Monte Carlo framework to estimate expected payoffs of the hedging strategies and discount them at the prevailing risk-free rate, thereby capturing both the time value of money and probability-weighted outcomes. Related studies have applied Monte Carlo simulations with variance reduction techniques for pricing exotic options such as Bermudan options [18], showing the versatility of Monte Carlo approaches in derivative valuation.

However, the standard Monte Carlo simulation method has a well-known limitation: it often requires a very large number of iterations to achieve convergence or the desired level of accuracy. To improve this computational efficiency, various variance reduction techniques can be applied. One of the most common and effective techniques is the Antithetic Variate method [19]. Its basic principle is to reduce the variance in the simulation results by generating pairs of random variables that have a negative correlation, thus making the simulation results more stable without needing to increase the number of iterations [20]. As a comparison to the standard Monte Carlo simulation, the application of the Antithetic Monte Carlo method is carried out to evaluate whether this variance reduction technique can provide different results in assessing the effectiveness of the two hedging strategies.

Given the limited research on the application of options strategies to the Nikkei 225 Index, particularly through the Monte Carlo simulation approach, this study aims to evaluate the effectiveness of the Iron Condor and short Strangle strategies as hedging instruments against fluctuations in the index. The Monte Carlo approach and the comparative Antithetic Monte Carlo method are expected to provide a more accurate representation of the performance of these strategies under varying market conditions. Accordingly, this study not only contributes theoretically to the development of the literature on option strategies but also provides practical insights for portfolio management in the complex and risky markets [14]. The novelty of this research lies in its focus on evaluating and comparing two distinct option strategies, Iron Condor and Short Strangle, specifically applied to the Nikkei 225 Index using a Monte Carlo simulation framework and Antithetic Monte Carlo as a comparative method. Previous studies have primarily analyzed single-option strategies or applied these methods to other indices, leaving a gap in the literature regarding their effectiveness on the Nikkei 225. By combining the Black-Scholes-Merton pricing model with large-scale Monte Carlo simulations, this study provides a more comprehensive performance evaluation under low-to-moderate volatility conditions. Thus, the research not only extends the theoretical understanding of option-based hedging in Asian markets but also offers practical insights for risk managers and investors seeking to balance return and risk exposure.

2. RESEARCH METHODS

2.1 Data

The data utilized in this study consists of the daily closing prices of the Nikkei 225 stock index. The selected dataset covers the period from April 1, 2022, to December 29, 2023. These data were obtained from the Investing.com website (https://id.investing.com). The daily closing prices of the Nikkei 225 index are presented in Fig. 1. For clarity, all figures are presented with high-resolution rendering and standardized formatting to ensure that the axes, legends, and distribution patterns are clearly visible.

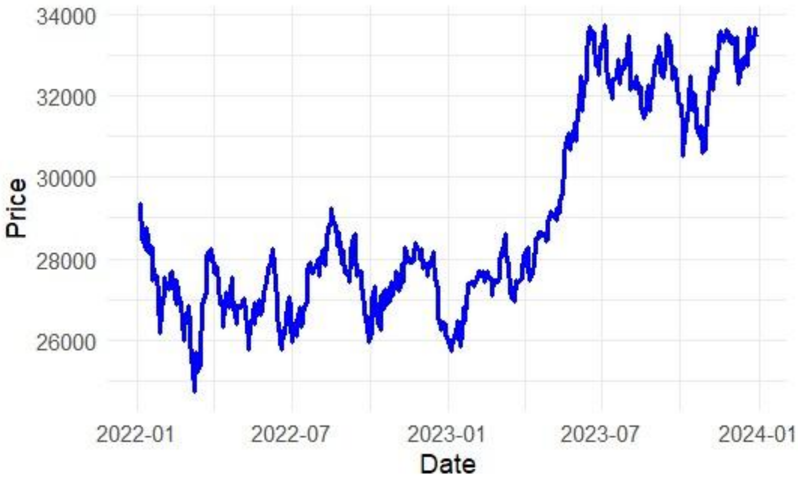


Figure 1. Daily Closing Price of Nikkei 225 Index

Fig. 1 shows the movement of the Nikkei 225 stock index, which remained in the range of 25,000 to 34,000 during the period from 1 April 2022 to 29 December 2023. The index showed a fluctuating behavior, with a notable increase observed between April 2023 and July 2023.

The risk-free interest rate (r) is represented by the yield of a 1-month Japanese Government Bill (JGB), obtained from the Japanese government bond market. The use of a domestic Japanese risk-free rate is consistent with derivative pricing theory, which requires that the risk-free asset be denominated in the same currency as the underlying asset. Since the Nikkei 225 Index is quoted in Japanese Yen (JPY), the short-term JGB yield provides a more theoretically appropriate benchmark than foreign sovereign yields. Furthermore, the one-month maturity aligns closely with the 30-day option horizon adopted in this study. The time to maturity (T) is therefore set at 30 days or 0.119 years.

Although the Nikkei 225 stock index has relatively low volatility, hedging strategies remain crucial, especially for institutional investors or individuals with large capital exposures. With large investments, even small price movements can have a significant financial impact on a portfolio. The Nikkei 225 is also one of the most important indices in Asia and is often used as a benchmark in various derivative instruments, resulting in significant exposure for regional investors. In addition, the index reflects the economic performance of Japan, which is an important trading partner for many countries, including Indonesia. Movements in the index can influence expectations about exports, capital flow, and regional economic stability. In times of global uncertainty, such as changes in monetary policy, geopolitical tensions, or supply chain disruptions, hedging serves as a protective measure against potential losses while helping to maintain the stability of asset values. Understanding and applying hedging strategies to the Nikkei 225 is therefore important in both theory and practice, particularly when managing risk and optimizing portfolios in the dynamic Asian markets.

2.2 Data Normality

To ensure that the Geometric Brownian Motion (GBM) model can be applied to the simulation of Nikkei 225 index prices, a normality test is performed on the distribution of the index's log returns. GBM assumes that the log returns of assets are normally distributed and independently and identically distributed (i.i.d). Therefore, the necessary step is to perform a normality test on the historical log returns of the Nikkei 225 index.

In this study, the normality test is performed using the Jarque-Bera test, which measures the deviation from normality based on the skewness and kurtosis of the data distribution. If the p-value is > 0.05, it can be concluded that the log return data follows a normal distribution, thus satisfying the assumption of the GBM model.

The hypotheses for the test are as follows:

H_0: The log-return data for the index follow a normal distribution.

H_1: The index's log-return data do not follow a normal distribution.

Although the Jarque-Bera test indicates approximate normality of log returns, this result alone does not fully validate the GBM assumptions. The GBM framework is adopted as a parsimonious benchmark model widely used in option pricing literature. Potential deviations from assumptions, such as volatility clustering and regime shifts, are acknowledged as limitations of the study.

2.3 Black Scholes Merton Model

The Black Scholes Merton (BSM) model was first developed by Fisher Black, Myron Scholes, and Robert Merton in the early 1970s as a breakthrough in European option pricing [21]. This model provides a strong mathematical foundation for calculating the prices of European call and put options, which has had a significant impact on the development of the derivatives market. The BSM model uses several key inputs, including the strike price, the current price of the underlying asset, time to expiration, the risk-free interest rate, and the assumption of constant asset volatility [21].

The Black-Scholes-Merton model is based on several important assumptions [21]:

1. European Style Options: The options used in this model can only be exercised on the expiration date, meaning there is no possibility to exercise the option before the specified time, in line with the characteristics of European-style options.
2. Stock Price Movement: The underlying stock price follows a geometric Brownian motion process, indicating that stock price movements are random but continuous.
3. No Transaction Costs: It is assumed in this model that there are no transaction costs when buying or selling options, so the calculated prices are not affected by additional costs.
4. No Dividends: The underlying asset is assumed not to pay any dividends or other distributions during the life of the option.
5. Constant Volatility and Interest Rate: Throughout the life of the option, the volatility of the underlying asset and the risk-free interest rate are assumed to remain constant and are known.
6. Market Efficiency: This model assumes that markets are efficient, meaning asset price movements cannot be predicted, in line with the theory of random markets.
7. Log-Normal Distribution: The changes in the underlying asset price are assumed to follow a log-normal distribution, meaning the asset price is more likely to fluctuate within a lower range, with greater chances of price jumps over time.
8. No Arbitrage: The model assumes there is no risk-free arbitrage opportunity, which ensures that the option prices calculated using this model are valid and cannot be exploited for risk-free profit.

This model provides a mathematical solution in the form of an explicit formula to calculate the prices of European call and put options. The formula obtained from solving the partial differential equation in this model is as follows:

$$c = S_0 N(d_1) - Ke^{-rT} N(d_2), \tag{1}$$

$$p = Ke^{-rT} N(-d_2) - S_0 N(-d_1), \tag{2}$$

with:

$$d_1 = \frac{\ln\left(\frac{S_0}{K}\right) + \left(\frac{r - q + \sigma^2}{2}\right)T}{\sigma\sqrt{T}}, \tag{3}$$

$$d_2 = \frac{\ln\left(\frac{S_0}{K}\right) + \left(\frac{r - q - \sigma^2}{2}\right)T}{\sigma\sqrt{T}} = d_1 - \sigma\sqrt{T}, \tag{4}$$

where c is the price of the call option, p price of the put option, S_0 is the current strike price at time zero, K is strike price, r is a risk-free interest rate calculated continuously, q is dividend yield, σ is the volatility of the stock price, T is the time until the option expiration, and $N(x)$ is a cumulative probability distribution function for a variable x with a standard normal distribution.

2.4 Monte Carlo Simulation

Monte Carlo simulation is a stochastic method based on probability distributions and random number generation, frequently applied to model random phenomena in uncertain decision-making environments. It is widely recognized as a versatile tool for analyzing potential scenarios through repeated computational experiments [22]. In practice, the method is typically implemented in five steps: (i) constructing the probability distribution of key variables, (ii) forming the corresponding cumulative distribution, (iii) defining random number intervals, (iv) generating random numbers, and (v) performing repeated simulations to compute outcomes. This structured process has been highlighted in financial applications as an essential approach for modeling complex systems and assessing risk [23]. In the financial world, Monte Carlo simulation is widely employed to simulate stock prices and evaluate derivative instruments. One widely adopted framework is risk-neutral valuation, in which a large number of random paths are generated under the risk-neutral measure to estimate the expected payoff, which is then discounted using the risk-free interest rate. This approach has been shown to provide consistent and theoretically grounded results in option pricing, including entropy-based models that derive risk-neutral distributions from observed option prices [16]. More recent applications illustrate how Monte Carlo simulations under the risk-neutral measure can be calibrated to improve the pricing accuracy of spread options and related derivatives [17]. The application of Monte Carlo methods in option pricing has been demonstrated in various contexts, including basket options with variance reduction techniques [24], further supporting the robustness of the simulation approach used in this study.

Suppose there is a derivative instrument whose value depends on a single market variable, S, and provides a payoff at time T. Assuming a constant interest rate, the valuation of this instrument can be done through the following steps [25]:

1. Take a random path for S in the risk-neutral world.
2. Calculate the payoff of the derivative.
3. Repeat steps 1 and 2 to obtain multiple payoff samples of the derivative in the risk-neutral world.
4. Calculate the average of the payoff samples to obtain the estimated expected payoff in the risk-neutral world.
5. Discount the expected payoff with the risk-free interest rate to obtain the estimated value of the derivative.

Mathematically, the stochastic process followed by the underlying market variable in the risk-neutral world can be written as:

$$dS = \hat{\mu} S dt + \sigma S dz, \tag{5}$$

where dz is the Wiener process, $\hat{\mu}$ is the expected return rate in the risk-neutral world, and σ is the volatility. To discretize this process, the following approach is used:

$$S(t + \Delta t) - S(t) = \hat{\mu} S(t)\Delta t + \sigma S(t)\varepsilon\sqrt{\Delta t} \tag{6}$$

where ϵ is a random number from the standard normal distribution.

In practice, it is usually more accurate to stimulate $\ln S$ rather than S. According to Ito's Lemma, the process followed by $\ln S$ is:

$$d \ln S = \left(\hat{\mu} - \frac{\sigma^2}{2}\right) dt + \sigma\, dz. \tag{7}$$

Thus, in discrete form, it can be written as

$$\ln S(t + \Delta t) - \ln S(t) = \left(\hat{\mu} - \frac{\sigma^2}{2}\right)\Delta t + \ \sigma\varepsilon\sqrt{\Delta t}\,. \tag{8}$$

Solving for S, we have:

$$S(t + \Delta t) = S(t) \exp\left[\left(\hat{\mu} - \frac{\sigma^2}{2}\right)\Delta t + \sigma\varepsilon\sqrt{\Delta t}\right]. \tag{9}$$

This provides the formula for building the simulation path of S. Using $\ln S$ yields more accurate values compared to directly using S. Also, if $\hat{\mu}$ and σ are constant, then

$$\ln S(T) - \ln S(0) = \left(\hat{\mu} - \frac{\sigma^2}{2}\right)T + \sigma\varepsilon\sqrt{T} \tag{10}$$

holds for any value of T. Therefore, the explicit form for the stock price at time T becomes:

$$S(T) = S(0)\exp\left[\left(\hat{\mu} - \frac{\sigma^2}{2}\right)T + \sigma\varepsilon\sqrt{T}\right]. \tag{11}$$

2.5 Antithetic Monte Carlo

The antithetic variates method is a fundamental variance reduction technique employed to enhance the efficiency and accuracy of Monte Carlo simulations. Its primary objective is to achieve more precise simulation outcomes using a smaller number of iterations (N) [26]. The method's working principle involves replacing independent samples with pairs of samples that are intentionally designed to be negatively correlated. This is achieved by pairing every random number used with its opposite or antithesis. If a simulation requires a random number, Z, drawn from a standard normal distribution $\phi(0,1)$, the method mandates that the simulation also be executed using its counterpart, $-Z$. By pairing each ε_n with $-\varepsilon_n$, the new combined sequence, now consisting of $2N$ data points, is guaranteed by construction to have an exact mean of zero.

The fundamental implementation of this principle in derivative pricing arises when simulating the future asset price (S_T). A standard asset price path following Geometric Brownian Motion depends on the random variable Z [27]:

$$S(T) = S(0)\exp\left(\left(r - \frac{1}{2}\sigma^2\right)T + \sigma\sqrt{T}Z\right). \tag{12}$$

To apply the antithetic technique, an antithetic path or paired simulation $S_T^{(\text{antithetic})}$ is created using the same formula, but with the random variable replaced by its opposite, $-Z$:

$$S(T)^{(antithetic)} = S(0)\exp\left(\left(r - \frac{1}{2}\sigma^2\right)T + \sigma\sqrt{T}(-Z)\right). \tag{13}$$

From these two simulated prices, two payoff values are computed: $f(Z)$, based on S_T, and $f(-Z)$, based on $S_T^{(\text{antithetic})}$. The estimator for a single simulation trial is not the individual value, but rather the average of the pair:

$$\bar{f} = \frac{f(Z) + f(-Z)}{2}. \tag{14}$$

The final estimate of the derivative's value is the average of all $\bar{f}$ obtained from a total of M simulation pairs. This mechanism effectively reduces variance because each pair of values offsets one another. Intuitively, if a large value of Z produces a very high S_T (a positive extreme), the value $-Z$ will produce a very low $S_T^{(\text{antithetic})}$ (a negative extreme). When the payoffs are averaged, these extremes cancel out [27].

2.6 Iron Condor Strategy

An Iron Condor combines a bullish put spread and a bearish call spread; the investors achieve maximum profit if S_T remains between K_2 and K_3 [29]. Iron Condor Strategy constructed by taking the following positions: long 1 put option with an out of the money (OTM) strike price at K_1 purchased at price p_1, short 1 put option with an at the money (ATM) strike price at K_2 sold at price p_2, short 1 call option with an out of the money (OTM) strike price at K_3 sold at price c_3, and long 1 call option with an out of the money (OTM) strike price K_4 purchased at price c_4. The sequence of strike prices satisfies $K_1 < K_2 \le K_3 < K_4$ [29]. The value of the Iron Condor strategy equals:

$$\text{Initial Cash Flow} = p_2 - p_1 + c_3 - c_4, \tag{15}$$

$$\text{Payoff} = \max(K_1 - S_T, 0) - \max(K_2 - S_T, 0) - \max(S_T - K_3, 0) + \max(S_T - K_4, 0), \tag{16}$$

$$\text{Profit} = \text{Payoff} + \text{Initial Cash Flow}. \quad (17)$$

The payoff and profit calculations for the Iron Condor strategy are shown in Table 1. Table 1 illustrates how each option position contributes to the overall payoff and profit at various asset prices S_T within the range of the strike prices.

Table 1. Payoff and Profit Iron Condor Strategy

	$S_T < K_1$	$K_1 \le S_T < K_2$	$K_2 \le S_T < K_3$	$K_3 \le S_T < K_4$	$S_T \ge K_4$
Long 1 put (K_1)	$K_1 - S_T$	0	0	0	0
Short 1 put (K_2)	$-(K_2 - S_T)$	$-(K_2 - S_T)$	0	0	0
Short 1 call (K_3)	0	0	0	$-(S_T - K_3)$	$-(S_T - K_3)$
Long 1 call (K_4)	0	0	0	0	$S_T - K_4$
Payoff	$K_1 - K_2$	$S_T - K_2$	0	$-(S_T - K_3)$	$K_3 - K_4$
Initial Cash Flow	$p_2 - p_1 + c_3 - c_4$	$p_2 - p_1 + c_3 - c_4$	$p_2 - p_1 + c_3 - c_4$	$p_2 - p_1 + c_3 - c_4$	$p_2 - p_1 + c_3 - c_4$
Profit	$K_1 - K_2 + p_2 - p_1 + c_3 - c_4$	$-K_2 + S_T + p_2 - p_1 + c_3 - c_4$	$p_2 - p_1 + c_3 - c_4$	$-S_T + K_3 + p_2 - p_1 + c_3 - c_4$	$K_3 - K_4 + p_2 - p_1 + c_3 - c_4$

2.7 Short Strangle Strategy

The short Strangle strategy is constructed by taking a short position in 1 call option that is out of the money (OTM) at a price of c with a strike price of K_2, and a short position in 1 put option that is also out of the money at a price of p with a strike price of K_1, where $K_1 < K_2$ [30]. Below is the calculation of the payoff and profit for the strategy:

$$\text{Initial Cash Flow} = c + p, \quad (18)$$

$$\text{Payoff} = -\max(S_T - K_2, 0) - \max(K_1 - S_T, 0), \quad (19)$$

$$\text{Profit} = \text{Payoff} + \text{Initial Cash Flow}. \quad (20)$$

The payoff and profit calculation for the short Strangle strategy is shown in Table 2. Table 2 illustrates how each option position contributes to the total payoff and profit at various asset prices S_T within the strike price interval.

Table 2. Payoff and Profit Short Strangle Strategy

	$S_T < K_1$	$K_1 < S_T < K_2$	$S_T > K_2$
Short put (K_1)	$-(K_1 - S_T)$	0	0
Short call (K_2)	0	0	$-(S_T - K_2)$
Payoff	$-(K_1 - S_T)$	0	$-(S_T - K_2)$
Initial Cash Flow	$c + p$	$c + p$	$c + p$
Profit	$-K_1 + S_T + c + p$	$c + p$	$-S_T + K_2 + c + p$

2.8 Performance Evaluation Metrics

2.8.1 Mean

The mean is defined as the sum of the observation values divided by the number of observations. It is interpreted as the balance point of the distribution [31]. The formula for mean is

$$\bar{x} = \frac{\Sigma_{i=1}^{n} x_i}{n} \quad (21)$$

where n is the total number of Monte Carlo simulations, x_i is the profit obtained from the strategy in the i-th simulation.

2.8.2 Standard Deviation

Standard deviation is a statistical measure used to assess how dispersed or volatile the data is around its mean value. A low standard deviation indicates consistent outcomes that do not deviate much from the average, which is an ideal characteristic for a hedge [32]. Mathematically, the standard deviation (Stdev) is the positive square root of the variance (S^2). The formula used is for the sample standard deviation based on a sample of data. The formula is given as in Eq. 22.

$$\text{Stdev} = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{n-1}} \tag{22}$$

where n is the total number of Monte Carlo Simulations, x_i is the profit obtained from the strategy in the i-th simulation, and $\bar{x}$ is the average (mean) of all simulated profit results.

2.8.3 Value at Risk (VaR 5%)

Value at Risk (VaR) is a risk measurement that defines risk as potential loss. The accuracy of VaR estimation depends critically on the selection of methodology and the distributional assumptions underlying asset returns. Misaligned assumptions can distort the results, rendering VaR unreliable as a risk measure. Recent studies emphasize the need for models that incorporate high-frequency and cross-market information to improve predictive performance. Wang and Cheng [33] propose a generalized autoregressive score (GAS) Factor-X framework that integrates realized volatility from domestic and international markets, demonstrating that such an approach enhances the accuracy of both VaR and Expected Shortfall forecasts. Consistent with this evidence, in this study, VaR is defined as the maximum potential loss of a portfolio over a given horizon at a specified confidence level, and the adopted methodology is aligned with the empirical return distribution to ensure robust risk assessment.

Several methods are used to calculate VaR, including historical simulation, variance-covariance, and Monte Carlo Simulation. VaR using the Monte Carlo simulation method involves generating a distribution through simulation, from which the VaR can then be calculated. This method requires more computing resources than the other two methods.

Mathematically, the value-at-risk (VaR) at a confidence level of α can be defined as the $(1-\alpha)$ quantile of the loss distribution:

$$\text{VaR}_\alpha^n = L_{[\alpha n]:n} \tag{23}$$

with $L_{[\alpha n]}$ is the n-th order statistic from n loss simulations. In practice, VaR is calculated as the value at the fifth percentile (for $\alpha = 95\%$) of the simulation result vector [34].

2.8.4 Sharpe Ratio

Sharpe Ratio is the ratio of excess return over risk-free rate to the standard deviation of the excess return [21]. The formula for the Sharpe Ratio is:

$$\lambda = \frac{\mu - r}{\sigma} \tag{24}$$

with μ is the return of the portfolio, r is the risk-free rate return, and σ is the standard deviation of portfolio return. If the Sharpe Ratio is high, it means the portfolio provides a good return relative to the risk taken. If the Sharpe Ratio is low or negative, it means the returns of the portfolio are low or even negative compared to the risk involved.

3. RESULTS AND DISCUSSION

3.1 Normality Test

In the normality test using the Jarque-Bera test, a p-value of 0.555 was obtained, which is greater than the significance level of 0.05. This indicates that the log return data of the Nikkei 225 Index follows a normal distribution. For further illustration, the following is a histogram of the log returns of the closing prices of the Nikkei 225 Index.

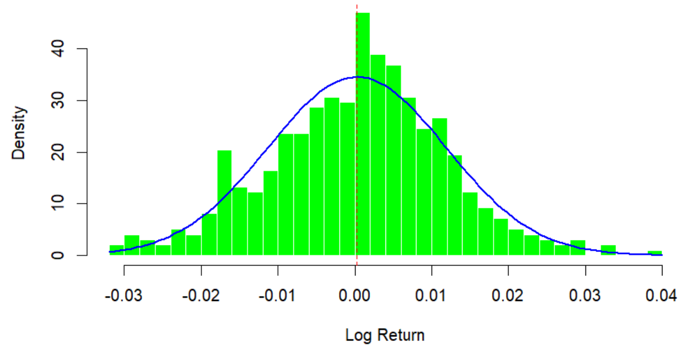


Figure 2. Histogram of Log Returns of Nikkei 225 Index Closing Prices

The histogram in Fig. 2 supports the conclusion that the distribution of log returns of the Nikkei 225 Index closing prices follows a normal distribution. This can be seen from the characteristics of the graph, which resemble a normal curve with the highest peak in the middle and asymmetric tails on both sides. A normal distribution indicates that the price fluctuations of the Nikkei 225 Index tend to be evenly distributed and do not exhibit significant skewness or kurtosis.

3.2 Parameter Estimation for Simulation

Based on the daily log return data of the Nikkei 225 Index, the average daily log return is 0.000272, and the standard deviation is 0.011563. After conversion to annual values, the estimated annual return (μ) is 0.068451, and the annual volatility (σ) is 0.183554. Thus, the estimated annualized volatility is 18.36%, which is relatively moderate compared with historical volatility levels reported for major equity indices in previous studies.

3.3 Monte Carlo Simulation for Stock Price

A Monte Carlo simulation was performed 100,000 times to project the distribution of the final price of the Nikkei 225 index in 30 days. The model used was Geometric Brownian Motion (GBM), which assumes that price changes follow a normal distribution and generate a log-normal distribution of the final price.

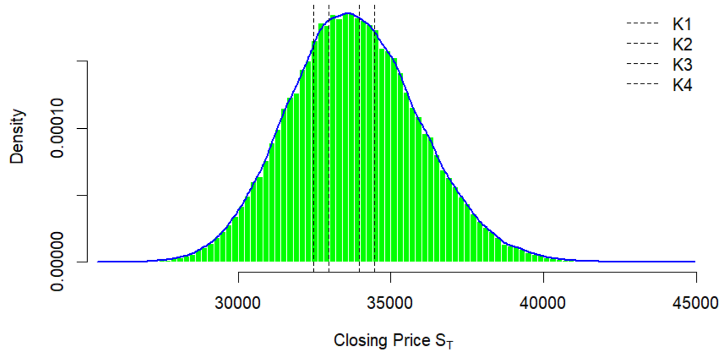


Figure 3. Distribution of Closing Price (S_T) from Monte Carlo Simulation

Fig. 3 shows the simulation results of the S_T distribution. The S_T distribution is highly concentrated between K_2 and K_3, which are the zones with the maximum profit potential in the Iron Condor strategy. This indicates that, given the current market conditions, this strategy has the potential to be optimal, as the majority of the final prices of the Indices fall within the safe range. Therefore, this simulation provides a solid foundation for calculating the payoff and profit of the option strategy, as well as evaluating the effectiveness of Iron Condor and short Strangle in managing the risk of short-term price fluctuations in the Nikkei 225 index.

3.4 Profit and Payoff Distribution

3.4.1 Iron Condor

To illustrate the simulated outcomes, Fig. 4 displays the payoff and profit distribution of the Iron Condor strategy generated from 100,000 Monte Carlo iterations. This visualization highlights the range of potential outcomes and provides a basis for evaluating the strategy's hedging effectiveness.

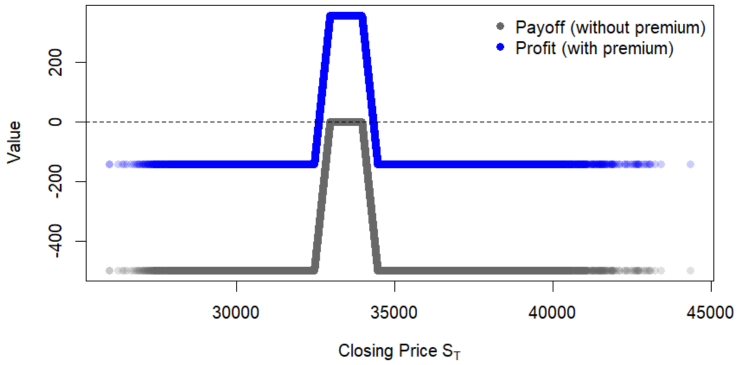


Figure 4. Monte Carlo Simulation of Payoff and Profit for The Iron Condor Strategy

Fig. 4 shows that the Iron Condor strategy generates a maximum profit of $358.448 when the final price of S_T is between K_2 and K_3. Outside of this range, profits decrease symmetrically, but potential losses remain limited due to the protection of the long options on both sides. The wide distribution of simulation points shows that, although this strategy is defensive, the probability of reaching the maximum profit zone is low in volatile market conditions.

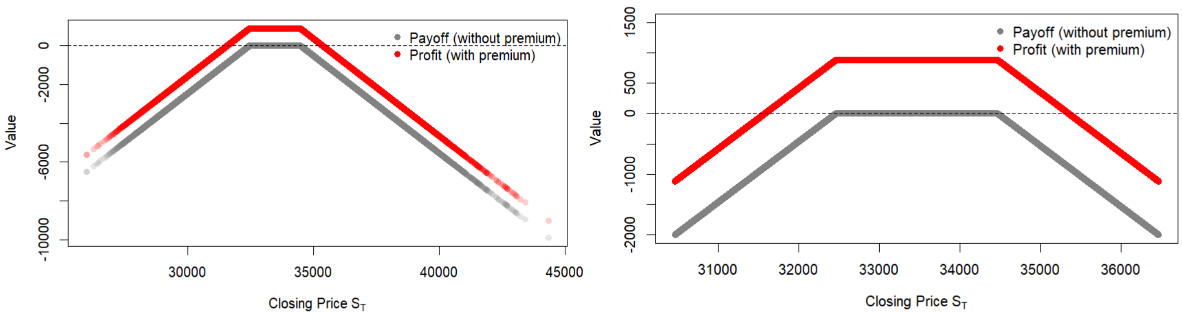
To strengthen the analysis of the simulated outcomes, Fig. 5 presents the payoff and profit distribution of the Iron Condor strategy generated using the Monte Carlo simulation with antithetic variates.

Figure 5. Monte Carlo Antithetic Variates Simulation of Payoff and Profit for The Iron Condor Strategy

Fig. 5 shows that the Iron Condor strategy under the antithetic simulation retains the same maximum profit region as in Fig. 4, occurring when the final price of S_T is between K_2 and K_3. Specifically, the maximum profit generated is $358.448, a value that is identical to the $358.448 obtained from the standard simulation. This confirms that the Iron Condor's defensive characteristics are robust. Even after variance reduction, the strategy continues to offer limited downside risk.

3.4.2 Short Strangle

Fig. 6 illustrates the payoff and profit distribution of the Short Strangle strategy based on Monte Carlo simulations. Panel (a) shows the unfiltered results covering the full profit range, while panel (b) presents a filtered view to enhance the visibility of the central distribution.



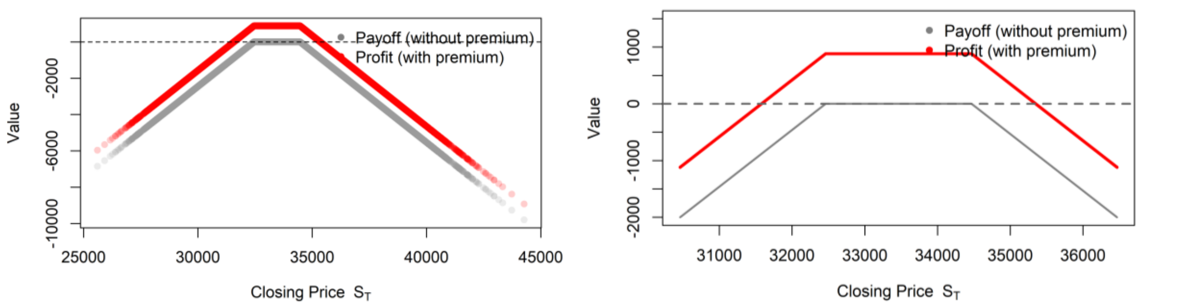
(a) **(b)**

Figure 6. Monte Carlo Simulation of Payoff and Profit for The Short Strangle Strategy (a) Unfiltered, (b) Filtered

Fig. 6 shows that the maximum profit of $881.09 is attained when the final index price falls within the range between the put and call strikes. However, when the price moves past either strike price, the profit begins to decline and can become significantly negative. This strategy is very sensitive to extreme price movements due to the lack of protection on both sides. This is evident from the sharp slope of the profit graph on the left and right. While the profit zone is wider than that of the iron condor strategy, the short strangle strategy carries a much greater risk if the market moves beyond expectations.

For visualization purposes, the Monte Carlo Simulation profit distribution graph is filtered to display only a portion of the profit range. Although most simulation results fall outside this range, filtering is done to highlight the shape of the distribution in the middle zone. This shape is an important visual reference for understanding the strategy. In strategies such as short Strangle, the simulation results are often extreme, with very large profit or loss values that cause the graph to appear disproportionate. This makes it difficult to interpret the main distribution when the graph is displayed in full. Therefore, filtering the graph improves the readability of the distribution shape around the mean point and transition zone, even though it means displaying only a portion of the data. All simulation results are used to calculate evaluation metrics, such as mean, standard deviation, value at risk (VaR), and loss probability. Thus, the analysis conclusions are based on the full data set, not just the visualization results.

Fig. 7 illustrates the payoff and profit distribution of the Short Strangle strategy based on Monte Carlo simulations with antithetic variates, to further examine the robustness of the Short Strangle results. Panel (a) shows the unfiltered results covering the full profit range, while panel (b) presents a filtered view to enhance the visibility of the central distribution.



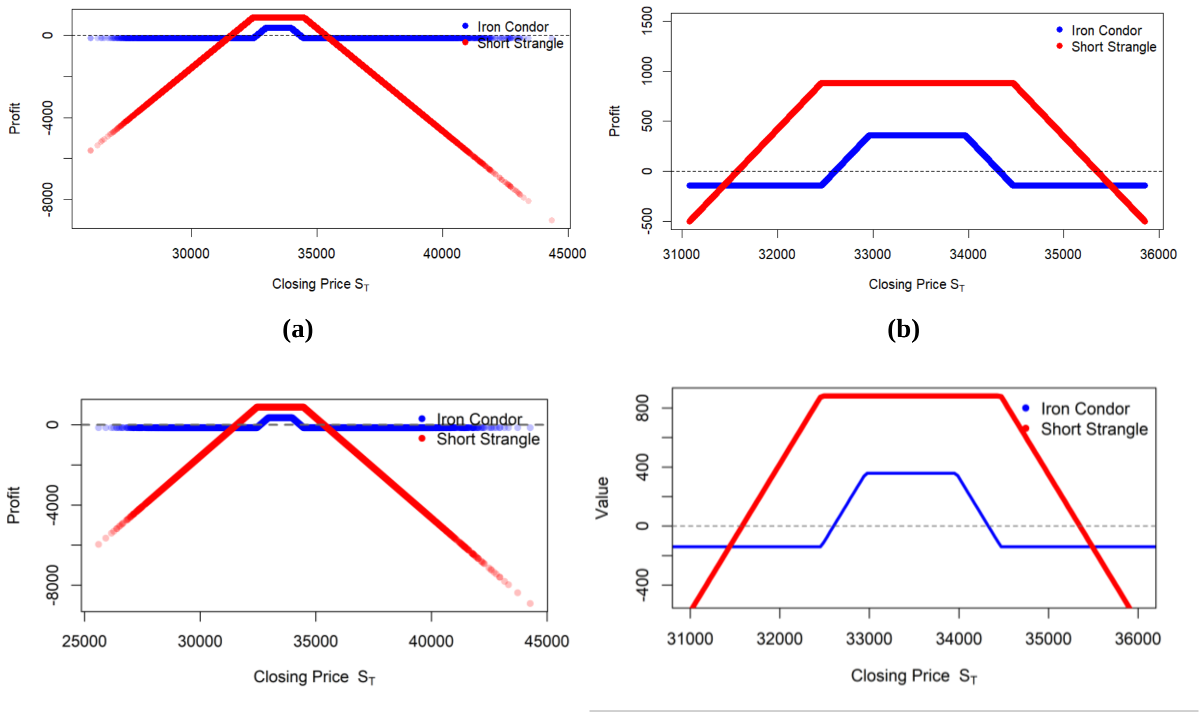
(a) **(b)**

Figure 7. Monte Carlo Simulation with Antithetic Variates of Payoff and Profit for The Short Strangle Strategy (a) Unfiltered, (b) Filtered

This shows a profit and payoff profile that visually confirms an identical strategy shape to the standard Monte Carlo simulation in Fig. 6. The profile retains the characteristic trapezoidal shape of the Short Strangle strategy, consisting of a flat maximum profit zone and two sloped sides representing unlimited losses. In this antithetic simulation, the recorded maximum profit is $881.503, a value essentially identical to the 881.09 obtained from the standard simulation. This confirms that the theoretical maximum profit is constant (i.e., the initial premium received), which is achieved when the asset price S_T expires between the two strike prices. This result reinforces the conclusion that the extreme risk profile of the Short Strangle is a robust and inherent characteristic of the strategy itself.

3.5 Comparative Analysis of Strategies

To further evaluate the relative performance of both strategies, Fig. 8 presents a side-by-side comparison of the Iron Condor and short Strangle profit distributions under Monte Carlo simulations and Antithetic Monte Carlo. The figure highlights the broader profit zone of the short Strangle as well as its steeper downside slope, contrasted with the narrower yet more controlled outcome of the Iron Condor. Panels (a) and (c) show the complete profit distribution, while panels (b) and (d) provide a zoomed-in perspective to emphasize the central region where most outcomes are concentrated.



(a) (b)

(c) (d)

Figure 8. Profit Comparison of Iron Condor and Short Strangle Strategy (a) Unfiltered Monte Carlo, (b) Filtered Monte Carlo, (c) Unfiltered Antithetic Monte Carlo, (d) Filtered Antithetic Monte Carlo

It shows a direct comparison of the profitability of the Iron Condor and short Strangle strategies against the final price of the index. As can be seen, the short Strangle provides a greater profit opportunity with a wider profit zone but carries the risk of extreme losses when the price moves far from the expected range. In contrast, the Iron Condor offers stability and risk protection, though its profit potential is limited. Thus, Iron Condor is better suited to conservative investors in a sideways market, while short Strangle is better suited to aggressive investors pursuing higher premiums with extreme risk tolerance.

3.6 Performance Evaluation Metrics

The Iron Condor and short Strangle strategies were evaluated using a quantitative approach based on a Monte Carlo simulation of 100,000 iterations, under the assumption that the final asset price follows a geometric Brownian motion (GBM) process. This evaluation aims to measure the effectiveness of these strategies for hedging a low-volatility index, using the following metrics:

Table 3. Performance Evaluation Metrics for Iron Condor and Short Strangle Strategy with Monte Carlo Simulation

Metrics	Iron Condor	Short Strangle
Mean Profit	-3.249	-20.540
Standard Deviation	205.682	1149.501
Max Profit	358.448	881.503
Min Profit	-140.502	-9013.047
Probability of Loss (%)	68.576	37.834
VaR 5%	-140.502	-2371.439
Sharpe Ratio	-0.016	-0.018

As presented in Table 3, the comparative results demonstrate a clear trade-off between risk and return. The Short Strangle strategy provides a higher maximum profit and a larger proportion of profitable outcomes, yet it is accompanied by substantially higher volatility and extreme downside risk, as shown by its large negative minimum profit and VaR. On the other hand, the Iron Condor offers more modest profits but delivers significantly greater stability, with narrower ranges of both gains and losses and a better-controlled risk profile. These contrasting characteristics highlight the fundamental difference between the two strategies: the Short Strangle favors aggressive investors seeking higher returns despite substantial tail risk, while the Iron Condor better suits conservative investors aiming for consistent outcomes with limited exposure to extreme losses.

Table 4. Performance Evaluation Metrics for Iron Condor and Short Strangle Strategy with Antithetic Monte Carlo

Metrics	Iron Condor (Antithetic)	Short Strangle (Antithetic)
Mean Profit	-3.000	-13.132
Standard Deviation	191.266	1106.977
Max Profit	358.448	881.503
Min Profit	-140.472	-7448.212
Probability of Loss (%)	68.990	37.852
VaR 5%	-140.472	-2307.267
Sharpe Ratio	-0.016	-0.012

As shown in Table 4, the results from the Antithetic Monte Carlo simulation also confirm a clear trade-off between risk and return. The Short Strangle (Antithetic) strategy once again provides a higher maximum profit. However, this is offset by very high volatility and substantial extreme downside risk, as shown by its Min Profit and 5% VaR. On the other hand, the Iron Condor (Antithetic) offers more moderate profits but delivers significantly greater stability. Its range of gains and losses is much narrower, with a more controlled risk profile, where the Min Profit and 5% VaR are both limited to -140.472.

When compared to Table 3, the results in Table 4 (Antithetic) show slightly lower standard deviation values and slightly better mean profits (smaller average losses) for both strategies. This is consistent with the purpose of the antithetic variates method as a variance reduction technique. The following subsections provide a more detailed discussion of each performance metric.

3.6.1 Mean Profit

The mean profit indicates the expected long-term outcome of repeated implementation. Based on the standard Monte Carlo simulation (Table 3), both strategies produced negative mean profits, with -3.249 for the Iron Condor and -20.540 for the short Strangle. This suggests that under the simulated conditions, both tend to generate losses. However, the Iron Condor's smaller magnitude of loss reflects a more stable performance, as it reduces the average downside relative to the short Strangle. This implies that in markets with low-to-moderate volatility, the Iron Condor is more effective in mitigating cumulative losses, whereas the short Strangle exposes investors to higher average erosion of portfolio value.

This finding is reinforced by the results from the Antithetic Monte Carlo simulation in Table 4. In this simulation, both strategies again produced negative mean profits, with -3.000 for the Iron Condor (Antithetic) and -13.132 for the Short Strangle (Antithetic). Although the values are slightly different, the pattern remains consistent, whereby the Iron Condor's magnitude of average loss remains significantly smaller. This reflects a more stable performance and reduces the average downside compared to the Short Strangle.

The mean profit results from the Antithetic simulation in Table 4 show slightly smaller average losses (a slightly better outcome) for both strategies compared to the standard Monte Carlo simulation in Table 3. This is consistent with the purpose of the antithetic variates method being applied as a variance reduction technique. By reducing the simulation's variance, this method produces a more precise and stable estimate of the expected value (mean profit), thereby reducing statistical noise and resulting in slightly lower average losses.

3.6.2 Standard Deviation

Standard deviation measures the dispersion of profit outcomes around the mean, serving as an indicator of volatility and risk. The Iron Condor shows a standard deviation of 205.682, while the Short Strangle exhibits an exceptionally high value of 1,149.501. This stark contrast highlights that the short Strangle's returns are far more unpredictable, exposing investors to extreme fluctuations. By comparison, the Iron Condor delivers outcomes clustered closer to the mean, reinforcing its role as a conservative hedging strategy.

When the simulation is refined using the Antithetic Monte Carlo method, these patterns remain consistent, and the variance of both strategies is reduced. The Iron Condor shows a standard deviation of 191.226, whereas the Short Strangle has a standard deviation of 1,106.977, but the Short Strangle still exhibits significantly greater dispersion than the Iron Condor. This suggests that the observed difference in risk is not merely the result of simulation noise, but an inherent characteristic of the strategies themselves. Thus, when stability is prioritized, the Iron Condor is clearly preferable.

3.6.3 Maximum and Minimum Profit

The contrast between maximum and minimum profit underscores the fundamental risk-return trade-off. The Short Strangle achieves a maximum profit of 881.503, more than double the Iron Condor's maximum of 358.448. However, this potential gain comes at the cost of an extreme downside: the Short Strangle's minimum profit plunges to -9,013.047 compared to only -140.502 for the Iron Condor. This massive disparity illustrates the severe tail risk associated with the Short Strangle, where rare but catastrophic losses dominate its risk profile. Conversely, the Iron Condor provides investors with bounded outcomes on both sides, ensuring losses remain within a controllable range.

When the analysis is repeated using the Antithetic Monte Carlo method, the pattern remains consistent. The Iron Condor records a maximum profit of approximately 358.448 and a minimum of -140.472, while the Short Strangle reaches about 881.503 at its peak but still falls to around -7,448.212 at its worst. Although variance reduction slightly moderates the most extreme losses, it does not alter the fundamental ordering of risk and return between the two strategies. This alignment between standard and antithetic Monte Carlo results confirms that the Iron Condor's capped downside is a structural feature, whereas the Short Strangle's superior upside is inherently tied to much greater tail risk.

3.6.4 Probability of Loss

The probability of loss captures how often a strategy produces negative outcomes across simulations. Based on the standard Monte Carlo simulation in Table 3, interestingly, the Iron Condor records a higher probability of loss at 68.58%, compared to only 37.84% for the short Strangle. At first glance, this may suggest that the short Strangle performs better. However, this interpretation is misleading because the magnitude of losses in short Strangle scenarios is disproportionately larger. Thus, while the Iron Condor incurs losses more frequently, these losses are relatively minor, whereas the short Strangle produces fewer but potentially devastating losses. This distinction emphasizes the need for investors to consider not only the frequency but also the severity of negative outcomes.

The same pattern is also confirmed by the results of the Antithetic Monte Carlo simulation (Table 4). In this simulation, the Iron Condor (Antithetic) records a probability of loss of 68.990%, while the Short Strangle (Antithetic) records 37.852%. Once again, the Short Strangle shows a lower frequency of loss. However, as has been explained, this interpretation cannot stand alone without considering the magnitude of the risk. This finding reinforces the conclusion that the risk characteristics of these strategies (frequency vs. severity) are consistent: the Iron Condor incurs small losses more frequently, while the Short Strangle incurs losses less often but with a much greater risk of extreme losses.

Unlike the Mean Profit or Standard Deviation metrics, which showed a slight improvement (a better value) as a result of the variance reduction technique, the Probability of Loss value in the Antithetic simulation in Table 4 is almost identical to the standard Monte Carlo simulation results in Table 3. This is expected, as the antithetic variates method is designed to reduce the variance (magnitude) of outcomes and stabilize the mean, but it does not necessarily change the underlying probability (frequency) of an outcome falling inside or outside the profit zone. This strong consistency in the probability figures further validates the study's findings regarding the inherent loss frequency profile of both strategies.

3.6.5 Value at Risk (VaR 5%)

The 5% Value-at-Risk (VaR) quantifies the maximum expected loss in the worst-case scenarios. The Iron Condor's VaR of -140.502 indicates that even under the most adverse 5% of conditions, the strategy's losses remain capped at a moderate level. By contrast, the short Strangle records a VaR of -2,371.439, reflecting an extremely high downside potential. This substantial difference highlights the asymmetric risk exposure. The Iron Condor provides strong downside protection, while the short Strangle subjects investors to severe tail risk. For risk-averse investors, this metric strongly favors the Iron Condor as a hedging instrument.

When VaR is recalculated using the Antithetic Monte Carlo method, the results remain consistent with this conclusion. The Iron Condor's 5% VaR is approximately -140.472, very close to its bounded minimum profit, confirming that downside risk is tightly controlled. In contrast, the Short Strangle still exhibits a much larger 5% VaR of about -2,307.267, indicating that even after variance reduction, the potential losses in the worst 5% of cases are several times greater than those of the Iron Condor. Thus, the Antithetic Monte Carlo results reinforce the evidence that VaR-based risk considerations clearly favor the Iron Condor over the Short Strangle for conservative investors.

3.6.6 Sharpe Ratio

The Sharpe Ratio measures the efficiency of a strategy by comparing excess returns relative to the risk-free rate against the volatility of those returns. Based on the standard Monte Carlo simulation in Table 3, both strategies exhibit negative Sharpe Ratios, with -0.016 for Iron Condor and -0.018 for short Strangle. This indicates that neither delivers sufficient return to compensate for the risk undertaken. Nevertheless, the Iron Condor's slightly higher value (closer to zero) suggests a marginally better risk-adjusted performance. While the difference is small, it aligns with the broader conclusion that the Iron Condor offers a more balanced trade-off between risk and return. This finding reinforces its suitability as a conservative hedging approach, particularly when preservation of capital is prioritized.

This pattern changes slightly in the Antithetic Monte Carlo simulation results in Table 4. Here, the Iron Condor (Antithetic) records a Sharpe Ratio of -0.016, the same value as the standard simulation. However, the Short Strangle (Antithetic) records a value of -0.012. This value represents a marginal improvement (slightly better/closer to zero) compared to its standard Monte Carlo result (-0.018).

This improvement in the Short Strangle's Sharpe Ratio is consistent with the purpose of the antithetic variates method as a variance reduction technique. As previously discussed (and confirmed in Table 4), this method tends to produce slightly smaller average losses (Mean Profit) and a lower Standard Deviation. For the Short Strangle strategy, the combination of the improvement in average loss (the numerator) and the reduction in volatility (the denominator) jointly results in a slightly better risk-adjusted ratio. Nonetheless, the fact that both strategies still produce negative Sharpe Ratios continues to support the original conclusion that the Iron Condor offers a more stable and balanced trade-off.

4. CONCLUSION

This study examined the problem of risk exposure in the Nikkei 225 index, which remains vulnerable to volatility and uncertainty. The research objective was to evaluate two option-based hedging strategies, namely the Iron Condor and the short Strangle, by applying Monte Carlo simulation and Antithetic Monte Carlo together with the Black-Scholes-Merton model. Historical data were used to estimate the parameters required for the simulation.

The findings show that the short Strangle strategy provides higher profit potential, but it also exposes investors to substantial volatility and extreme downside risk. This makes the strategy less attractive for risk-averse investors. The Iron Condor, on the other hand, offers more consistent performance with lower variance and clearly bounded losses. It is therefore a more reliable instrument for hedging under stable or moderately volatile market conditions. The novelty of this research lies in the direct comparison of the two strategies in the context of the Nikkei 225. The results provide practical implications for investors, portfolio managers, and policymakers in managing financial risk in Asian markets.

Author Contributions

Donny Citra Lesmana: Conceptualization, Supervision, Validation, Writing—Review and Editing. Dicky Mardiansyah: Data Curation, Methodology, Software, Writing—Original Draft. Fernando Alonso Sitorus: Formal Analysis, Writing—Original Draft. Olivia Putri Mustafa: Formal Analysis, Writing—Original Draft. All authors discussed the results and contributed to the final manuscript.

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Declarations

The authors declare no conflicts of interest to report study.

Declaration of Generative AI and AI-assisted Technologies

Generative AI tools (e.g., ChatGPT) were used solely for language refinement, including grammar, spelling, and clarity. The scientific content, analysis, interpretation, and conclusions were developed entirely by the authors. All final text was reviewed and approved by the authors.

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