“Maximizing returns under capped risks: An optimization framework for options trading”

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MAXIMIZING RETURNS UNDER CAPPED RISKS: AN OPTIMIZATION FRAMEWORK FOR OPTIONS TRADING

Abstract

Precise risk management is crucial in options trading, especially in strategies with limited risk and capped profit potential. The Short Iron Condor is a widely adopted strategy due to its structured risk-reward profile. It provides traders with controlled exposure in low-volatility markets while maintaining defined profit and loss parameters. This paper deals with developing an optimization framework using a mixed-integer programming model to evaluate key factors influencing return efficiency, including maximum loss limits, price confidence intervals, and holding periods. Using 2023 options data for 14 U.S. equities and 9 ETFs, filtered and selected using Out of the Money Strategy (OTM), 324 option contracts from as many snapshots as possible, the study analyzes 324 trading scenarios with maturities ranging from 5 to 20 days. Results indicate that increasing the maximum loss limit raises total return but reduces return efficiency. A $100 loss limit generates an average return of $30 with a 40.7% return on investment, while a $900 limit increases returns to $131 but lowers return on investment to 18.8%. These findings demonstrate that higher risk exposure does not always enhance return efficiency in capped-risk strategies. The proposed framework provides actionable insights for traders aiming to refine strategy selection within well-defined risk constraints. Risk managers can utilize these findings to sustain stable investment portfolios, while algorithmic trading systems may integrate this optimization model for automated strategy refinements and real-time adjustments. This study enhances decision-making in options trading, portfolio risk management, and financial strategy development.

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INTRODUCTION

The increasing complexity of financial markets necessitates the adoption of more systematic approaches to risk management and return optimization. In this context, options strategies have emerged as essential tools that enable investors to manage market fluctuations with controlled exposure. Among these, the Short Iron Condor strategy is particularly noteworthy as a market-neutral approach designed to generate steady income in low-volatility environments by capitalizing on time decay while maintaining a predefined risk-reward profile. Although this strategy has a well-defined structure, there is a lack of systematic analysis regarding the impact of different parameter configurations on its overall performance.

In current practice, Short Iron Condor strategies are often constructed based on investor intuition, past experiences, or fixed heuristic rules. However, critical parameters – such as the maximum allowable loss, the width of the strike price range, and the holding period – are fre-

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quently determined without formally assessing their impact on risk-adjusted returns. This absence of systematic optimization suggests that traders may be making suboptimal decisions, limiting the strategy's full potential.

The fundamental scientific problem addressed in this study is the insufficient examination of how different parameter configurations influence the risk-return trade-off in the Short Iron Condor strategy. To implement this strategy optimally, a structured framework is required to analyze the effects of various parameter combinations on return performance. Such an approach would provide investors and risk managers with data-driven insights, leading to more informed decision-making and a more effective deployment of the Short Iron Condor strategy.

1. LITERATURE REVIEW

The relationship between risk and return has been a central focus in financial research, with extensive studies analyzing its implications across different asset classes. The foundation of modern portfolio theory was established by Markowitz (1959), who introduced the concept of diversification to mitigate risk while maintaining optimal returns. In particular, the Capital Asset Pricing Model (CAPM), formulated by Sharpe (1964), Lintner (1965), and Mossin (1966), provided a structured approach to quantifying risk premiums and expected returns. This framework underpins the fundamental assumption that higher risk is associated with higher expected returns.

Beyond traditional stock markets, options strategies have been extensively studied. Board et al. (2000) examined covered call strategies, demonstrating superior risk-adjusted returns in certain conditions, while Niblock and Sinnewe (2018) provided empirical validation of these findings. Kedžo and Šego (2021) optimized covered call structures, enhancing risk-return efficiency. Conversely, Leggio and Lien (2002) and Hoffmann and Fischer (2012) identified scenarios where covered calls exhibited a negative risk-return relationship, emphasizing market dependency.

Straddle strategies, widely employed in volatility trading, have yielded mixed results. Guo (2000) found straddles profitable under high volatility, but Broadie et al. (2007) and Coval and Shumway (2001) noted that straddles underperformed in stable markets. Goltz and Lai (2009) suggested that straddle returns inadequately capture volatility risk premiums, while Samuel (2018) identified significant monthly returns when incorporating option-implied beta. Chen and Leung (2003) and Chong (2004) further examined straddle profitability, with the latter reporting insignificant profits when forecasted volatility was considered. Sheu and Wei (2011) studied the effectiveness of long and short straddle strategies in Taiwan's stock market, finding positive average monthly returns.

Research on strangle strategies, where out-of-the-money calls and puts are purchased, has also been extensive. Gordiaková and Lalić (2014) emphasized their effectiveness in volatile markets, while Fahlenbrach and Sandås (2010) confirmed their profitability under specific volatility conditions. Bhat (2021) found that short strangles outperform long ones in terms of returns, albeit with higher risk exposure. Aramonte and Szerszeń (2020) underscored the utility of strangles as a risk management tool, particularly in structured portfolios. In comparative studies, Chaput and Ederington (2002) analyzed the effectiveness of straddles and strangles in currency options, concluding that these were among the most actively traded combinations. Chang et al. (2010) suggested that individual investors leverage the volatility information in strangles more effectively than in straddles.

Butterfly strategies, combining multiple call or put options, offer limited risk and return potential. Studies by Goyal and Saretto (2009) highlighted their consistent but limited return structure. Harvey and Whaley (1992) contended that volatility trading strategies do not produce abnormal returns when transaction costs are factored in.

Research in the broader domain of options pricing and valuation has provided theoretical underpinnings for the performance of these strategies. Black and Scholes (1973), Mercurio and Vorst

(1996), Larikka and Kanniainen (2012), and Dixit et al. (2019) analyzed option pricing models, while Kavussanos and Visvikis (2008) and Elices and Giménez (2013) focused on option contract valuation. Furthermore, option hedging has been widely studied, with contributions from Ahn et al. (1999), Aguilera and López-Pascual (2013), and Bajo et al. (2015), who examined various hedging techniques for mitigating investment risk.

Given the gaps in the existing literature, particularly in understanding the risk-return trade-off of the short iron condor strategy, this study aims to provide a comprehensive analysis of its performance under different market conditions. The research seeks to investigate the impact of risk and various option premiums on strategy payoff while evaluating the effectiveness of selected options strategies from an investor's perspective. Despite the extensive research on various options strategies, the short iron condor strategy remains underexplored. This strategy combines two credit spreads and offers limited profit and risk while profiting from low volatility. Unlike other options strategies that rely on directional market movement, the short iron condor capitalizes on stable price conditions. Given the limited research into the risk-return trade-off of short iron condors, further exploration is necessary, particularly from an optimization perspective.

2. METHODOLOGY

The optimization framework is constructed as a Mixed Integer Programming (MIP) model, adhering to the principles outlined below. The methodology collected option chain data as snapshots at specific points in time for various expiration dates. To align with the Short Iron Condor strategy, options were filtered based on Out of the Money (OTM) criteria. In a Short Iron Condor strategy, OTM options are typically selected for low volatility and premium collection by selling a put and call spread away from the current price and buying further OTM protection, while ITM options may be chosen less commonly for higher volatility expectations, depending on market outlook and risk tolerance. The optimization model was applied under predefined maximum loss thresholds, along with upper and lower price bounds calculated from historical return data over the past year. This ensured precise alignment with the strategy's objectives. Each asset and expiration date were analyzed independently to maintain the integrity of the results. By combining these parameters within the MIP framework, the Short Iron Condor strategy was optimized to evaluate its performance under various risk and return constraints.

2.1. Datasets and experimental designs

This study analyzes the Short Iron Condor strategy using a dataset of option chains from 23 U.S. stocks and ETFs; the dataset, detailed in Table 1, is based on historical data from September 2023 and includes options with maturity periods of 5, 10, 15, and 20 days from the snapshot dates setup enables a comprehensive evaluation of the strategy's performance across different time horizons by selecting Out of the Money (OTM) option selection strategy. By applying the strategy to options with varying maturities, we can compare its effectiveness under diverse market conditions, offering insights into its robustness and adaptability.

Figure 1 illustrates the profit/loss dynamics of a Short Iron Condor strategy. The diagram visualizes the capped risk-return framework, highlighting key elements such as the maximum profit, maximum loss, and break-even points. This graphical representation complements the dataset analysis by demonstrating how the strategy performs when the underlying asset's price remains within the specified range of strike prices.

In this methodology, the optimization model was applied separately to 23 assets with maturity periods of 5, 10, 15, and 20 days, aiming to identify the optimal Short Iron Condor strategy for each scenario. A five-day maturity represents typical weekly trading cycles, while a twenty-day maturity aligns with monthly trading cycles. This framework enables a comprehensive analysis of the strategy's performance across short-term (weekly) and medium-term (monthly) horizons. By examining these time frames, the study provides valuable insights into the adaptability and effectiveness of the Short Iron Condor strategy under varying market conditions in the options market.

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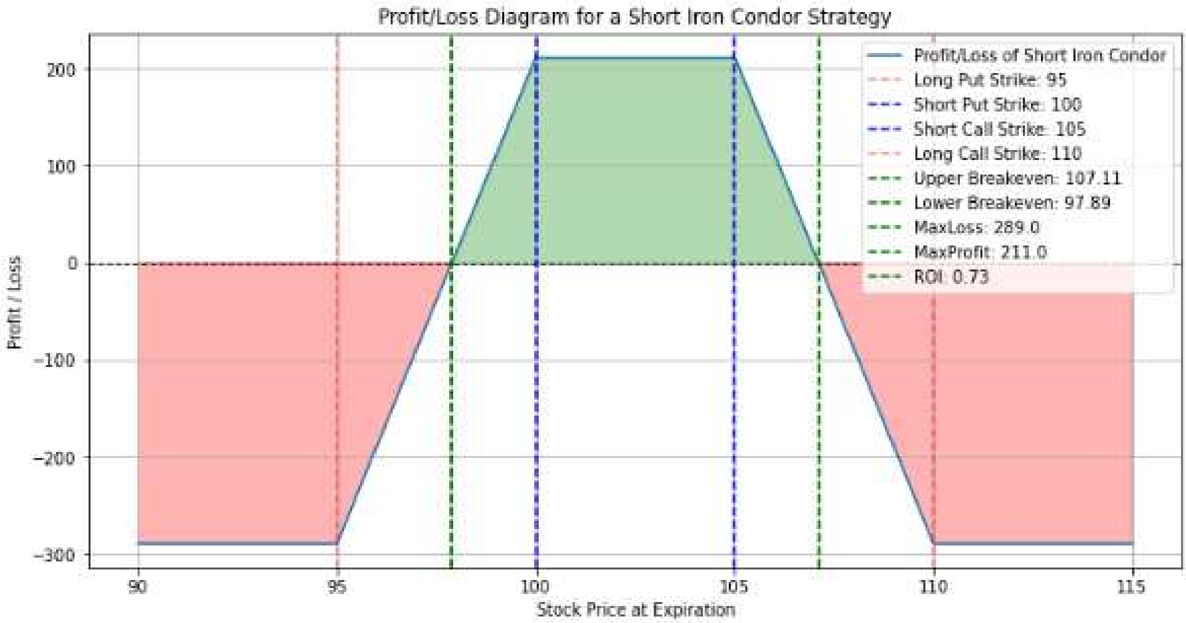

Figure 1. Short iron condor strategy

Table 1. US stocks and ETFs

Symbols	Name
AAPL	Apple Inc.
AMC	AMC Entertainment
AMD	Advanced Micro Devices
AMZN	Amazon.com Inc.
ARKK	ARK Innovation ETF
BABA	Alibaba Group
BAC	Bank of America Corp.
EEM	iShares MSCI Emerging Markets ETF
EWZ	iShares MSCI Brazil ETF
F	Ford Motor Company
GOOGL	Alphabet Inc. (Google)
HYG	iShares iBoxx Corporate Bond ETF
META	Meta Platforms, Inc.
MSFT	Microsoft Corporation
NFLX	Netflix, Inc.
NIO	NIO Inc.
NVDIA	NVIDIA Corporation
QQQ	Invesco QQQ ETF
SPY	SPDR S&P 500 ETF
TLT	iShares 20+ Year Treasury Bond ETF
TQQQ	ProShares UltraPro QQQ ETF
TSLA	Tesla, Inc.
UVXY	ProShares Ultra VIX ST Futures ETF

For the experimental setup, three key input factors, outlined in Table 2, were examined in the optimization model for the Short Iron Condor strategy: Maximum Loss Limit, Price Confidence Interval, and Days to Maturity. The Maximum Loss Limit specifies the upper threshold for potential losses in the strategy. The Price Confidence Interval, calculated using one year of historical data for each asset, establishes the expected high and low-price bounds based on different probability levels. This ensures that returns remain positive within the breakeven range. Days to Maturity represents the time remaining until the option strategy's expiration. The experimental design incorporates 324 scenarios, combining 9 distinct maximum loss limits, 9 price risk levels, and 4 maturity periods, applied across 23 assets listed in Table 1. This comprehensive approach allows for an in-depth evaluation of the strategy's performance under diverse risk and time conditions, ensuring robust insights into its adaptability across varying market environments.

In each scenario, the optimization model aims to maximize returns while maintaining losses below the predefined loss limit. The Return on Investment (ROI) is used to evaluate risk-adjusted returns, calculated as the ratio of optimized return to maximum loss. This metric provides a practical measure of the strategy's effectiveness, highlighting the balance between risk and reward. By analyzing ROI across the different scenarios, the study offers valuable insights into how the Short Iron Condor strategy performs under varying market conditions and risk thresholds.

Table 2. Experimental design setups

Max Loss Limits (USD)	Price Confidence Interval (Probabilities)	Days to Maturity
100	0.01	5
200	0.1	10
300	0.2	15
400	0.3	20
500	0.4	
600	0.5	
700	0.6	
800	0.7	
900	0.8	

2.2. Objective

Maximize the total net premium received from the selected options for a specific asset across various time-to-maturity intervals, while ensuring risk is limited by choosing protective options from the option chain.

2.3. Decision variables

The model considers different options, where i indicates the position within the option chain, representing the specific sequence or strike price for each call or put option.

$x^i_{put\_sell}$: Takes a value of 1 if the put option i is sold; otherwise, it is 0.

$x^i_{put\_buy}$: Takes a value of 1 if the put option i is bought; otherwise, it is 0.

$x^i_{call\_sell}$: Takes a value of 1 if the call option i is sold; otherwise, it is 0.

$x^i_{call\_buy}$: Takes a value of 1 if the call option i is bought; otherwise, it is 0.

2.4. Parameters – premiums, strike prices, and spot prices

$P^i_{put\_sell}$: The premium for selling the put option i.

$P^i_{put\_buy}$: The premium for buying the put option i.

$P^i_{call\_sell}$: The premium for selling the call option i.

$P^i_{call\_buy}$: The premium for buying the call option i.

$K^i_{put\_sell}$: Strike price for the sold put option i.

$K^i_{put\_buy}$: Strike price for the bought put option i.

$K^i_{call\_sell}$: Strike price for the sold call option i.

$K^i_{call\_buy}$: Strike price for the bought call option i.

S_0 : Spot price of the underlying asset.

2.5. Objective function

Optimize Net Premium (Z) subject to constraints

This function maximizes the total net premium while considering the premiums paid and received for each option selected.

$$Maximize\ Z_i = \sum \begin{pmatrix} \left(P^i_{put\_sell} \cdot x^i_{put\_sell} - P^i_{put\_buy} \cdot x^i_{put\_buy} \right) \\ + \left(P^i_{call\_sell} \cdot x^i_{call\_sell} - P^i_{put\_buy} \cdot x^i_{put\_buy} \right) \end{pmatrix}. \tag{1}$$

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2.6. Constraints

2.6.1. *Strike price constraints*

The strike price of the sold put must be lower than the current stock price

$$K^i_{put\_sell} < S_0. \tag{2}$$

The strike price of the bought put must be lower than the strike price of the sold put

$$K^i_{put\_buy} < K^i_{put\_sell}. \tag{3}$$

The strike price of the sold call must be higher than the current stock price

$$K^i_{call\_sell} > S_0. \tag{4}$$

The strike price of the bought call must be higher than the strike price of the sold call

$$K^i_{call\_buy} > K^i_{call\_sell}. \tag{5}$$

2.6.2. *Premium non-negativity*

The premium for selling options must be non-negative

$$P^i_{put\_sell}\ \ 0,\ P^i_{call\_sell}\ 0. \tag{6}$$

Similarly, the premium for buying options must be non-negative

$$P^i_{put\_buy}\ \ 0,\ P^i_{call\_buy}\ 0. \tag{7}$$

2.6.3. *Option selection constraints*

The goal is to ensure that exactly one put option and one call option are chosen for both buying and selling from the option chain. The decision variables are binary, indicating whether a specific option is selected (1) or not (0).

$$x^i_{put\_sell},\ x^i_{put\_buy},\ x^i_{call\_sell},\ x^i_{call\_buy} \in \{0,1\}. \tag{8}$$

$$\begin{matrix} \sum_i x^i_{put\_sell} = 1 & \sum_i x^i_{put\_buy} = 1 \\ \sum_i x^i_{call\_sell} = 1 & \sum_i x^i_{call\_buy} = 1. \end{matrix} \tag{9}$$

2.6.4. *Maximum loss constraints*

The maximum potential loss arising from put options is calculated by subtracting the difference between the selling and buying strike prices for each put option and the net premium (Z). This calculation is also applied to call options in the same manner.

$$MaxLoss_{put} = \sum_i \left(K^i_{put\_sell} - K^i_{put\_buy} - Z_i \right). \tag{10}$$

$$MaxLoss_{call} = \sum_i \left(K^i_{call\_buy} - K^i_{call\_cell} - Z_i \right). \tag{11}$$

The overall maximum potential loss from both put and call options is determined by taking the larger of the two calculated losses. This ensures that the worst-case scenario is accounted for in the risk assessment.

The total maximum loss is defined as:

$$MaxLoss_{total} = \max\left(MaxLoss_{put}, MaxLoss_{call} \right). \tag{12}$$

To ensure that this maximum loss stays within acceptable risk limits, a constraint is applied:

$$MaxLoss_{total}\ \ L_{limit}. \tag{13}$$

Here, L_{limit} represents the predefined maximum loss limit or risk tolerance level. This constraint guarantees that the total potential loss from the options portfolio does not exceed the allowed risk threshold, providing a controlled approach to managing financial exposure.

2.6.5. *Break-even constraints*

The breakeven points define the upper and lower price bounds within which the underlying asset price is expected to remain until the option's expiration. These bounds ensure that the option strategy remains within a manageable risk level, taking into account both potential gains and losses.

$$Breakeven_{lower} = K^i_{put\_sell} - Z_i. \tag{14}$$

$$Breakeven_{upper} = K^i_{call\_sell} + Z_i. \tag{15}$$

The total risk exposure must remain within predefined upper and lower bounds, calculated from historical return data for different probability levels over the past year, ensuring that the asset price stays within an acceptable range.

$$Breakeven_{upper} \geq Price\_Risk_{upper}. \quad (16)$$

$$Breakeven_{lower} \leq Price\_Risk_{lower}. \quad (17)$$

These constraints ensure that the asset price is expected to remain within the specified breakeven range up to the option's expiration date. By setting these bounds, the strategy controls the risk exposure arising from price upper and lower limits while aiming for potential returns within a safe price range.

3. RESULTS

For each of the 23 assets, experiments were conducted as outlined in Table 2. The optimization model determined the maximized return values and corresponding maximum loss levels within the predefined loss limits, price confidence intervals, and maturity periods. The average return and ROI (calculated as the ratio of optimized return to maximum loss) provide key insights into the strategy's performance under varying loss constraints.

As illustrated in Table 3, increasing the maximum loss limits leads to higher potential returns. However, this comes at the expense of lower unit profitability, as reflected in the declining average ROI. This inverse relationship underscores the trade-off between risk and reward, where higher risk exposure increases total profit potential but diminishes the efficiency of returns relative to risk. These findings highlight the importance of balancing risk levels to achieve optimal outcomes, particularly when managing strategies with capped profit potential like the Short Iron Condor.

Table 3. Comparison of loss limits, average return, and ROI

Max Loss Limits	Average Return	Average ROI
100	30	40.7
200	55	33.7
300	78	31.3
400	97	29.5
500	94	23.3
600	102	21.8
700	113	20.8
800	122	19.6
900	131	18.8

Furthermore, the aggregated results are visually represented in Figure 2, where each point corresponds to an experiment and its respective optimization outcome. The figure reveals a clear trend: as the maximum loss limits increase, the Return on Investment (ROI) declines consistently. For each asset, the downward slope illustrates that while higher loss thresholds allow for greater risk exposure, they fail to deliver proportionally higher returns. This inverse relationship highlights the concept of diminishing returns, where increasing risk levels reduce the efficiency of returns, emphasizing the need for a balanced approach to risk management.

Figure 2. Maximum loss vs ROI

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As shown in Table 4, the experimental results demonstrate that increasing price risk levels leads to a decline in both average return and ROI. This is a direct consequence of the Short Iron Condor strategy's capped structure, where both profit and loss are limited. As the price confidence interval widens, the potential for profit decreases, resulting in lower profitability relative to risk. Unlike typical market dynamics, where higher volatility is often associated with increased returns, the capped nature of this strategy creates the opposite effect. Regardless of how much price volatility increases, the capped profit potential restricts return, highlighting the inherent trade-off in this strategy.

Table 4. Comparison of price confidence interval, average return, and ROI

Price Confidence Interval (prob.)	Average Return	Average ROI
0.01	304,86	81,53
0.1	178,90	46,34
0.2	119,25	31,57
0.3	84,22	21,85
0.4	60,07	15,87
0.5	40,91	9,94
0.6	27,88	6,71
0.7	19,20	4,47
0.8	9,60	2,13

As shown in Table 5, the analysis reveals that longer maturity periods increase both the average return and average ROI. However, the average ROI per day decreases significantly as the maturity period extends. This demonstrates that while longer maturities yield higher cumulative gains, the efficiency of daily returns diminishes. Shorter maturity periods offer more efficient daily returns, whereas longer-term strategies provide higher overall returns but at a slower daily rate. The diminishing marginal benefit of holding risk over extended periods highlights the trade-off between maximizing total returns and maintaining return efficiency daily.

Table 5. Days to maturity-based comparisons

Days to Maturity	Average Return	Average ROI	Average ROI per Day
5	64,3	18,7	3,7
10	88,8	22,8	2,3
15	109,2	28,4	1,9
20	112,8	28,9	1,4

The findings suggest that investors and risk managers should carefully evaluate the diminishing returns on risk as maturity periods extend. Additionally, increasing the maximum loss level does not provide additional marginal benefits from the increased risk. In a capped return and risk environment, higher volatility further reduces the return per unit of risk. Therefore, optimizing the balance between risk and return can lead to more efficient outcomes. This analysis challenges the traditional belief that extending the time horizon or increasing risk exposure will always yield better results. A more strategic approach is required to maximize return efficiency over time.

4. DISCUSSION

Maximizing returns under capped risks requires an optimization framework that accounts for volatility, strategy structure, and market conditions. Previous studies, such as those by Israelov and Klein (2015) and Israelov et al. (2017), emphasize the importance of risk-adjusted performance over absolute profitability. Bollen and Whaley (2004) found that volatility spreads impact returns in structured options strategies, reinforcing the necessity of optimizing exposure.

Empirical research in stock markets has extensively tested the risk-return relationship. Bali and Peng (2006) utilized high-frequency data to establish a strong link between risk and return, supporting the CAPM premise. Ghysels et al. (2005) implemented the Mixed Data Sampling (MIDAS) technique, reinforcing the significance of conditional variance in stock return dynamics. Chiang and Zhang (2018) applied a TARCH-M model in the Chinese equity market, affirming that increased volatility aligns with higher stock returns. Yu and Yuan (2011) introduced investor sentiment as a critical factor, highlighting its role in amplifying the risk-return trade-off. Extending this analysis across different economies, Ang et al. (2006) illustrated that risk-return dynamics differ between advanced and emerging markets.

Contrary to the positive correlation, several studies have identified a negative risk-return relationship. French et al. (1987) argued that volatility feedback effects can lead to immediate price declines despite expectations of higher future returns. Campbell and Hentschel (1992) introduced an asymmetric volatility model, demonstrating that negative shocks elevate future volatility, adversely impacting returns. Ang et al. (2009) found that past idiosyncratic volatility negatively predicts future returns, contradicting classical CAPM assumptions. Brandt and Kang (2004) employed a latent vector autoregression (VAR) model, consistently confirming a negative correlation between returns and volatility. Patton and Sheppard (2015) explored intraday market behavior, further supporting the presence of volatility-driven return fluctuations.

This study's results indicate that while increasing the maximum loss limit enhances potential returns, it simultaneously diminishes risk-adjusted performance. This aligns with the findings of Whaley (2002) and Mugwagwa et al. (2012), who demonstrated that risk management is critical in optimizing options strategies, particularly in emerging markets where volatility is more pronounced. Similarly, Shivaprasad et al. (2022) highlighted that the excess returns in short volatility strategies are accompanied by greater risk exposure, emphasizing the need for optimization.

Additionally, higher price volatility, traditionally associated with profit potential in directional trading, was found to negatively impact profitability in defined-risk strategies. This observation supports the arguments of Maris et al. (2007) and Bondarenko (2014), who identified the dependency of butterfly strategies on accurate volatility predictions.

By systematically optimizing key parameters, including maximum loss thresholds, price confidence intervals, and maturity periods, this study offers actionable insights for traders and portfolio managers. Future research should explore adaptive models incorporating real-time volatility adjustments, ensuring that structured options strategies such as the short iron condor remain viable under evolving market conditions. Overall, this study contributes to the optimization of risk-controlled investment strategies, enhancing decision-making frameworks for market participants.

CONCLUSION

This study aims to optimize the risk-return trade-off in the Short Iron Condor strategy by employing a structured optimization model within a capped-risk environment. Leveraging data from 2023 on 14 U.S. equities and 9 ETFs, with maturities ranging from 5 to 20 days, a total of 324 scenarios were analyzed to identify maximum returns under predefined constraints. The findings underscore the complex interplay between risk and return, highlighting the diminishing marginal efficiency of increased risk in strategies with limited profit potential.

The optimization results yield several key insights. Higher risk levels, as defined by maximum loss limits, increase potential returns but lead to a decline in risk-adjusted returns (ROI), emphasizing the need for controlled risk exposure. Similarly, greater price volatility widens price bounds, yet reduces both average returns and ROI, demonstrating that elevated volatility does not guarantee proportional gains in capped-profit strategies. Additionally, while longer maturity periods enhance cumulative returns, they diminish daily return efficiency, revealing a trade-off between total gains and time-adjusted performance. These outcomes collectively affirm that balancing risk and return is critical, as escalating risk does not consistently improve efficiency in such strategies.

The findings offer actionable insights for traders and risk managers, providing a deeper understanding of how constraints like maximum loss limits, price volatility, and holding periods shape returns. Traders can use this framework to refine strategy selection within defined risk parameters, while risk managers can maintain portfolio stability by prioritizing efficiency over unchecked risk exposure. Looking ahead, future research will explore the integration of machine learning-driven prediction models to assess the risk-return dynamics of directional strategies, such as Bear Call and Bull Put Spreads. Unlike the

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neutral Short Iron Condor, these strategies depend on accurate trend forecasting, and AI/ML-driven approaches may enhance predictive precision, potentially improving the optimization of returns while managing associated risks.

AUTHOR CONTRIBUTIONS

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Formal analysis: Alp Ustundag, Mahmut Sami Sivri, Emre Ari.
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Project administration: Alp Ustundag.
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Validation: Mahmut Sami Sivri, Emre Ari.
Visualization: Mahmut Sami Sivri, Emre Ari.
Writing – original draft: Emre Ari.
Writing – review & editing: Alp Ustundag, Emre Ari.

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