Optimizing Options Selling: Using OptionWheel (OW) for Combined Volatility Prediction and Strategic Income Generation

Alexander Nowak, CFA. NWK Group.

Abstract — We explore OptionWheel (OW), an innovative tool in equity options trading. The program's two focuses 1) leveraging automation to optimize an income-generating option selling strategy of cycling of cash-secured puts and covered calls; 2) using machine learning tools to predict future volatility in comparison to current implied volatility, to greatly optimize the option selling "wheel". This paper examines the architectural framework, methodological strategies, and predictive capabilities of OW, offering an analysis of its performance and efficacy in maximizing premium retention while minimizing risk exposure, particularly within the realm of stable, high-quality stocks.

OW seeks to generate stable income through the strategic cycling of options. By alternating between cash-secured puts and covered calls, the program strives to enable a stable income stream in all market conditions. The income target is 20%+ per annum. Required for the cycling of option selling is a strict risk-management system, which OW has fully automated, allowing for a headless, live-trading program with minimal user intervention. By minimizing human control, the program can manage risk in an automized, precise manner. The program seeks this continous option premium income from high-quality stocks, which also minimizes our long-term risk and heightens our long-term returns.

Adding to the cycling of option selling, OW was built with a robust technological stack, which is anchored by a custom-built predictive model. This ensemble model uses machine learning algorithms, including recurrent neural networks and categorical boosting classifiers, to predict future volatility and its comparison to current implied volatility. The goal of this classifier is to predict when future volatility is below current implied volatility. This can inform our strategy of which options to sell, and which to avoid. By making this prediction, OW aims to achieve better outcomes in premium retention and risk management. Classifier results on unseen data demonstrates an area-under-the-curve (AUC) of 0.77-0.88 in predicting future volatility for large-cap stocks, and an AUC of 0.58-0.62 for tradable indices (SPY & QQQ).

The findings from building OW suggest that this innovative tool holds promise in the realm of options trading. By effectively leveraging automation and machine learning, OW not only enhances the efficiency of the option selling cycle but also significantly improves the predictive accuracy regarding future volatility. This dual approach allows traders to make more informed decisions, potentially leading to enhanced premium retention and reduced risk exposure. The impressive predictive performance, especially with large-cap stocks, is promosing. Additional work is needed in leveraging this classifier or similar tools across equity derivatives trading.

I. Introduction

The world of equity options trading is characterized by its complexity and the constant need for innovative tools and strategies to generate an outsized return. Among the myriad of trading strategies, option selling has carved out a niche for investors looking to generate consistent income streams. This strategy involves writing options contracts, such as calls and puts, to earn premiums from buyers who anticipate significant movements in the underlying assets. In other words, option sellers are selling volatility. While the potential for generating income through option selling is considerable, the strategy's success hinges on a trader's ability to accurately predict market conditions, particularly volatility, and manage associated risks effectively.

Option selling strategies, writing covered calls and cash-secured puts, are designed to capitalize on market inefficiencies and the natural decay of options' time value, referred to as theta. These strategies offer traders a means to enhance portfolio returns, particularly in stable or moderately bullish markets. Covered calls enable investors to generate additional income on stocks they own by selling call options, while cash-secured puts provide an opportunity to acquire stocks at favorable prices while collecting premiums. However, there are significant inherent risks. By being "short" the option, the option seller is at risk of being assigned in either scenario. This either requires the seller to purchase stock at above-market-prices, or sell stock at below-market-prices. An efficient option selling system requires a deep understanding of market dynamics and robust risk management practices. We think automation in this strategy can help immensely.

Central to the efficacy of option selling is the ability to predict option pricing and market volatility. Volatility, a measure of the asset's price fluctuations, is a critical determinant of options pricing and directly influences the premiums received by option sellers. Implied volatility, derived from current market prices via models such as Black Scholes, reflects the market's expectations of future volatility, while realized volatility offers a historical perspective.

Traditional statistical methods, such as GARCH models, have long been employed to forecast volatility, leveraging historical data to capture patterns and trends. However, the advent of machine learning has revolutionized volatility prediction, offering more sophisticated tools that can analyze complex datasets and adapt to changing market conditions.

In this paper, we delve into the tools and methodologies OW employed to predict volatility and enable a stable income stream via option selling automation. As the financial markets evolve, the integration of advanced predictive tools will undoubtedly play a crucial role and we hope OW adds to this toolset.

Alexander Nowak, CFA. NWK Group LLC. Alex@nwk.group.

II. Option Selling

Option selling, often referred to as writing options, is a fundamental strategy in options trading that involves creating and selling options contracts on the market. This approach is primarily employed by traders seeking to generate income through the collection of premiums paid by the buyers of these options. Unlike option buyers, who hold rights without obligations, option sellers assume obligations without rights. This role reversal inherently involves a unique risk-reward dynamic that necessitates a thorough understanding of market conditions and strategic execution.

At its core, option selling can be divided into two primary categories: selling calls and selling puts. Each type has distinct characteristics and applications, tailored to different market outlooks and risk appetites.

Selling Calls

- Covered Call Writing: This is perhaps the most well-known strategy among option sellers, particularly among those who hold long positions in underlying stocks. When an investor sells a call option against a stock they already own, it is termed a covered call. This strategy allows the investor to generate additional income through premiums while potentially capping upside gains if the stock price exceeds the option's strike price.

- Naked Call Writing: In contrast to covered calls, naked call writing involves selling call options without owning the underlying asset. While this strategy can yield substantial premiums, it exposes the seller to unlimited risk if the asset's price surges beyond the strike price, as they would have to purchase the asset at the elevated market price to fulfill the contract.

Selling Puts

- Cash-Secured Put Selling: This strategy involves selling put options while maintaining sufficient cash reserves to purchase the underlying asset at the strike price should the option be exercised. This approach is often employed by investors willing to acquire the asset at a lower price, with the added benefit of earning income from premiums if the option expires worthless.

- Naked Put Writing: Similar to naked call writing, naked put selling involves selling put options without setting aside the required capital to buy the underlying asset, potentially exposing the seller to significant risk if the asset's price falls sharply.

Option Selling Considerations

Option selling is inherently riskier than buying options, as the potential losses can be substantial, particularly in naked positions. However, the strategy can be highly rewarding when executed with precision and discipline. Key strategic considerations include:

1. Market Outlook and Volatility: Successful option selling hinges on accurate predictions of market direction and volatility. Sellers typically thrive in stable or slightly bullish markets, where the likelihood of options expiring worthless is higher. Conversely, periods of high volatility can increase the risk of options being exercised. Being able to predict future volatility can greatly aid in option selling.

2. Premium Collection: The primary objective of option sellers is to maximize premium income while managing potential liabilities. This necessitates careful selection of strike prices and expiration dates, often influenced by factors such as implied volatility and market sentiment.

3. Risk Management: Effective risk management is paramount in options selling. This includes setting stop-loss orders, diversifying option positions across different securities, and employing hedging techniques to mitigate potential losses.

The Role of OW in Option Selling

The OW system has two components: 1) automation of options selling and 2) prediction of future volatility. The second element is discussed in the next chapter. Regarding the first element, OW seeks to generate a stable income stream from option premium by constantly cycling between writing cash-secured puts and covered-calls. If either option write expires in the money (ITM), the position is assigned and another option is written against the position. This process repeats continuously.

For example, if 100 contracts of AAPL cash-secured puts at 7 days to expiration (DTE) are written, the writer will receive an income of ~\$12,000. If these puts expire out of the money (OTM), the writer keeps the premium. Another set of 100 contracts will be written on this stock. Once the written option expires ITM, the stock will be assigned to the writer. The writer keeps the option premium, but now has to buy stock at a higher-than-market price, although the premium reduces the effective net price. Once this occurs and the writer holds shares of AAPL, the trader will write 100 covered calls on this position generating another ~\$12,000 in income. If the option expires OTM the writer keeps the premium. If expired ITM, the stock is sold and the cycle repeats. By being precise with option selling and risk management, an attractive, stable income stream can be generated on high-quality stocks.

The limitation of option selling is a stock's upside is capped. For example, by writing cash-secured puts, if the stocks moves up the trader keeps the premium, but misses out on upsized share appreciation. Furthermore, by writing covered calls, if the stocks moves up, the writer may need to sell the stock upon appreciation. This strategy does not seek to generate outsized capital gains – it seeks to generate income.

III. Volatility Modeling

Volatility is a critical concept in options trading, reflecting the degree to which the price of a financial asset is expected to fluctuate over a given period. It is a cornerstone of options pricing, as it directly influences the premiums that traders are willing to pay or receive. Understanding and forecasting volatility is therefore essential for effective trading strategies, including those employed by the OW system.

Implied Volatility vs. Realized Volatility

- Implied Volatility (IV): Implied volatility represents the market's expectation of future volatility, as derived from the prices of options. It is a forward-looking measure and is embedded in the options pricing model, such as Black-Scholes. A higher implied volatility suggests that the market anticipates significant price movements in the underlying asset, leading to higher option premiums.

- Realized Volatility (RV): Realized volatility, also known as historical volatility, is a backward-looking measure that quantifies the actual volatility observed in an asset's price over a specific past period. It is calculated using the standard deviation of past price changes and provides a factual account of how volatile an asset has been.

The relationship between IV and RV is pivotal in options trading strategies. When implied volatility is higher than realized volatility, options are perceived to be overvalued, presenting an opportunity for option sellers to capitalize on inflated premiums. Conversely, when realized volatility exceeds implied volatility, options might be undervalued, potentially benefiting option buyers. If future volatility can be predicted or forecast, and compared relative to current implied volatility, it could lead to an effective trading strategy.

Forecasting Volatility: Traditional and Modern Approaches

Forecasting future volatility is a challenging task. Various approaches, ranging from traditional statistical methods to modern machine learning techniques have been employed.

- GARCH Models: Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models are widely used in financial markets to forecast volatility. They model volatility as a function of past variances and can capture the clustering effect of volatility, where periods of high volatility are followed by high volatility and vice versa. Studies reported that GARCH models could predict short-term volatility with reasonable accuracy.

- Historical Volatility Models: These models utilize historical price data to estimate future volatility, assuming that past patterns will continue. While simple, these models may not account for sudden market shifts or structural changes.

The application of machine learning to volatility forecasting represents a significant advancement over traditional methods, offering enhanced predictive capabilities and adaptability to complex market dynamics.

- Recurrent Neural Networks (RNNs): RNNs, particularly Long Short-Term Memory (LSTM) networks, are designed to handle sequential data, making them suitable for time-series prediction tasks such as volatility forecasting. Their ability to capture temporal dependencies allows them to model intricate patterns in financial data effectively.

- Categorical Boosting (CatBoost): This gradient boosting algorithm is adept at handling categorical features and can be employed to predict volatility by leveraging a wide array of market indicators. CatBoost's robustness and speed make it a viable tool for real-time volatility forecasting.

- Random Forests and Support Vector Machines (SVMs): These algorithms have been adapted for financial predictions, including volatility. Random forests, with their ensemble learning approach, can handle large datasets with high dimensionality, while SVMs are effective for classification tasks, such as determining whether future volatility will exceed implied volatility.

IV. Data

The prediction classifier of OW was designed to specifically address this question of predicting future volatility vs. current implied volatility. The classifier was built using an ensemble method of machine learning tools on a large dataset.

Developing the training dataset was a particular challenge due to option's multi-dimensionality. To streamline the first training dataset, as referenced in this paper, we gathered 10+ years of options pricing data for tickers: AAPL, NVDA, SLV, TSLA, SPY and QQQ. This option pricing data included all end-of-day metrics across all strike prices and days to expiration. Each options dataset encombassed >2M rows.

For each ticker, a feature set was built to predict volatility. This feature set includes technical, fundamentals, quantitative metrics, historical volatilies, implied Greek calculations, among others. A volatility forecast cut-off was determined at 7 DTE and 30% Delta.

This training dataset was ran through the ensemble model. 10% was reserved for testing and 20% used for hyperparameter tuing.

V. Model Performance

Using all training data, the classifier was asked to predict: if future volatility would be above (-1) or below (1) the current implied volatility. The current implied volatility is via the Black Scholes options pricing model. The future volatility was defined as the Garman-Klass volatility calculation 7 days in the future (due to 7 DTE on the options).

The classifier achieved an average ROC AUC of 0.71 and an average accuracy of 0.81. Individual stocks performed the best with a ROC AUC of 0.88 and accuracy of 0.94, whereas indices performed considerably worse. The results are as follows:

Model Name	Performance Scores	
	ROC AUC	***Accuracy***
AAPL	0.88	0.94
NVDA	0.73	0.88
SLV	0.65	0.94
TSLA	0.77	0.86
SPY	0.62	0.61
QQQ	0.62	0.63

VI. Trading Strategy Implementation

OW was built for live-trading. In addition to training and re-training the models, OW performs: 1) automatically writing cash-secured puts and covered calls, plus rolling strategies as needed; 2) autonomously handling capital allocation and risk management; 3) making predictions on volatility, which can aid in the option writing strategy.

The entire program is constructed into a Docker container and deployed on Google Cloud. The strategy database uses Airtable, while logs are stored in Firestore. Various computational tools on AWS EC2 and Google Vertex are use for model training.

VII. Conclusion

In the rapidly evolving landscape of financial markets, the integration of advanced technologies has become a cornerstone for innovation and efficiency. OW represents a new tool in options trading by merging automation with machine learning algorithms to optimize income-generation strategies. Through its approach to cycling cash-secured puts and covered calls, while making volatility predictions, OW is uniquely positioned to provide traders with a stable income stream, even in fluctuating market conditions.

At the heart of OW is its ability to effectively manage risk—a fundamental aspect of option selling. By automating the execution of trades, capital allocation, risk management and position logging, OW minimizes human error and removed behavorial inconsistencies, thereby enhancing the precision and efficiency of its income generation capability.

Adding to this automation is OW's advantage via volatility forecasting. By employing an ensemble of machine learning models, including recurrent neural networks and categorical boosting classifiers, OW has shown success in predicting future volatility. This capability allows the system to make informed decisions regarding which options to sell. The empirical evidence supporting the predictive performance of OW, particularly its strong area-under-the-curve results for large-cap stocks, underscores its potential to change the way traders approach volatility prediction and option selling.

There is still significant room for additional research and enhancement of OW. While the system's performance with large-cap stocks is promising, the results for tradable indices such as SPY and QQQ suggest areas for further exploration and refinement. Additional options data, and feature refinement, is needed for broader applicability across a more diverse asset class.

OW epitomizes the transformative potential of technology in financial markets. By leveraging automation and machine learning, the system not only optimizes the efficiency of the option selling cycle but also elevates the precision of volatility forecasting. This dual approach could achieve favorable outcomes, while minimizing risk. As financial markets continue to evolve, the integration of innovative tools will play a role in shaping the future of trading. OW is one such example in the realm of options trading.

REFERENCES

[1] Bakshi, G., & Kapadia, N. Delta-hedged gains and the negative market volatility risk premium. The Review of Financial Studies. 2003.

[2] Christoffersen, P., & Jacobs, K. The importance of the loss function in option valuation. Journal of Financial Economics. 2004.

[3] Cont, R., & da Fonseca, J. Dynamics of implied volatility surfaces. Quantitative Finance. 2002.

[4] Duan, J. C., & Wei, J. Systematic risk and the price structure of individual equity options. The Review of Financial Studies. 2009.

[5] Fischer, B., & Scholes, M. The pricing of options and corporate liabilities. Journal of Political Economy. 1973.

[6] Gatheral, J. The Volatility Surface: A Practitioner's Guide. John Wiley & Sons. 2006.

[7] Hansen, P. R., & Lunde, A. A forecast comparison of volatility models: does anything beat a GARCH(1,1)? Journal of Applied Econometrics. 2005.

[8] Hull, J., & White, A. Optimal delta hedging for options. Journal of Banking & Finance. 2017.

[9] Jiang, G. J., & Tian, Y. S. The model-free implied volatility and its information content. The Review of Financial Studies. 2005.

[10] Liu, J., Longstaff, F. A., & Pan, J. Dynamic asset allocation with event risk. The Journal of Finance. 2003.

[11] Malliaris, M., & Salchenberger, L. Using neural networks to forecast the S&P 100 implied volatility. Neurocomputing. 1996.

[12] Poon, S. H., & Granger, C. W. Forecasting volatility in financial markets: A review. Journal of Economic Literature. 2003.

[13] Prokopczuk, M., & Wese Simen, C. The importance of the volatility risk premium for volatility forecasting. Journal of Banking & Finance. 2014.

[14] Santa-Clara, P., & Saretto, A. Option strategies: Good deals and margin calls. Journal of Financial Markets. 2009.

[15] Stein, E. M., & Stein, J. C. Stock price distributions with stochastic volatility: an analytic approach. The Review of Financial Studies. 1991.

[16] Taylor, S. J., & Xu, X. The incremental volatility information in one million foreign exchange quotations. Journal of Empirical Finance. 1997.

[17] Tian, Y. S. Extracting risk-neutral density and its moments from American option prices. Journal of Derivatives. 2011.

[18] Wang, Y. H., & Yen, K. C. The information content of implied volatility term structure on future volatility. European Financial Management. 2019.

[19] Whaley, R. E. Return and risk of CBOE buy write monthly index. Journal of Derivatives. 2002.

[20] Zhang, J. E., & Zhu, Y. VIX futures. Journal of Futures Markets: Futures, Options, and Other Derivative Products. 2006.