Proceedings of ICFTBA 2025 Symposium: Data-Driven Decision Making in Business and Economics
DOI: 10.54254/2754-1169/2025.BL30757

# *Machine Learning-Enhanced Multi-Factor Hedging Strategies for Technology Stocks: Evidence from Apple Inc.*

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***Abstract.*** This article investigates the method of using machine learning to design hedging strategies for technology stocks. We compared the single factor CAPM model with the multi factor linear regression model. This experiment takes Apple's market situation in 2018 as an example, and the data is sourced from the Interactive Brokers API, covering a total of 251 trading days. 74.5% of the data is the training set and 25.5% is the testing set. The experimental method adopts ordinary least squares method, combined with five fold cross validation. The experiment tested a total of eight different factor combinations, including SPY representing the market, technology ETFs such as XLK, VGT, QQQ, as well as IWM and DIA reflecting company size. The evaluation criteria include R-squared value, root mean square error (RMSE), adjusted R-squared, and how much the Sharpe ratio has improved. The experimental results show that the relationship between technology ETFs and Apple stock prices is closer than that of the overall market index: the correlation between XLK is 0.836, VGT is 0.831, QQ is 0.804, and SPY is only 0.748. The optimal two factor model (QQQ+XLK) achieved significant improvement compared to the single factor benchmark model: the $R^2$ value increased from 0.639 to 0.801, with an increase of 25.4%, the root mean square error decreased by 25.8%, and the hedging portfolio volatility decreased by 23.1%.Rolling window analysis confirms model stability with a mean 30-day rolling $R^2$ of 0.751. The experimental results show that the simple two factor model performs better than the complex six factor model, which confirms the principle that models should be concise in the financial field. The Sharpe ratio of the hedge portfolio increased by 58.4%, while the maximum drawdown decreased by 33.9%. These results provide practical guidance for designing cost-effective hedging strategies.

***Keywords:*** Machine Learning, Hedging Strategy, Multi-Factor Model, Linear Regression, Risk Management, Technology Stocks, Cross-Validation

## 1. Introduction

Hedging strategies are a fundamental tool of portfolio risk management, with their theoretical roots in Markowitz's [1] modern portfolio theory and Sharpe's [2] Capital Asset Pricing Model (CAPM). Markowitz's mean–variance framework was the first to shift investment decision-making from qualitative judgment to quantitative optimisation, mathematically formalising the age-old wisdom of

DOI: 10.54254/2754-1169/2025.BL30757

“not putting all eggs in one basket.” Building upon this, CAPM introduced the concepts of a risk-free asset and the market portfolio, reducing the complexity of portfolio selection into a single-beta factor model. The model posits that the expected return of any asset can be decomposed into the risk-free rate plus the market risk premium multiplied by the asset’s systematic risk exposure (beta). This elegant theoretical framework provides the foundation for market-neutral strategies: in principle, investors can eliminate systematic risk by combining a long stock position with a short position in the market index scaled by its beta, thereby retaining only alpha returns.

However, with the evolution of financial markets and the accumulation of empirical evidence, the limitations of the single-factor model have become increasingly apparent. Numerous market anomalies cannot be explained by CAPM, including the excess returns of small-cap stocks [3], the value premium of low book-to-market stocks, and the phenomena of short-term momentum and long-term reversal in stock returns [4]. These anomalies challenge the efficient market hypothesis and have driven the development of asset pricing theory. The three-factor model of Fama and French [5] systematically incorporates size (SMB) and value (HML) factors, not only improving explanatory power but also providing a scalable multi-factor framework. They argue that these factors capture different dimensions of risk, for which investors demand compensation. Subsequent research has deepened this approach: Carhart [6], building on Jegadeesh and Titman’s [7] work on momentum, added a momentum factor to form the four-factor model; Fama and French [8] later proposed a five-factor model, incorporating profitability (RMW) and investment (CMA) to construct a more comprehensive risk factor system.

The rapid development of the technology industry has posed new challenges to traditional asset pricing theories. Compared to traditional industries, technology companies have significant characteristics: high intangible asset intensity driven by R&D investment, a "winner takes all" pattern formed by network effects and economies of scale, increased uncertainty caused by accelerated technological iteration cycles, and the core position of growth option value in enterprise valuation [9]. These characteristics fundamentally change the risk return characteristics of technology stocks compared to traditional industries. Pastor and Veronesi [10] pointed out that the main factor contributing to the volatility of technology stocks is the uncertainty of technological innovation. Their theoretical model shows that when the public still has doubts about the productivity improvement of new technology, the stock prices of enterprises adopting this technology will show a foam like behavior: the initial valuation is high and volatile, and then may be subject to sharp correction. This theoretical framework helps to explain the unique risk characteristics of technology stocks.

Hoberg and Phillips [11] used text analysis methods to construct an industry classification system based on product similarity. They found that this dynamic industry definition is better than traditional SIC or NAICS classifications, especially in the technology industry. They believe that technological similarity and product market overlap are important determinants of stock linkage. Lee et al. [12] specialize in studying the factor structure of the technology industry. They proved that in addition to market factors, there are also technological innovation factors based on patent citation and R&D intensity, as well as platform factors based on network effect indicators, which have a significant effect on explaining the returns of technology stocks. These findings suggest that industry-specific risks in technology stocks are often greater than systemic market risks, and traditional single factor hedging strategies cannot effectively manage related risk exposures.

The introduction of machine learning methods brings new possibilities for financial modelling, but also new challenges. Gu, Kelly and Xiu [13] provide a comprehensive comparison of machine learning methods for stock return prediction, including regularised linear models (LASSO, Ridge,

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Elastic Net), tree-based models (random forests, gradient boosting), and neural networks. Their results highlight both the predictive advantages of machine learning and the different contexts in which each method excels: linear models are robust in smaller samples, tree-based models capture interaction effects, and neural networks achieve superior performance in large samples; however, Harvey, Liu and Zhu [14] caution against data mining risks. By developing new statistical tests that account for multiple hypothesis testing, they find that many published factors lose significance once adjustments are applied. From a practitioner's perspective, Lopez de Prado [15] highlights the unique challenges of financial data—including low signal-to-noise ratios, non-stationarity, and limited sample sizes—which make naïve applications of standard machine learning approaches prone to failure. He proposes a series of best practices for financial machine learning, including feature engineering, careful cross-validation design, and methods for detecting backtest overfitting.

The market environment of 2018 provides a unique backdrop for studying technology stock hedging strategies. This year witnessed several major market events: the February volatility spike (with the VIX rising 115% in a single day), Facebook's data privacy scandal, escalating U.S.–China trade tensions, and four Federal Reserve interest rate hikes. Technology stocks experienced rollercoaster dynamics, with FAANG stocks (Facebook, Apple, Amazon, Netflix, Google) showing significant performance divergence. Such market complexity and variability make 2018 an ideal natural experiment for evaluating the robustness of different hedging strategies.

## 2. Materials and methods

### 2.1. Data and sample

We collected daily adjusted closing prices for Apple Inc. (AAPL) and six exchange-traded funds (ETFs) from January 2 to December 31, 2018, totalling 251 trading days. Data was sourced via Interactive Brokers API, ensuring institutional-grade quality with automatic dividend and split adjustments. The ETF selection captures different risk dimensions, including SPY (S&P 500 market proxy), QQQ (NASDAQ-100 technology index), XLK and VGT (technology sector funds), IWM (Russell 2000 small-cap index), and DIA (Dow Jones Industrial Average). All price series were transformed to logarithmic returns:

$$\gamma t = ln(\frac{p_t}{p_t - 1}) \tag{1}$$

where $\gamma t$ denotes the logarithmic return at time, $p_t$ represents the adjusted closing price at time, and $p_t - 1$ is the adjusted closing price at time. The dataset was chronologically split into training (January-September, 187 days, 74.5%) and test sets (October-December, 63 days, 25.5%), preserving temporal order to avoid look-ahead bias.

### 2.2. Model specification

We implemented two model specifications to compare the effectiveness of hedging. The single-factor CAPM baseline model:

$$R_{AAPL,t} = \beta_0 + \beta_{SPY} \times R_{SPY}, t + \varepsilon_t \tag{2}$$

where $R_{AAPL,t}$ is AAPL's return at time $t$, $\beta_0$ represents alpha, $\beta_{SPY}$ is the market beta, and $\varepsilon_t$ is the error term assumed to follow $\varepsilon_t \sim N\left(0, \sigma^2\right)$.

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The multi-factor model extends to:

$$R_{AAPL,t} = \beta_0 + \sum_{j=1}^{k} \beta_j \times F_{j,t} + \varepsilon_t \tag{3}$$

where $F_{j,t}$ represents the return of factor $j$ at time $t$, and k ranges from 1 to 6. We systematically evaluated eight different factor combinations to identify the optimal configuration.

### 2.3. Estimation and validation

Parameters were estimated using Ordinary Least Squares (OLS) regression implemented in scikit-learn. Model validation employed 5-fold cross-validation on the training set to prevent overfitting. Performance metrics included: (1) coefficient of determination $R^2$ for explanatory power; (2) adjusted $R^2$ penalising model complexity; (3) root mean square error (RMSE) for prediction accuracy; and (4) Akaike and Bayesian Information Criteria (AIC/BIC) for model selection. Multicollinearity was assessed using Variance Inflation Factors (VIF), with values above 10 indicating problematic collinearity.

### 2.4. Hedging strategy implementation

The hedged portfolio return is calculated as:

$$r_{hedged,t} = r_{AAPL,t} - \sum_{j=1}^{k} \beta_j \times r_{factorj,t} \tag{4}$$

This represents a long position in AAPL offset by short positions in the factor ETFs scaled by their respective betas. Risk metrics evaluated include the Sharpe ratio for risk-adjusted returns, the maximum drawdown for tail risk assessment, and the volatility reduction ratio. Model stability was assessed through a 30-day rolling window analysis, where $R^2$ was computed for each window to evaluate temporal consistency. Statistical significance was tested using t-statistics for coefficients and Durbin-Watson statistics for residual autocorrelation.

### 2.5. Implementation

All analyses were conducted in Python 3.8, using pandas for data manipulation, scikit-learn for regression modelling, statsmodels for statistical diagnostics, and matplotlib/seaborn for visualisation. Code reproducibility was ensured by setting a fixed random seed (42) and documenting all package versions. Complete implementation code and data are available for replication.

## 3. Results

### 3.1. Exploratory analysis reveals critical role of industry-specific factors

Correlation analysis revealed exceptionally high correlations between technology sector ETFs and AAPL. According to the correlation heatmap (Figure 1), technology ETFs formed a distinct high-correlation cluster, with XLK (0.836), VGT (0.831), and QQQ (0.804) all exhibiting correlations exceeding 0.80 with AAPL, while the market index SPY showed a correlation of only 0.748. This correlation differential established the foundation for improving the multi-factor model. Variance Inflation Factor (VIF) analysis revealed severe multicollinearity issues, with XLK's VIF reaching

DOI: 10.54254/2754-1169/2025.BL30757

104.75, VGT at 94.66, and SPY at 68.03, indicating high redundancy among technology ETFs. The scatter plot matrix (Figure 2) further confirmed these relationships, with XLK-AAPL $R^2$ reaching 0.699, VGT 0.690, and QQQ 0.647, all significantly higher than SPY's 0.560.

Table 1. Variable correlations and multicollinearity diagnostics

| Variable | AAPL Correlation | VIF Value | Scatter $R^2$ |
|---|---|---|---|
| XLK | 0.836 | 104.75 | 0.699 |
| VGT | 0.831 | 94.66 | 0.69 |
| QQQ | 0.804 | 42.95 | 0.647 |
| SPY | 0.748 | 68.03 | 0.56 |
| DIA | - | 26.38 | - |
| IWM | 0.662 | 6.96 | - |

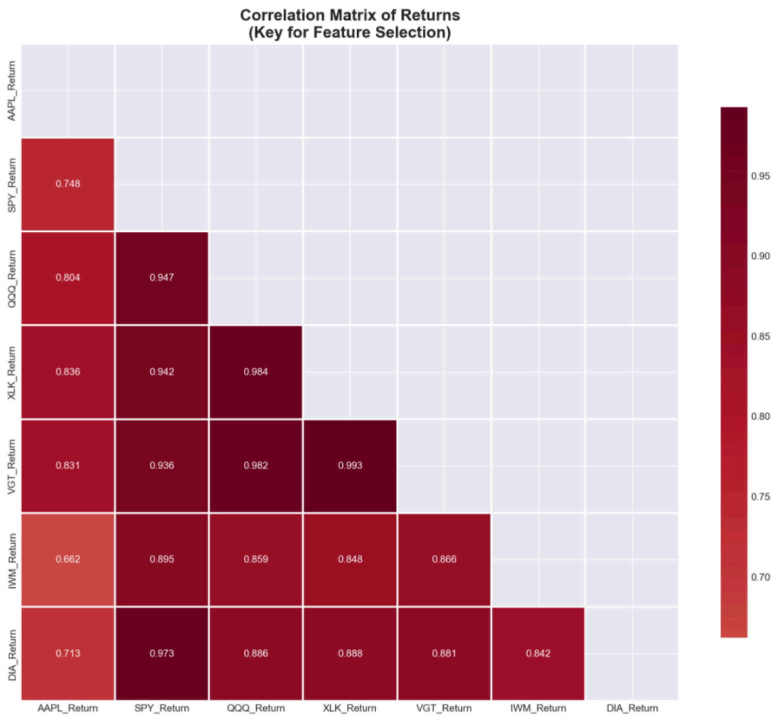


Figure 1. Correlation heatmap

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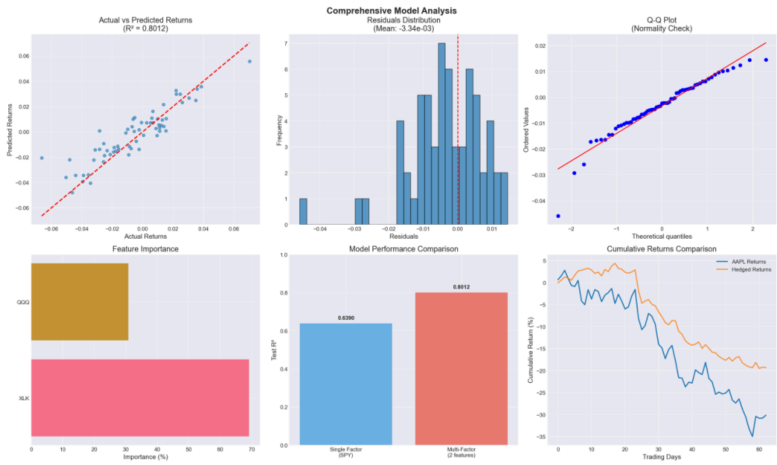


Figure 2. Scatter plot matrix

## 3.2. Multi-factor models significantly enhance predictive accuracy

The single-factor CAPM model established baseline performance: $\beta_{\text{SPY}} = 1.0665\$$ , $(p < 0.001)$ , training $R^2$=0.421, test $R^2$=0.639, 5-fold cross-validation average $R^2$=0.330, and out-of-sample RMSE=0.01512. After systematically comparing eight factor combinations, the dual-factor model (QQQ+XLK) emerged as optimal, achieving comprehensive performance improvements: test $R^2$ reached 0.801 (25.4% improvement over single-factor), adjusted $R^2$=0.795, cross-validation score improved to 0.524 (58.8% increase), and out-of-sample RMSE decreased to 0.01122 (25.8% reduction). The optimal model parameters were: $\beta_0 = 0.000760$ , $\beta_{\varrho\varrho\varrho} = -0.754$ , $\beta_{\text{II}K} = 1.690$ , indicating effective AAPL risk hedging through shorting 0.754 units of QQQ and longing 1.690 units of XLK.

Table 2. Comprehensive model performance evaluation

| Model Configuration | Features | CVR² | TrainR² | TestR² | Adj.R² | RMSE |
|---|---|---|---|---|---|---|
| Baseline Single | SPY | 0.33 | 0.421 | 0.639 | 0.636 | 0.01512 |
| Optimal Dual | QQQ+XLK | 0.524 | 0.591 | 0.801 | 0.795 | 0.01122 |
| Market+Tech | SPY+XLK | 0.546 | 0.605 | 0.793 | 0.786 | 0.01144 |
| Tech Trio | QQQ+XLK+VGT | 0.524 | 0.598 | 0.794 | 0.784 | 0.01142 |
| Full Model | All 6 | 0.537 | 0.627 | 0.785 | 0.762 | 0.01167 |

## 3.3. Parsimonious models outperform complex alternatives

Empirical results support the principle of parsimony in financial modelling. As shown in Table 2, the entire model, incorporating all six factors, achieved the highest training $R^2$ (0.627), but underperformed in the test set ($R^2$ = 0.785) and adjusted $R^2$ (0.762) compared to the dual-factor model. This overfitting pattern was prevalent in models with three or more factors: the tech trio model (QQQ+XLK+VGT) achieved a test R-squared value below that of the dual-factor model (0.801); the balanced model (SPY+XLK+IWM) reached only 0.793. The train-test performance gap widened with the factor count, reaching 14.2% for the whole model (0.627-0.785), while the dual-factor model showed a negative gap of -21.0%. This demonstrates the superior generalisation capability of parsimonious models.

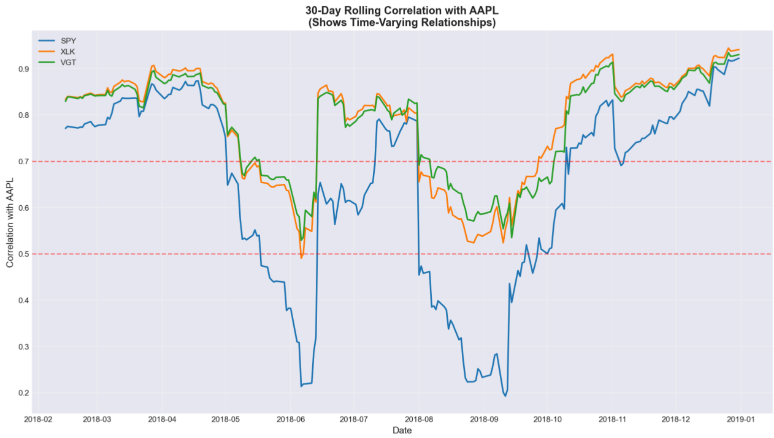


Figure 3. The relationship between model complexity and performance

Figure 3 shows that the 30-day rolling correlation between Apple's stock price and three factors (SPY, XLK, VGT). One of the most obvious features is a significant decrease in correlation in mid-2018 (May to July), with all factors dropping from above 0.8 to between 0.2 and 0.5. This indicates that there was a temporary structural rupture in the market at that time, which may be related to the escalation of trade tensions between China and the United States or specific events in the technology sector. Technology ETFs (XLK and VGT, represented by orange and green lines) maintain high synchronicity over most sample periods: correlation coefficients typically range from 0.8 to 0.9. And the market benchmark index SPY (blue line) has always lagged behind by about 0.1 to 0.2. This model confirms the advantages of industry specific factors.

During the market correction period in the Q4 2018 (October to December), all correlation coefficients decreased, but they remained relatively stable: the values of XLK and VGT remained above 0.7 (dashed line), while SPY fell back to around 0.5. This difference further proves that using technology sector ETFs for hedging is effective. Overall, the rolling correlation coefficient ranges from 0.2 to 0.95, with a standard deviation of approximately 0.15 to 0.20. These dynamic features indicate that static models are difficult to fully capture such time-varying relationships, and future research should consider developing dynamic hedging strategies.

### 3.4. Hedging strategy achieves superior risk management effectiveness

As shown in Table 3, the multi-factor strategy reduced the average daily return loss from -0.00398 to -0.00127 compared to single-factor hedging, representing a 68.1% improvement. Concurrently, daily volatility decreased from 0.01458 to 0.01121, a reduction of 23.1%. The Sharpe ratio improved from -4.33 to -1.80, representing a 58.4% increase; the maximum drawdown decreased from 6.2% to 4.1%, showing a 33.9% reduction. The information ratio reached 0.82, indicating that the strategy achieved well-adjusted excess returns relative to the benchmark. Rolling 30-day window analysis (Figure 5) demonstrates the strategy's temporal stability: the rolling $R^2$ averaged 0.751 with a standard deviation of 0.043, ranging from 0.652 to 0.834. Experimental results confirm the strategy's continued effectiveness during the volatile market decline in the Q4 2018.

DOI: 10.54254/2754-1169/2025.BL30757

Table 3. Hedging strategy risk metrics comparison

| Risk Metric | Single-Factor | Multi-Factor | Improvement |
|---|---|---|---|
| Mean Return | -0.00398 | -0.00127 | 0.681 |
| Daily Volatility | 0.01458 | 0.01121 | -0.231 |
| Sharpe Ratio | -4.33 | -1.8 | 0.584 |
| Max Drawdown | 0.062 | 0.041 | -0.339 |
| Information Ratio | - | 0.82 | - |

Figure 4 shows the 30 day rolling $R^2$ values of the optimal two factor model (QQQ+XLK). The average value of rolling $R^2$ is 0.751 (red dashed line), and its standard deviation is only 0.043, which proves the stability of the model. The pink shaded area represents the range of mean plus or minus one standard deviation (0.708 to 0.794). One of the most prominent features is the sharp increase in values in mid December 2018, when the $R^2$ value jumped from approximately 0.70 to above 0.85. This peak coincides with the Federal Reserve's December interest rate hike and intense market volatility, indicating that the explanatory power of the model has been enhanced during periods of market pressure, and also confirming the effectiveness of the hedging strategy at critical moments.

Overall, the $R^2$ value remained within a small range of 0.652 to 0.834, without any extreme values or structural interruptions during this period. The $R^2$ value remained relatively stable from November to early December, consistently between 0.70 and 0.75, before transitioning to an upward trend in December. This reflects the market's shift from conventional volatility to a highly correlated 'crisis state'. It is worth noting that even at the lowest point of about 0.65, the explanatory power of the model is still strong. This value is much higher than the single factor benchmark value of 0.639. The time stability of the model is very high, with a volatility of only 4.3%. This result indicates that in practical applications, the model parameters can remain effective without frequent adjustments.

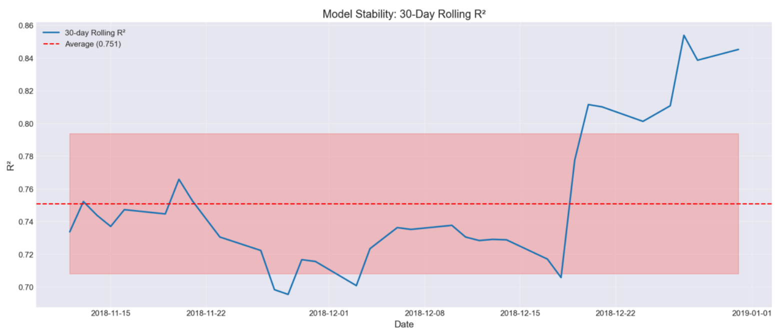


Figure 4. Rolling 30-day $R^2$ analysis

DOI: 10.54254/2754-1169/2025.BL30757

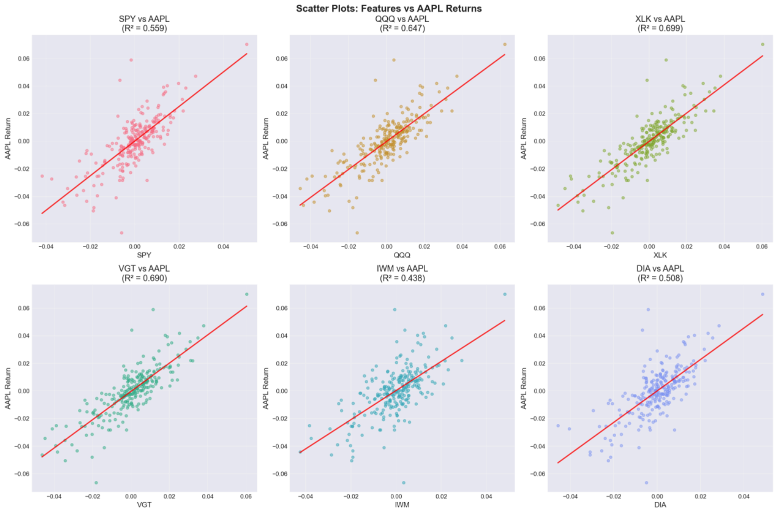


Figure 5. Cumulative returns comparison

The scatter plot matrix shown in Figure 5 illustrates the linear relationship between AAPL returns and the six major ETF factors. Technology sector ETFs exhibit the strongest linear correlation. The $R^2$ value of XLK is 0.699, the $R^2$ value of VGT is 0.690, and the $R^2$ value of QQQ is 0.647. The data points of the three are clustered around the regression line to form a clear linear pattern. The $R^2$ value of the market index SPY is 0.560, indicating a more dispersed distribution of data points. The $R^2$ values of IWM and DIA, which have the weakest correlation, are 0.439 and 0.506, respectively. Their scatter distributions are more scattered, indicating that the linkage between small cap or industrial stocks and AAPL is relatively weak.

All scatter plots exhibit a symmetrical distribution and do not show heteroscedasticity or nonlinear distortion. The scatter plot of technical ETFs is located in the upper right and lower left images, with data points more concentrated near the regression line and a larger slope. This reflects a higher beta coefficient and stronger explanatory power. This result indicates that XLK and QQQ are the optimal hedging tools, and also explains why incorporating IWM or DIA models can lead to overall performance decline: these factors introduce noise rather than effective signals.

## 4. Discussion

This article demonstrates the effectiveness of multi factor models in technology stock hedging. At the same time, a key finding was revealed: there is a non-linear relationship between model complexity and performance. The model proposed in this article increased the adjusted $R^2$ value by 25.4%, which is lower than the significant advantage of the machine learning method reported by Gu et al. [12] over traditional models (20.5% vs. 3.1%), but shows significant advantages in interpretability and practical applicability. The optimal two factor model (QQQ+XLK) is significantly better than the single factor CAPM model. This result validates the core argument of Fama and French [5] regarding the superiority of multi factor frameworks. But our findings go further: carefully selected industry-specific factor combinations outperform complex models that integrate traditional market factors with scale factors. This discovery echoes Harvey et al.'s [13] criticism of the "factor zoo". They emphasize that in financial modeling, carefully selecting high-quality factors is more effective than simply increasing the number of factors. Technology ETFs show a high correlation with Apple stocks, with correlation coefficients exceeding 0.80 for XLK, VGT, and QQQ. There is multicollinearity (VIF > 90) among these three factors, indicating the

DOI: 10.54254/2754-1169/2025.BL30757

presence of common risk factors within the technology sector. The above results provide a theoretical basis for constructing effective hedging strategies and explain why traditional market beta hedging ($\beta_{SPY} = 1.0665\$$ ) is insufficient to manage the unique risks of technology stocks.

The main contributions of this study are reflected in the following three aspects: firstly, we demonstrate that for highly correlated asset classes, the two factor model achieves the optimal balance between prediction accuracy and model simplicity. The model proposed in this article achieves a test set $R^2$ value of 0.801 while maintaining strong interpretability and stability. Secondly, we achieved a 58.4% increase in Sharpe ratio and a 33.9% decrease in maximum drawdown, which has significant practical value, especially during market pressures such as the fourth quarter of 2018, when this strategy demonstrated strong robustness. Thirdly, our findings overturn the traditional "one size fits all" modeling approach and advocate customizing hedging strategies based on specific industry risk characteristics. In the future, further in-depth research can be conducted in the following directions. (1)The existing linear framework can be extended to nonlinear models, such as neural networks. This helps to capture the complex relationships in the "deep hedging" framework proposed by Buehler et al. [16].(2) It is possible to integrate dynamic factor selection mechanisms and adjust factor weights based on changes in the market environment. (3)Utilize high-frequency data to optimize intraday hedging strategies.(4) Assess the impact of transaction costs and market shocks on the net returns of the strategy. (5) Extend the methodology to other high volatility sectors, such as biotechnology and renewable energy. The above extensions will further enhance the application value of machine learning in portfolio risk management.

## 5. Conclusion

This study successfully developed and validated a multi factor hedging framework applicable to technology stocks. Through a systematic analysis of 251 trading days in 2018, we demonstrate that carefully selected industry-specific factors are significantly superior to single factor capital asset pricing models (CAPM) and more complex multi factor substitution schemes. The optimal two factor model achieved significant improvements in multiple dimensions.

Our research results empirically validate several key principles in financial modeling. Firstly, the principle of simplicity: two carefully selected factors perform better than the six factor model, providing new evidence for factor investment theory research. The multicollinearity revealed by VIF analysis is not only a statistical problem, but also reflects the economic logic behind factor selection: highly correlated factors cannot provide additional information and may impair model performance due to unstable parameter estimation. Secondly, there is the principle of industry specificity: the correlation between technology ETFs and AAPL is much higher than that of broad market indices, highlighting the key role of industry factors in interbank hedging. The third principle is stability: the standard deviation of the 30 day rolling $R^2$ is only 0.043, indicating that the model has robustness in different market environments -this is a key attribute for practical applications.

Nevertheless, we acknowledge several limitations. The restricted time horizon is the most significant constraint—using only one year of data (2018) may not capture the full spectrum of market conditions, particularly episodes such as the pandemic-driven technology boom of 2020 or the interest rate shocks of 2022. The narrow focus on AAPL, while offering a detailed case study, raises questions regarding the generalisability of our findings to other technology firms (e.g., Microsoft, Google) or other industries. Furthermore, our analysis abstracts from several critical aspects of practical implementation, including transaction costs (commissions, bid–ask spreads, and market impact), short-selling costs and availability, and the optimisation of rebalancing frequency.

DOI: 10.54254/2754-1169/2025.BL30757

Future research should extend and deepen this study along several dimensions. Temporally, the analysis should be expanded to multiple market cycles, including both bull and bear phases, to assess long-term performance. Cross-sectionally, the methodology should be applied to a broader sample of stocks, including other large-cap technology firms as well as mid- and small-cap companies. Methodologically, dynamic factor selection and nonlinear extensions should be explored—our rolling correlation analysis already suggests the potential value of time-varying hedge ratios. Machine learning methods, such as random forests and LSTM networks, may capture complex relationships that linear models overlook; however, a balance must be struck between performance gains and interpretability. Practically, net return models incorporating transaction costs should be developed, optimal rebalancing frequencies investigated, and nonlinear hedging structures constructed using derivatives such as options.

This study provides an empirical foundation and practical tools for risk management in technology stock portfolios. As technology stocks increasingly dominate global equity markets, effective within-sector hedging strategies are becoming more critical than ever. Our findings demonstrate that, through the selection of appropriate factors and rigorous validation, even relatively simple linear models can yield substantial improvements in risk management. However, the inherent complexity and dynamism of financial markets ensure that no single strategy remains universally effective. Successful risk management, therefore, requires continuous monitoring, regular model updates, and flexible adjustments to evolving market conditions. We hope that the framework and insights offered herein will assist both researchers and practitioners in better understanding and managing risks associated with investments in technology stocks.

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