IDS 783: Derivatives and Risk Management Strategies

Risk Management for Tech Index Portfolio: Volatility-Targeted Hedging for a Tech Index Portfolio

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1. Executive Summary

Goal of the Study

This project aims to build a data-driven, regime-adaptive hedging framework that enhances downside protection and improves risk-adjusted returns for tech-heavy portfolios. The primary objective was to use machine learning, specifically XGBoost, to forecast short-term volatility and guide dynamic option-based hedging strategies.

Methodology Overview

We trained and evaluated two models, GARCH and XGBoost, using historical QQQ ETF data from 2020 to 2023 to predict one-day-ahead realized volatility. Based on the predicted volatility, market conditions were classified into three regimes:

- Low Volatility: Hedged using a light collar (5% OTM put + 5% OTM call)
- Moderate Volatility: Hedged using a protective put spread (5% OTM buy, 15% OTM sell)
- High Volatility: Hedged using simple protective puts (3–5% OTM)

These option-based strategies were rebalanced biweekly. The structure embedded a delta hedging component through strike selection, while targeting different volatility levels based on regime, functioning as volatility targeting.

Key Findings

- XGBoost outperformed GARCH, achieving an R^2 of 0.952 versus 0.835
- The hedged portfolio achieved a Sharpe Ratio of 0.70 (vs. 0.58 unhedged) and reduced annualized volatility by 24%
- Maximum drawdown improved slightly (–34.72% vs. –35.12%)
- Annualized return was slightly lower (13.38% vs. 14.54%), a tradeoff for improved stability and lower tail risk

Recommendations

We recommend incorporating ML-driven, regime-sensitive hedging frameworks for asset managers exposed to volatility-prone sectors like tech. In particular, XGBoost's accuracy enables proactive positioning with tailored protection. This study shows that adaptive delta and volatility targeting through option structures can stabilize returns while preserving flexibility.

Broader Implications

With tech firms increasingly vulnerable to rapid price swings (e.g., Nvidia's $600B+ drop in market value in 2025), the need for modernized, responsive risk management is more urgent than ever. Our research supports a shift from static hedging toward agile, machine-learning-based strategies that meet today's market demands with greater precision and resilience.

2. Introduction and Background Context

In today's financial markets, where volatility is often driven by unexpected geopolitical shifts, rapid technological disruption, and tightening monetary policy, the need for intelligent and adaptive risk management is more urgent than ever. Nowhere is this more critical than in the tech sector, where valuation sensitivity to macro shocks and innovation cycles can lead to extreme swings in market value. For instance, in January 2025, Nvidia lost nearly $600 billion in market capitalization in a single trading session, triggered by fears of intensifying competition from Chinese AI firm DeepSeek. This staggering loss, one of the largest single-day drops in corporate history, illustrates how even market leaders can face severe drawdowns, and it highlights the importance of robust hedging frameworks that can respond to such shocks in real time. (CNBC News)

Yet traditional hedging methods often fall short. A striking example is the 2012 JPMorgan "London Whale" incident, where the firm suffered over $6 billion in losses (Bloomberg). The trading desk attempted to hedge credit exposure using a complex portfolio of credit default swaps. However, the strategy was built on static assumptions and failed to respond adequately to market changes. As positions grew riskier and more illiquid, the hedge became more of a speculative bet than a protection mechanism. This failure was not due to the idea of hedging itself, but due to the inability of the hedging strategy to adapt to evolving conditions, a problem that remains relevant in modern markets.

Against this backdrop, dynamic hedging has gained significant attention. Unlike static methods, dynamic strategies allow hedge positions to evolve with the market, adjusting exposures based on real-time signals, volatility shifts, or predicted risks. This adaptability makes dynamic hedging especially suitable for high-beta portfolios like tech ETFs, where traditional models may misprice risk or act too slowly to provide meaningful protection.

Academic literature has also begun to embrace more sophisticated approaches. Rémiard et al. (2017) introduced a mean-variance dynamic hedging model under a multivariate regime-switching framework. Their work addressed key weaknesses in traditional models by capturing regime-dependent behavior and volatility clustering, offering more precise and responsive hedging in stochastic environments.

Building on this foundation, our study explores how machine learning, specifically XGBoost, can be used to forecast short-term volatility regimes and guide dynamic hedging decisions. By linking these predictions to tailored options-based strategies, our framework aims to enhance downside protection and improve risk-adjusted returns across varying market environments. Ultimately, our work contributes to the evolution of data-driven hedging practices, ones that are adaptive, cost-aware, and aligned with the volatility landscape faced by tech-indexed portfolios today.

3. Data Sourcing and Feature Engineering

To build an effective volatility-targeted hedging strategy for a tech-heavy portfolio, we required a robust and granular dataset capturing both market dynamics and option sensitivities over time.

This section outlines the process of sourcing, cleaning, and engineering features from multiple data streams, all centered around the QQQ ETF, which serves as both our proxy for a tech index portfolio and the underlying asset for hedging.

3.1. Data Collection and Preprocessing

Our data pipeline integrates both market-level and option-level datasets. Historical market data for QQQ, the VIX (broad-market volatility), the VXN (NASDAQ volatility), and macroeconomic indicators such as the Federal Funds Rate were collected using the “yfinance” Python library. This dataset spans from January 2015 to January 2025, ensuring we capture multiple market regimes including the 2020 crash and post-pandemic monetary tightening.

To complement market-level indicators, we extracted detailed option data from the OptionMetrics database, specifically focusing on QQQ options from 2018 through 2023. We filtered options to ensure data quality and relevance by including only contracts that:

- Had non-null values for delta, gamma, and implied volatility,
- Were close to the money (time to expiration between 25 and 45 days),
- Had positive volume and open interest.

This ensured that the options used in our hedge ratio calculations were both liquid and representative of real market activity.

3.2. Feature Engineering

We constructed a comprehensive feature set to inform both our volatility prediction models and dynamic hedge ratios. All features are engineered at a daily frequency and aligned by date to ensure temporal consistency across sources.

Final features include:

- QQQ daily return
- QQQ annualized realized volatility (21-day rolling window)
- QQQ trading volume
- VIX (S&P 500 implied volatility)
- VXN (NASDAQ implied volatility)
- RSI (14-day Relative Strength Index for QQQ)
- Fed Funds Rate
- Option Greeks (delta and gamma)
- Implied volatility of QQQ options
- Option-level bid/ask spreads, open interest, and moneyness

These features form the basis for both market risk quantification and hedge ratio calculation.

3.3. Exploratory Analysis and Visualization

To validate our engineering steps and motivate model choices, we visualized several core relationships between volatility, macro factors, and technical indicators.

The first visualization presents QQQ's annualized realized volatility computed using a 21-day rolling window as seen in **Figure 1**. Notably, there is a dramatic spike in volatility around March 2020, corresponding to the COVID-19 market crash. Volatility in that period exceeded 70%, underscoring the need for a dynamic hedging approach that can respond to such market shocks.

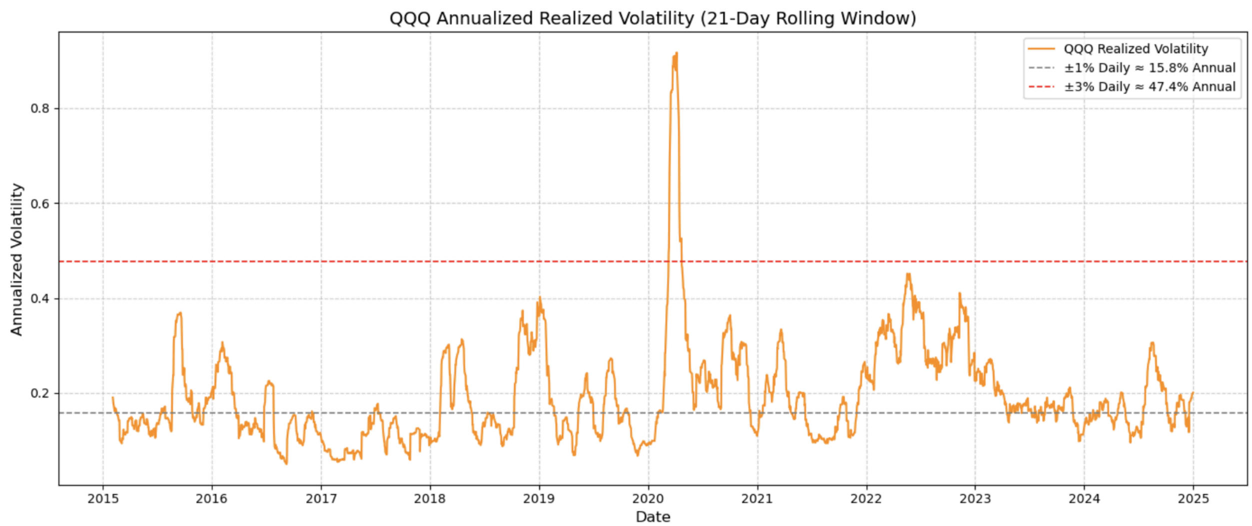

Figure 1*: Time Series of QQQ Realized Volatility with Key Volatility Thresholds (21-Day Rolling Window)*

We then examined how realized volatility tracks against market volatility indices, as shown in **Figure 2** Overlaying QQQ volatility with the VIX and VXN indices reveals a strong co-movement across all three, especially during periods of systemic stress. The VXN, being specific to tech, often shows slightly elevated levels relative to the VIX, reinforcing the sector-specific volatility exposure in our QQQ-based portfolio.

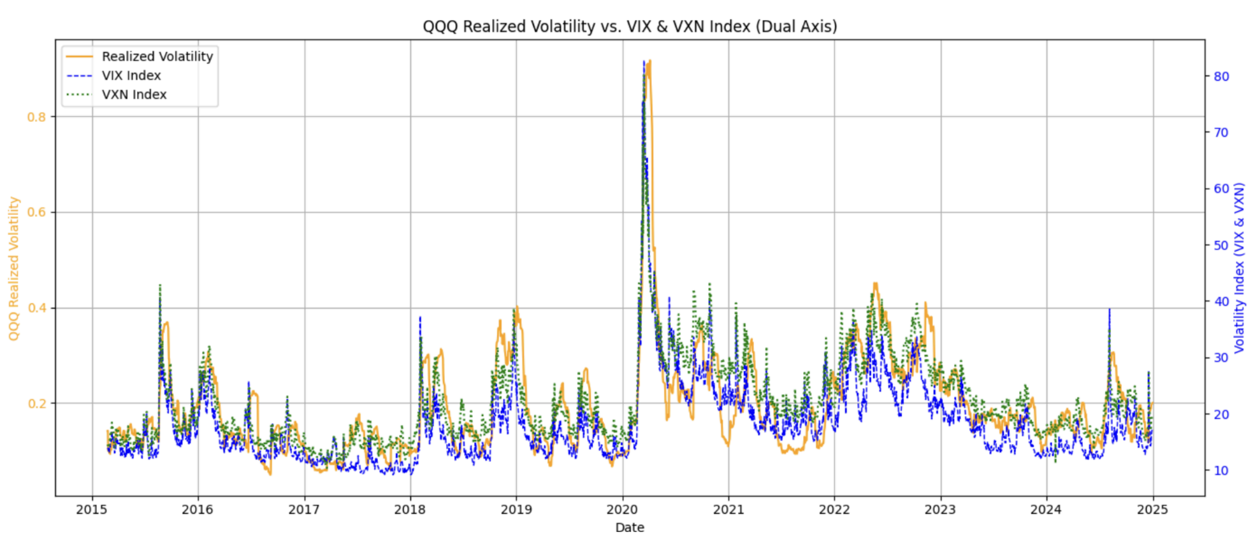

__Figure 2__: Comparison of QQQ Volatility with VIX and VXN Indices (2015–2025)

To deepen our understanding of market behavior, we investigated how QQQ's RSI, a technical momentum indicator, behaves relative to the volatility-to-return ratio. **Figure 3** shows that during high-stress periods, RSI tends to oscillate more erratically, while the volatility/return ratio spikes sharply, potentially flagging poor risk-adjusted returns. This reinforces the use of momentum signals and volatility stress as informative predictors for our models.

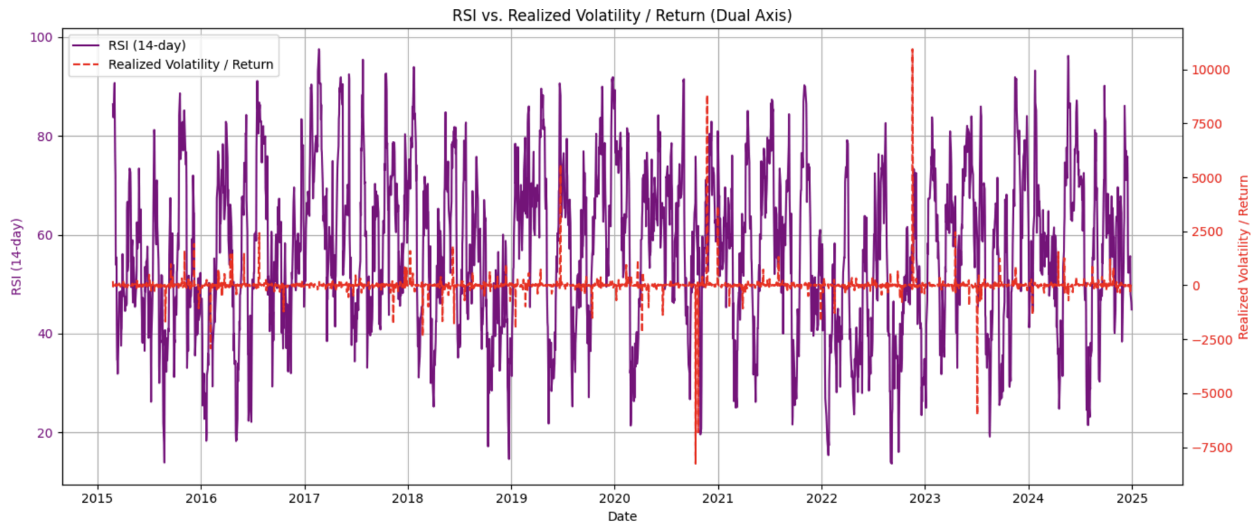

***Figure 3:** Relationship Between QQQ RSI and Volatility-Adjusted Returns*

Finally, we explored the relationship between macroeconomic policy and market volatility by overlaying the Fed Funds Rate with our volatility/return signal. **Figure 4** highlights that the recent rate hike cycle, beginning in 2022, coincided with an increase in volatility-adjusted return noise. This finding motivates the inclusion of the Fed Rate as an exogenous risk factor in both our modeling and hedging frameworks.

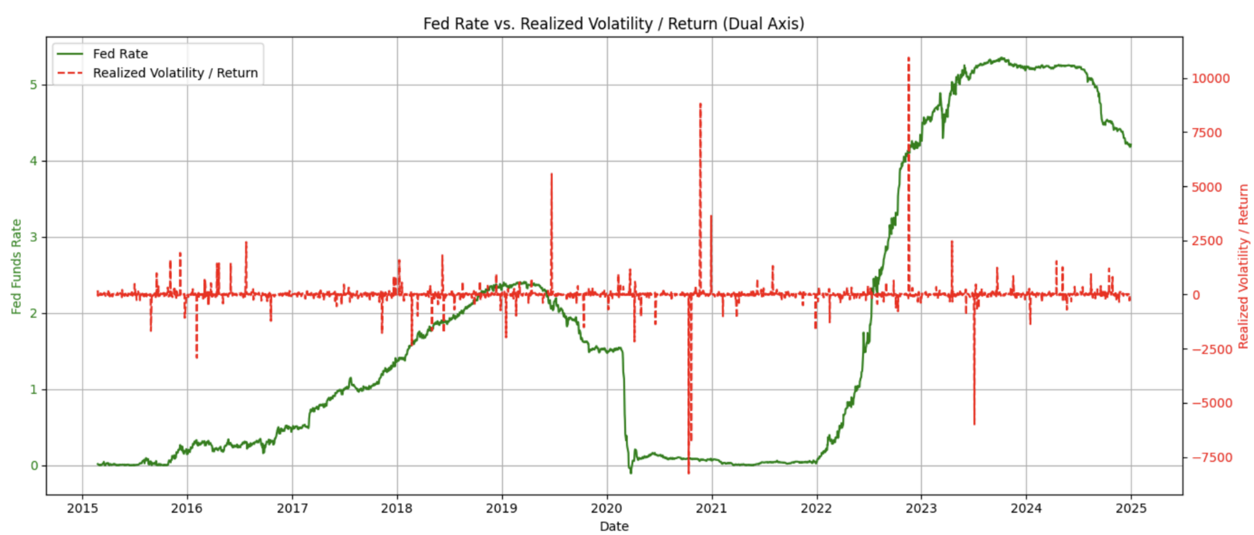

__Figure 4__: Impact of Federal Funds Rate on QQQ Volatility-Return Dynamics

4. Predicting Market Volatility

4.1 Objective and Modeling Approach

To effectively design a responsive and risk-aware hedging strategy, it is essential to anticipate periods of heightened market volatility. Volatility forecasts serve as the foundation for determining hedge ratios and timing adjustments, enabling a portfolio to maintain a target risk level through time. Rather than relying on static historical averages, our strategy incorporates *daily volatility predictions* to reflect evolving market conditions, particularly in the fast-moving tech sector.

In this section, we explore two modeling approaches to predict next-day realized volatility of the QQQ ETF: a traditional econometric method based on Generalized Autoregressive Conditional Heteroskedasticity (GARCH), and a machine learning approach using Extreme Gradient Boosting (XGBoost). The goal is not only to produce accurate forecasts but to assess the trade-offs between interpretable statistical models and more flexible, data-driven techniques.

Both models are designed to simulate real-world forecasting environments using *rolling windows*, where predictions are made one day at a time using only past data. This mimics the setting in which a portfolio manager updates hedge positions on a daily basis. For each method, we forecast the **annualized realized volatility** of QQQ one day ahead, and evaluate the predictions against the actual outcomes observed between 2020 and 2023.

The dual-model approach serves two purposes. First, it enables us to benchmark the performance of a widely accepted volatility forecasting method (GARCH) against a non-parametric, feature-rich model (XGBoost). Second, it allows us to assess how volatility predictions behave under different modeling assumptions, especially in high-risk regimes where accurate forecasts are critical for effective hedging.

4.2 GARCH Modeling

We first implemented a GARCH(1,1) model to predict QQQ's next-day realized volatility. GARCH models are widely used in finance due to their ability to capture time-varying volatility and volatility clustering, where periods of high volatility tend to be followed by more high volatility. This characteristic aligns well with our goal of anticipating short-term risk fluctuations that impact hedge ratios.

Before applying the model, we conducted preliminary statistical tests to validate the suitability of the GARCH framework. An Augmented Dickey-Fuller (ADF) test confirmed that QQQ's daily returns were stationary, which is a required assumption for GARCH modeling. Additionally, an ARCH effect test revealed statistically significant autocorrelation in the variance of returns, further justifying the use of conditional volatility modeling.

After confirming the underlying structure, we developed two forecasting frameworks using GARCH(1,1): rolling expanding-window and rolling fix-window one-step-ahead prediction framework.

4.2.1. Expanding-Window Forecast

In the expanding-window setup, the model is retrained daily using all available historical data up to the prediction date. This setup leverages long-term volatility patterns while adapting gradually as new data arrives. We forecasted daily one-step-ahead volatility from January 2020 to December 2023. Evaluation on this period yielded strong performance, with an R^2 of 0.835 and a low root mean squared error (RMSE) of 0.052. The predicted volatility tracked realized volatility closely, particularly during turbulent periods such as the pandemic recovery and rate hike cycles.

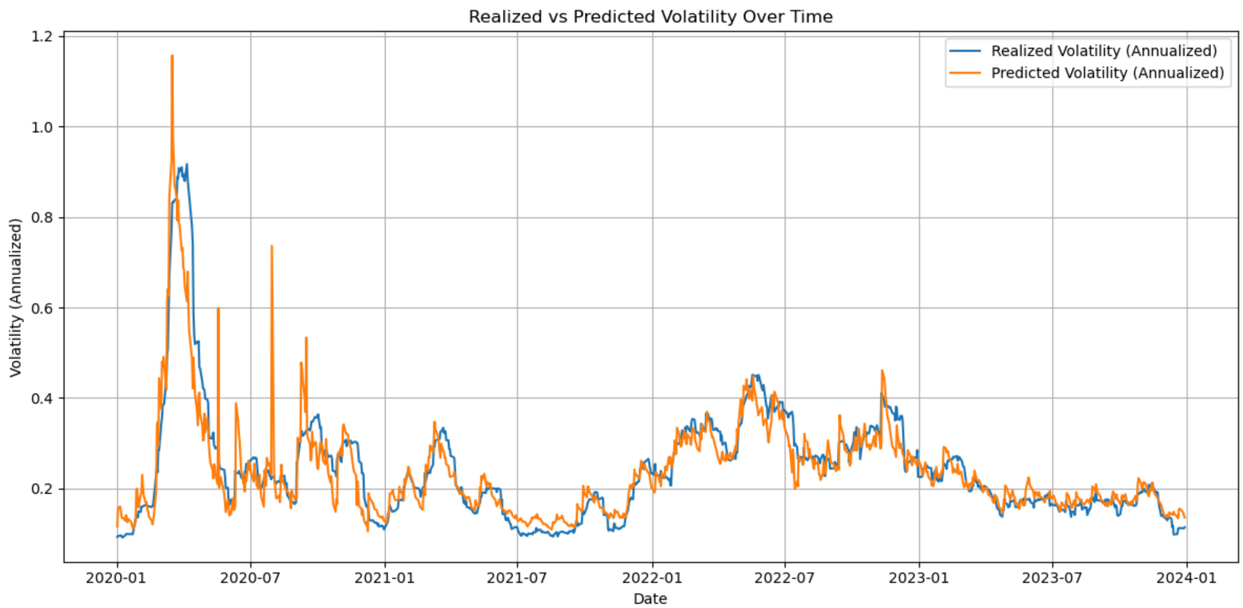

Figure 5: *Expanding-Window GARCH(1,1) Forecast vs. Realized QQQ Volatility (2020–2023)*

4.2.2. Fixed-Window Forecast

To test how well the model adapts using more recent information, we also applied a fixed-window rolling approach. Each forecast used exactly one year of prior data, updating the training window daily as new data became available. While this approach emphasizes recent trends and regime shifts, it introduces more noise due to smaller sample sizes. The fixed-window model achieved slightly lower performance than the expanding-window version, with an R^2 of 0.791 and RMSE of 0.0583. Nonetheless, it still demonstrated strong alignment with observed volatility trends.

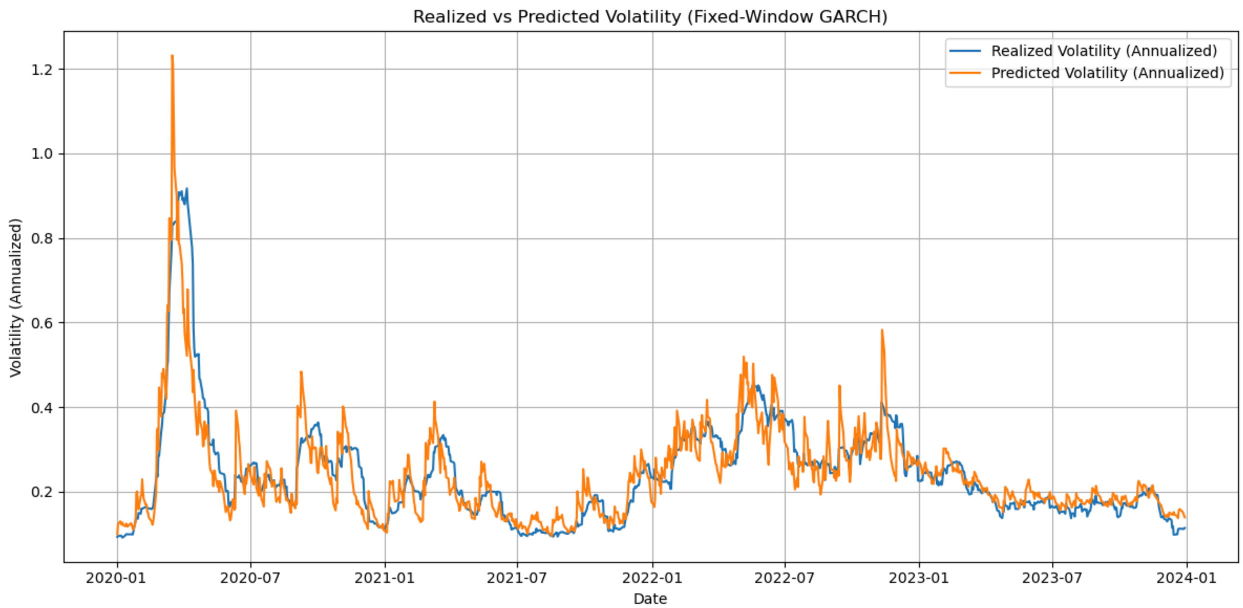

Figure 6*: Fixed-Window GARCH(1,1) Forecast vs. Realized QQQ Volatility (2020–2023)*

Theoretically, as a parametric model, the estimation of GARCH(1,1) relies on the maximum likelihood method (MLE) and assumes that the data satisfies certain stationarity and distribution characteristics. In order to stably estimate the model parameters, GARCH requires as much historical volatility data as possible. The use of a rolling expanding window can continuously introduce more samples, thereby improving the accuracy and robustness of parameter estimation. Therefore, the rolling expanding window is a more appropriate training method for the GARCH model. Our experimental results also verify this theoretical expectation. In the next section, we explore whether a machine learning model can improve predictive accuracy by integrating these additional signals.

4.3 XGBoost Modeling

While GARCH models offer strong theoretical underpinnings and perform well under stable statistical assumptions, they are inherently limited to using past returns to forecast future volatility. To capture a broader set of market signals and potentially improve prediction accuracy, we also implemented a machine learning approach using Extreme Gradient Boosting (XGBoost).

XGBoost is a tree-based ensemble learning algorithm known for its flexibility and predictive power. Unlike GARCH, it allows us to incorporate a wide range of engineered features, including technical indicators, macroeconomic variables, and volatility indices , to produce data-driven, nonlinear forecasts of market volatility. This is particularly useful in complex financial environments where the drivers of risk are not solely historical return patterns.

We defined the target variable as the next-day realized volatility of QQQ, consistent with the GARCH model. The training features included a combination of return-based, technical, and macroeconomic variables engineered in the previous step. These included:

- QQQ daily return
- Current realized volatility (21-day rolling window)
- Trading volume
- VIX and VXN indices
- 14-day RSI
- Federal Funds Rate

To maintain a realistic forecasting structure, we applied a rolling 3-year window for model training. For each prediction date from January 2020 to December 2023, the model was retrained using only the preceding three years of data. This approach balances the need for sufficient training data with the goal of capturing recent trends and structural shifts in the market.

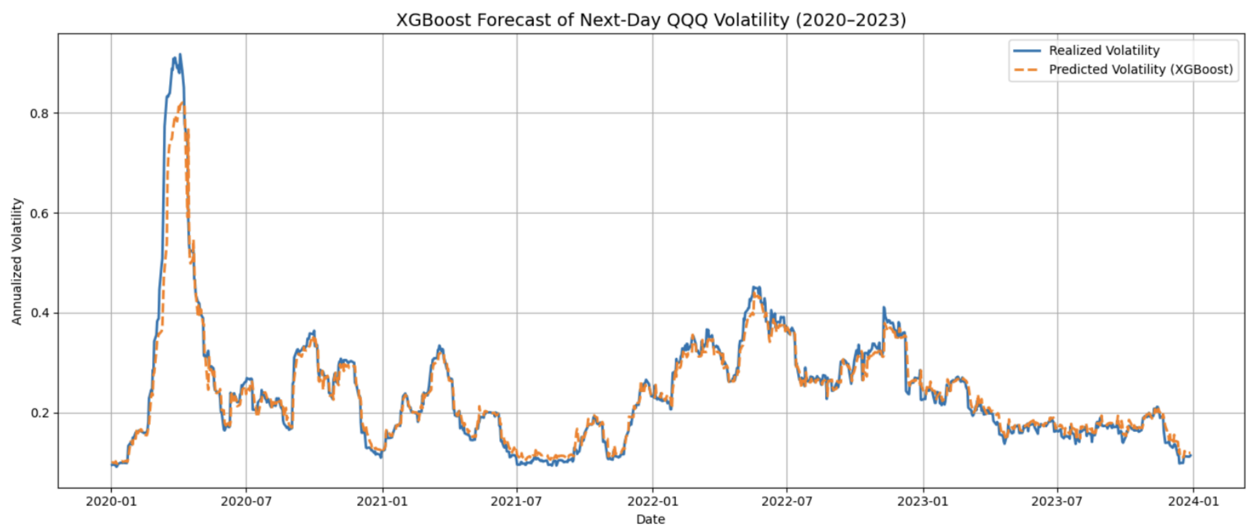

Figure 7: *XGBoost Forecast of Next-Day QQQ Volatility Using Rolling 3-Year Window (2020–2023)*

The XGBoost model delivered superior predictive performance compared to GARCH. It achieved an R^2 of 0.9521, with an RMSE of 0.0278 and a mean absolute error (MAE) of just 0.0146. This suggests that the inclusion of macro and technical variables significantly enhanced the model's ability to track day-to-day changes in volatility. The model was particularly accurate during periods of sharp volatility spikes and regime changes, where GARCH models tended to either over-smooth or lag behind.

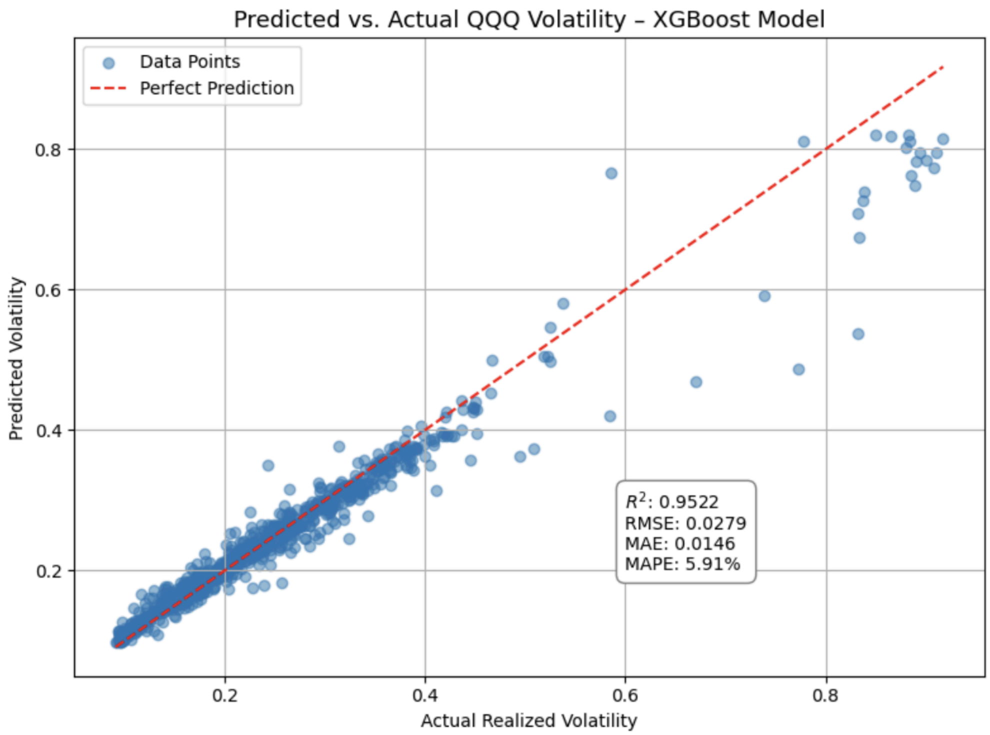

***Figure 8**: Predicted vs. Actual Volatility with Performance Metrics of XGBoost Model*

4.4 Model Comparison and Final Result

For this comparison, we use the standard GARCH(1,1) specification, which is a widely used real life volatility model. At this time we did not explore more advanced GARCH variants (such as EGARCH or GJR-GARCH) because our research focuses on comparing typical statistical methods with flexible, feature-rich machine learning models under realistic constraints.

To determine which volatility forecasting model would best support our hedging strategy, we compared the performance of GARCH and XGBoost over a shared test window spanning 2020 to 2023. The table below summarizes the key performance metrics for each model, including R^2, RMSE, and MAE:

Model Performance Comparison: GARCH vs. XGBoost

Model	R^2	RMSE	MAE
GARCH (Expanding)	0.835	0.028	0.021
GARCH (Fixed)	0.789	0.029	0.019
XGBoost	0.952	0.028	0.015

Figure 9: Model Performance Metrics Comparison: GARCH vs. XGBoost

From this comparison, it is evident that the XGBoost model substantially outperformed both versions of the GARCH(1,1) model. Its R^2 of 0.952 reflects a 14% improvement over the best-performing GARCH(1,1) setup (0.835), indicating that XGBoost captured a significantly greater proportion of the variance in realized volatility. Additionally, the MAE was reduced by 29%, from 0.021 in the expanding-window GARCH(1,1) model to 0.015 with XGBoost, while the RMSE showed a slight improvement as well.

The improvement in performance can be attributed to the ability of XGBoost to integrate diverse market signals beyond historical returns, including volatility indices (VIX, VXN), technical indicators (RSI), and macroeconomic variables (Fed Rate). This made it more responsive to rapid market regime changes and external shocks, features that are essential for timely and accurate hedge adjustments.

Given its superior predictive accuracy and flexibility, we selected XGBoost as the final model to power our volatility-targeted hedging system. Its forecasts serve as dynamic inputs for hedge ratio calculations and play a central role in helping the portfolio maintain a stable risk profile over time.

5. Hedging Strategy

5.1 Volatility Regime Classification

To enable regime-specific hedging, we began by classifying market conditions into distinct volatility regimes. Rather than relying on external volatility indices such as VIX or VXN, we grounded our approach in forward-looking forecasts from our XGBoost model, which generated daily predictions of QQQ's next-day realized volatility. This method ensured our classification system aligned closely with the volatility expectations used to guide our actual hedging decisions.

We defined three volatility regimes, low, moderate, and high, based on predicted annualized volatility levels. These thresholds were chosen with two guiding principles in mind: historical market behavior and practical trading considerations. First, we observed from our earlier data analysis that QQQ's realized volatility tends to cluster around distinct ranges depending on the macroeconomic environment. Second, we tailored the cutoff points to correspond with typical market sentiments and trading strategies. Volatility below 20% is often associated with stable or bullish periods where lighter risk controls may be appropriate. Volatility between 20% and 35% represents moderately turbulent conditions that call for more balanced protection, while volatility above 35% signals heightened uncertainty or crisis conditions requiring robust downside hedging.

Thus, we defined the regimes as follows:

- **Low Volatility**: Predicted volatility < 0.20
- **Moderate Volatility**: $0.20 \leq$ Predicted volatility ≤ 0.35

- **High Volatility**: Predicted volatility > 0.35

These cutoff points are not arbitrary but grounded in a balance between empirical patterns and the performance of common options strategies in real-world settings. For example, the 20% annualized volatility threshold is equivalent to approximately 1.25% daily movement often seen as a natural boundary between calm and choppy markets. Similarly, the 35% level aligns with stress conditions typically observed during major selloffs, such as the 2020 COVID shock or 2022 inflation-driven drawdowns.

A similar volatility regime framework was employed by the European Central Bank in its May 2018 Financial Stability Review, where researchers used a regime-switching model to analyze euro area equity market volatility. Their objective was to understand how market volatility clusters over time and how it transitions between distinct states under different macro-financial conditions. By fitting a three-state Markov-switching model to historical data, the ECB identified clear volatility bands corresponding to low, medium, and high regimes, with average annualized volatilities of approximately 9%, 14%, and 31% respectively. These findings support the notion that financial markets naturally exhibit regime-based volatility patterns and reinforce the validity of using similar thresholds, such as the <20%, 20–35%, and >35% cutoffs we adopt, for designing regime-specific risk management strategies (European Central Bank, 2018).

5.2 Strategy Design by Regime

Once the market volatility regime was classified, we mapped each regime to a specific options-based hedging strategy tailored to the prevailing level of market risk. The goal was to balance cost-efficiency and downside protection, acknowledging that more aggressive protection may be justified during turbulent periods but unnecessarily expensive during calm ones. Each strategy was designed with practical implementation in mind, using liquid, out-of-the-money QQQ options with consistent moneyness bands and biweekly rebalancing.

5.2.1. Low Volatility Regime: Light Collar Strategy

During periods of low predicted volatility (< 20%), the primary risk is complacency, markets tend to drift upward, but sudden shocks can still occur. To preserve upside exposure while capping potential losses, we implemented a light collar strategy. This involved purchasing a put option 5% out of the money (OTM) and simultaneously selling a call option 5% OTM. The premium received from the call sale helped offset the cost of the put, reducing the drag on returns while still providing insurance against moderate downturns. This approach reflects the well-established "cost-neutral hedge" principle commonly used by institutional investors and is supported by Bodie, Kane, and Marcus (2018), who highlight the collar's role in managing portfolio downside without sacrificing all upside potential.

5.2.2. Moderate Volatility Regime: Put Spread Strategy

When the market exhibited moderate volatility (20–35%), we adopted a protective put spread. This strategy involved buying a 5% OTM put while simultaneously selling a deeper 15% OTM put. The put spread allowed us to secure protection against mid-sized losses while significantly reducing premium costs compared to a standalone put. This approach is widely recognized for its efficiency in scenarios where downside risk is present but not extreme. As noted in Natenberg (2014), the spread structure limits the net cost while focusing insurance on the more probable loss range. In our context, it enabled meaningful downside hedging without overpaying for tail-risk protection during transitional markets.

5.2.3. High Volatility Regime: Protective Put Strategy

In periods of high predicted volatility (> 35%), we prioritized maximum downside protection by purchasing a standalone protective put roughly 3–5% OTM. No offsetting short position was included. In these conditions, the cost of insurance is higher, but so is the likelihood of steep drawdowns. By absorbing the full premium cost, we ensured the portfolio had a defined floor during crisis-like events, such as rate shocks or tech sell-offs. This strategy reflects guidance from Figlewski et al. (1993), who demonstrated the efficacy of protective puts in shielding portfolios from tail events when volatility is elevated and investor risk aversion spikes.

The choice to use consistent strike offsets (e.g., ±5%, 15%) across regimes also reflects operational realism, as options further OTM tend to be less liquid and more difficult to price accurately. Additionally, the biweekly rebalancing frequency balanced trading cost minimization with the need to stay responsive to regime changes.

5.3 Hedging Strategy Implementation

Once the strategies were designed, we implemented a dynamic hedging system that responded to predicted market volatility and adjusted the portfolio every 14 days. This biweekly rebalancing frequency was chosen to balance responsiveness with transaction cost minimization, reflecting realistic institutional rebalancing schedules.

At each rebalance date, the system identified the current volatility regime using the most recent XGBoost prediction. Based on that regime, the corresponding options strategy was applied. The portfolio began with a notional value of $10 million invested entirely in QQQ ETF shares. From this base, a hedge was constructed using a mix of long and short options positions chosen according to the strategy logic.

To operationalize the strategies, we used the following approach:

- For each date in the option dataset, the QQQ price was matched with available call and put options.

- The system searched for the closest strike prices to the target offset (e.g., ±5% or −15%) based on moneyness.
- If the exact offset was not available, the nearest available strike was selected using absolute difference minimization.
- Option bid and ask prices were used to estimate mid-market prices for entering positions.
- Implied volatility was extracted and fed into the **Black-Scholes model** to value the options daily, allowing us to mark positions to market.

We also accounted for cash movements in the portfolio. When selling options (e.g., the short call in a collar), the premium was added to cash; when buying protection, cash was reduced accordingly. This provided a realistic picture of the capital efficiency of each strategy.

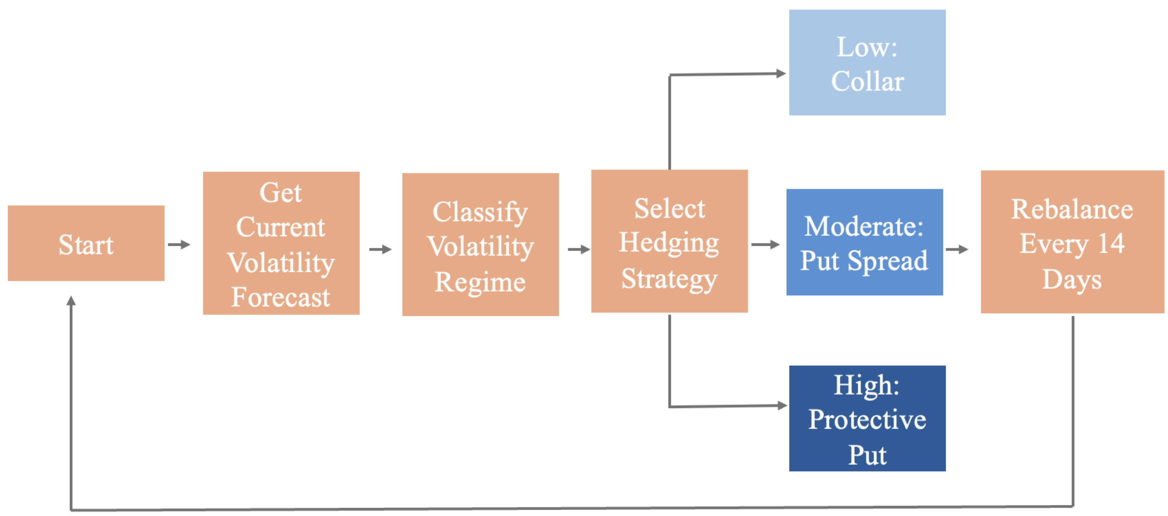

Figure 10*: Workflow of Regime-Based Hedging Logic*

Throughout the simulation, the system retained the same strike until the next rebalancing date. At that point, all existing hedges were closed, and new positions were established based on the updated regime and current QQQ price. This ensured that hedges remained relevant to the prevailing market conditions and volatility outlook, preserving the effectiveness of protection across market cycles.

5.4 Performance Metrics

To evaluate the effectiveness of our hedging strategies, we assessed the performance of the hedged portfolio relative to an unhedged QQQ benchmark using a range of risk-adjusted return metrics. These included cumulative return, annualized return, annualized volatility, Sharpe Ratio, and maximum drawdown.

The backtest simulation spanned January 2020 to May 2023, with biweekly rebalancing based on predicted volatility regimes. Option positions were marked to market daily using the Black-Scholes model to ensure accurate valuation across varying market conditions. The cumulative return was computed as the total geometric return from inception. Annualized return represented the geometric mean of daily returns over the period, while annualized volatility was derived from the standard deviation of daily returns, scaled to an annual basis. The Sharpe Ratio was calculated as the ratio of annualized return to annualized volatility, assuming a 0% risk-free rate. Maximum drawdown was measured as the largest observed peak-to-trough decline in portfolio value.

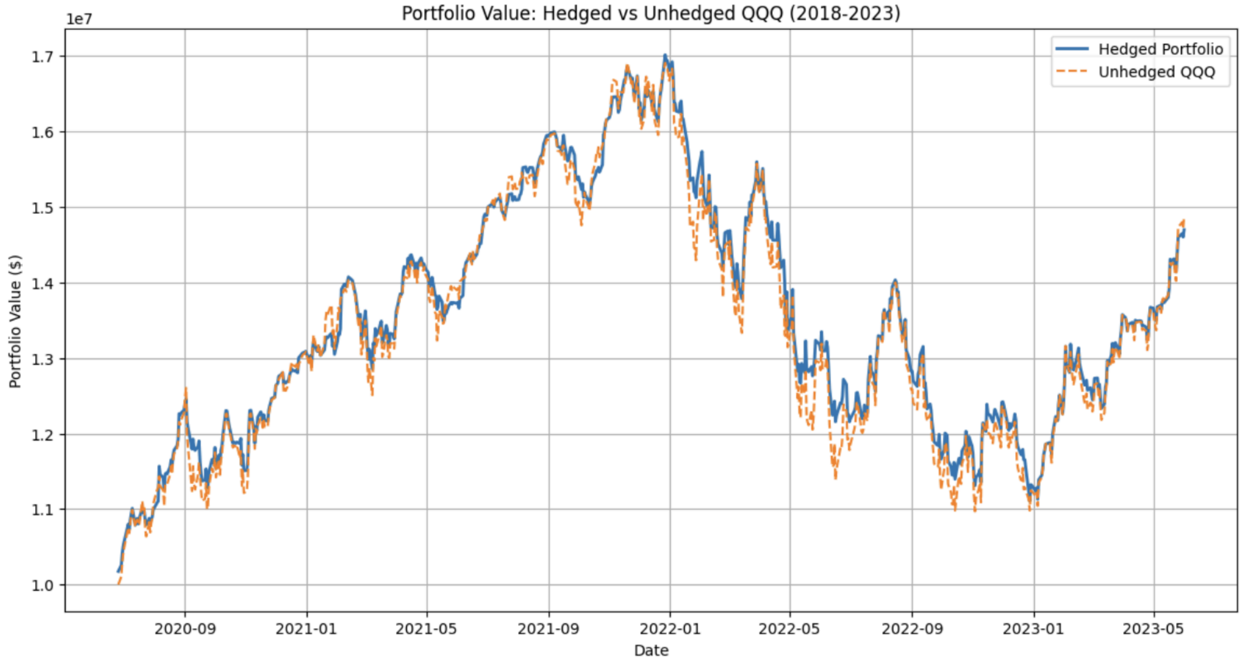

Figure 11: *Comparative Performance of Hedged vs. Unhedged QQQ Portfolio (2020–2023)*

The results indicated that the hedged portfolio outperformed the unhedged benchmark on a risk-adjusted basis. Specifically, the hedged portfolio achieved a Sharpe Ratio of 0.70, compared to 0.58 for the unhedged QQQ. It also demonstrated significantly lower annualized volatility (19.06%) relative to the unhedged counterpart (25.10%) and a slightly smaller maximum drawdown (−34.72% vs. −35.12%). While the unhedged QQQ portfolio delivered a higher annualized return (14.54% vs. 13.38%) and cumulative return (48.83% vs. 44.46%), this additional return came at the cost of substantially greater volatility and downside risk.

These findings validate the effectiveness of regime-based options hedging in reducing exposure to market stress while preserving long-term performance. The observed improvements in volatility and drawdown are consistent with prior work by Driessen & Maenhout (2013), who highlight the risk-mitigating benefits of dynamic, state-contingent hedging strategies. Nonetheless, we also observed that during prolonged low-volatility uptrends, the hedged portfolio underperformed due to persistent premium costs. This trade-off aligns with literature emphasizing the implicit cost of downside protection, especially in stable markets (Bakshi & Kapadia, 2003).

6. Backtesting

We conducted a historical backtest to evaluate the performance of our regime-based hedging strategies using QQQ ETF market data from January 2020 to May 2023. At bi-weekly intervals, hedge positions were updated based on the volatility regime classification generated by our XGBoost model, which informed whether to apply a light collar, protective put spread, or protective put.

The portfolio was initialized with a $10 million investment, fully allocated to the QQQ ETF. Depending on the predicted regime, options were selected and priced dynamically using the Black-Scholes model, which incorporated prevailing implied volatility, interest rates (sourced from historical U.S. Federal Reserve data), and the underlying asset's price.

Each hedging strategy was executed using a systematic logic that matched the portfolio's exposure to the appropriate number of option contracts, ensuring realistic sizing. These contracts were marked to market daily, and the portfolio value was adjusted accordingly to reflect gains, losses, and option premiums.

This backtesting framework allows us to simulate a realistic investment environment, accounting for market-driven regime changes and the costs and benefits of dynamic hedging. It provides a robust basis for evaluating how volatility-targeted strategies can reduce risk without sacrificing long-term performance. This approach follows the methodology recommended by Cont and Tankov (2004) for assessing derivative-based hedging in incomplete markets.

7. Limitations and Future Work

While our regime-based hedging framework shows promising results, several limitations must be acknowledged. These limitations pertain to assumptions in our modeling process, simplifications in execution, and constraints in the data used. Addressing these issues in future research could enhance both the realism and robustness of the strategy.

7. 1. Constant Implied Volatility Assumption

Our backtest assumes that implied volatility remains constant within each 14-day rebalancing period. In reality, implied volatility can change dramatically in response to market shocks or economic events. This simplification may understate hedging risk or overstate protection in volatile conditions. Future work could integrate dynamic volatility estimation methods such as intraday implied volatility updates or advanced models like stochastic volatility or jump-diffusion models (Bates, 1996), which better capture the discontinuities and clustering observed in real market volatility.

7. 2. Absence of Transaction Costs and Liquidity Constraints

We did not incorporate trading costs, bid-ask spreads, or liquidity issues in option execution. These factors can meaningfully erode performance, especially for protective strategies that require frequent rebalancing or trading less liquid contracts. To address this, future iterations should include realistic slippage, option spreads, and possibly limit-order fill probabilities, as seen in microstructure-aware simulations. Additionally, calibrating contract sizing based on open interest and volume thresholds could make the model more applicable to institutional-scale trading.

7. 3. Use of Predicted Volatility for Regime Classification

Although XGBoost yielded high out-of-sample accuracy, our regime classification depends entirely on predicted next-day realized volatility, which could introduce compounding errors, particularly if predictions systematically overshoot or undershoot in certain regimes. A potential improvement involves ensembling models (e.g., combining XGBoost with GARCH or LSTM forecasts) or incorporating confidence intervals to adjust for uncertainty in classification when allocating strategies.

7. 4. Narrow Hedging Instrument Set

Our strategies use only vanilla put and call options on the QQQ ETF. While this simplifies execution, it limits flexibility. For example, certain volatility regimes might be better hedged with instruments like variance swaps or sector-specific derivatives. Future work could expand the instrument set, including multi-asset hedging or cross-hedging with other ETFs or volatility indices, which might offer lower-cost protection or more targeted exposure adjustment.

7.5. Historical Period Scope

The backtest spans January 2020 to May 2023, a period characterized by unusual market conditions, including the COVID-19 shock and rapid interest rate hikes. While this adds stress-test value, it limits generalizability. Extending the backtest to earlier periods or applying the model to other asset classes (e.g., S&P 500, Russell 2000) could help validate robustness across different economic regimes.

8. Conclusion

Our study presents a practical and forward-looking approach to risk management by integrating machine learning–based volatility forecasting with regime-specific options hedging strategies. Through extensive backtesting from 2020 to 2023, we demonstrate that a dynamic, volatility-targeted framework significantly enhances risk-adjusted performance. Specifically, the hedged portfolio reduced annualized volatility by **24%** (from 25.10% to 19.06%) and improved the Sharpe ratio by **21%** (from 0.58 to 0.70), while maintaining comparable long-term returns to the unhedged benchmark. Although the cumulative return of the hedged strategy was slightly lower (44.46% vs. 48.83%), the reduction in drawdowns (−34.72% vs. −35.12%) and volatility reflects a more stable and resilient investment profile, especially critical during periods of elevated market stress such as in early 2022.

These results matter because they speak directly to the challenges faced by investors in today's volatile and uncertain markets, shaped by macroeconomic shocks, geopolitical instability, and rapidly evolving monetary policy. Traditional static hedging techniques often fail to respond effectively to shifting market regimes, exposing portfolios to either over-hedging during calm periods or under-hedging during crises. By contrast, our regime-aware framework adjusts hedge intensity and structure based on predicted market conditions, enabling more intelligent allocation of risk protection.

This research contributes to a growing body of evidence supporting the fusion of machine learning and financial engineering. In an era where data is abundant but actionable insights remain scarce, our work provides a concrete example of how predictive models can directly inform and enhance strategic portfolio decisions. For asset managers, pension funds, and fintech platforms alike, this approach offers a scalable, cost-aware solution to improving downside protection while preserving performance, delivering smarter hedging for a more volatile world.

9. References

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