# Algorithmic Trading - COMP0051

## Coursework 2

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# Introduction

This project focuses on defining and implementing trading strategies using the SPTL ETF and the Effective Federal Funds Rate (EFFR) as a benchmark for the risk-free rate. The goal of the analysis is to explore different trading strategies, starting with a significant amount of initial capital to try and maximize returns while dealing with the usual risks and market fluctuations. The main part of the project involved analyzing three specific leveraged trading strategies. These are tested using a dataset divided into two parts: 70% for training and 30% for testing. The results are compared by performing tests under different financial conditions. This report outlines the methods used, presents the results, and offers a critical review of what was found. The aim is to understand algorithmic trading and its effects on today's financial markets.

# Methodology

## Data Preparation

For this project, two types of financial data were used: the SPTL ETF end-of-day prices and the Effective Federal Funds Rate (EFFR), which is the risk-free rate. Both sets of data range from January 1, 2014, to December 31, 2019. The data were obtained from the sources below:

- SPTL ETF data: Yahoo Finance (Yahoo Finance, 2023)
- EFFR data: New York Federal Reserve (Federal Reserve Bank of New York, 2023)

Missing EFFR values were forward-filled to match SPTL data dates. The final, prepared datasets were then used for analysis and to test the trading strategies. The figure below showcase the data.

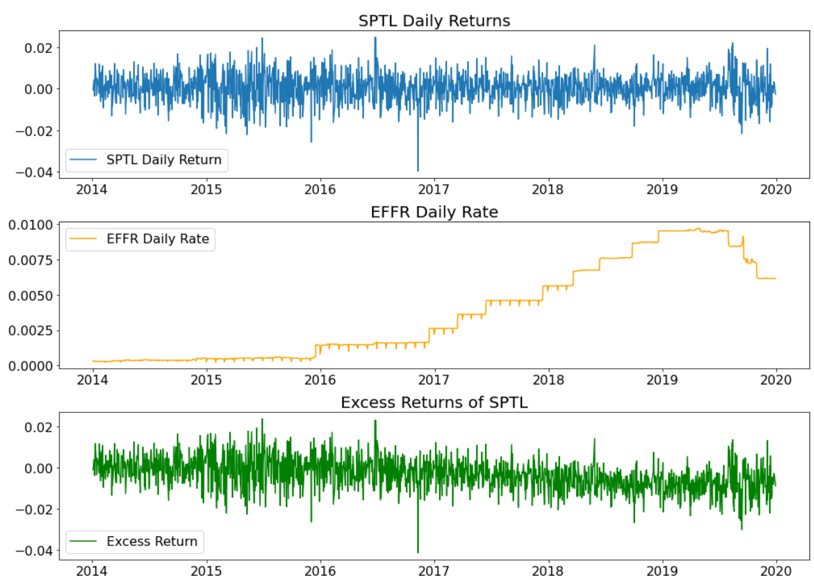


**Figure 1:** Trends in SPTL ETF Daily Returns, EFFR Daily Rates, and SPTL Excess Returns between 2014 and 2019.

The figure displays three distinct time series graphs which are the SPTL Daily Returns, the EFFR Daily Rates and the Excess Returns of SPTL between 2014 and 2019.

## Trading Strategies

In this project, three distinct trading strategies were developed. Each strategy employs a unique approach, blending traditional financial analysis with innovative techniques, including machine learning. These strategies are:

1. Momentum Leveraged Trading Strategy: This strategy leverages the concept of momentum, predicting that the SPTL ETF's price will continue to move in its current direction after significant price changes.
2. Machine Learning-Enhanced Mean Reversion Trading Strategy: This approach integrates machine learning to predict market movements and produce signals based on mean reversion.
3. Volatility Threshold-based Leveraged Trading Strategy: Focused on market volatility, this strategy uses a calculated volatility threshold to guide trading decisions.

## Implementation

In the implementation of the trading strategies discussed, the fixed gross-notional constraint was utilized. Specifically, every approach implemented, maintained the position size, $\theta_t$, within the constraints set by ten times the initial capital, $V_0$, which was set at \$200,000. This results in a maximum gross limit of \$2 million for the trading positions ($V_0 \times L$). This fixed approach minimizes the risk of financial ruin by ensuring that, even after significant losses, trading can continue because the size of the positions can remain active up to the predefined limit.

For each trading strategy, the daily position size, denoted as $\theta_t$, was determined by the formula: $\theta_t = V_0 \times L \times \text{SIGNAL}$. The variable SIGNAL varies depending on the specific strategy being employed: in some strategies ($2^{\text{nd}}$ and $3^{\text{rd}}$), this signal was binary, set to either 1 or -1, indicating a full buy or full sell position respectively. In the $1^{\text{st}}$ first strategy, however, the signal ranged continuously between -1 and 1, representing varying degrees of buying or selling based on the strength of the market indicators or predictions at that time.

1. **Momentum Leveraged Trading Strategy Implementation:**
   - Signal Generation: Firstly, momentum was evaluated as the rolling average of daily returns for each momentum window. To enhance their relevance while keeping them within the range of -1 to 1, the momentum values were scaled up by a factor of 100. The amplified momentum was then used to determine buy or sell signals. The strategy explored various holding periods to optimize performance.
   - Parameter Optimization and Testing: The momentum window and holding period parameters were optimized based on training data focusing on maximizing the annualized Sharpe Ratio. The optimal parameters derived from the training set were then applied to the testing dataset.
2. **Machine Learning-Enhanced Mean Reversion Trading Strategy Implementation:**
   - Data Preparation: Other than the historical SPTL ETF data combined with the Effective Federal Funds Rate, other features, such as technical indicators, were constructed to be further used in the machine learning model. These were Relative Strength Index (RSI) and the market volatility.
   - Signal-Based Trading: In this strategy a RandomForestClassifier machine learning model was trained to analyze historical trends and predict future market movements. The model presented 69.9% accuracy. The prediction aims to capture the market's momentum: a forecast of upward movement (positive momentum) or downward movement (negative momentum). Using the mean reversion principle, the strategy takes the opposite of the machine learning model's predictions to determine trading signals. Specifically, a prediction of an increase (positive momentum), labeled as '1' in the classification, is interpreted as a sell signal, whereas a prediction of a decrease (negative momentum), labeled as '-1', is interpreted as a buy signal.
   - Parameter Optimization and Testing: The momentum window and holding period parameters were optimized based on training data focusing on maximizing the annualized Sharpe Ratio. The optimal parameters derived from the training set were then applied to the testing dataset.
3. **Volatility Threshold-based Leveraged Trading Strategy Implementation:**

- Data Preparation: In this strategy, the 30-day rolling standard deviation of daily returns is used to measure market volatility, which is then annualized by multiplying it by the square root of 252. The choice of a 30-day window has been optimized based on testing various timeframes. The square root of 252 is used to annualize the volatility.
- Signal Generation: Trading signals were generated based on market volatility compared to a predetermined threshold. If market volatility exceeds this threshold, indicating a potentially overstretched market, a sell signal is issued, anticipating a reversion to lower volatility levels. Conversely, if market volatility is below the threshold, suggesting less active market conditions, a buy signal is issued, anticipating a return to higher activity or volatility.
- Parameter Optimization and Testing: The volatility threshold that maximizes the Sharpe Ratio was determined during the training phase. This threshold was then applied to the test data.

Based on the annualized Sharpe ratio metric, below are the optimized parameters chosen from the training of the strategies:

| **Strategy** | **Parameter** | **Best Value** |
|---|---|---|
| Momentum | Sharpe Ratio | 5.532 |
| | Window | 5 |
| | Holding Period | 1 |
| ML Signal Based Mean Reversion | Sharpe Ratio | 5.08 |
| | Window | 5 |
| | Holding Period | 1 |
| Volatility Threshold | Sharpe Ratio | 3.3201 |
| | Threshold | 0.0676 |

Table 1: Best Parameters for Each Strategy

# Results

## Position Plot and Turnover Analysis

Next, the positions of the strategies are plotted, and their turnovers are analyzed. The plots allow for a comparison between strategies, providing insights into their relative performance and trading behaviors.

1. **Momentum Leveraged Trading Strategy**

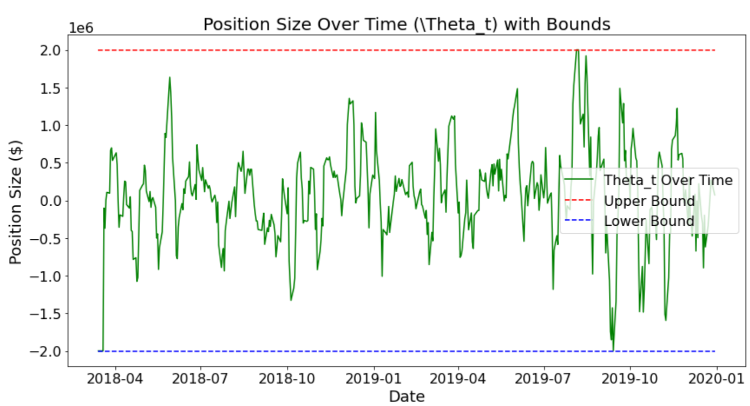


**Figure 2:** Position Size Over Time $\theta_t$ with Bounds for Strategy 1.

2. **Machine Learning-Enhanced Mean Reversion Trading Strategy**

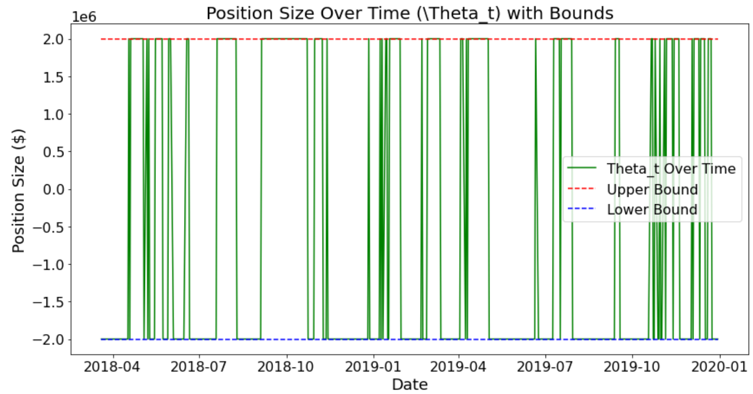


**Figure 3:** Position Size Over Time $\theta_t$ with Bounds for Strategy 2.

3. **Volatility Threshold-based Leveraged Trading Strategy**

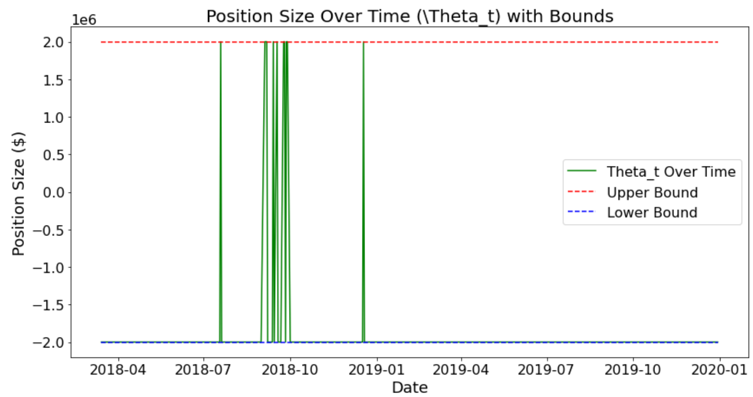


**Figure 4:** Position Size Over Time $\theta_t$ with Bounds for Strategy 3.

By tracking the changes in position size and comparing them against the adjusted close price, both dollar turnover and unit turnover are calculated and addressed.

| Strategy | Total Dollar Turnover ($) | Total Unit Turnover (Units) |
|---|---|---|
| 1 - Momentum | $1.2921 \times 10^8$ | $3.9659 \times 10^6$ |
| 2 - ML-Enhanced Mean Reversion | $2.8 \times 10^8$ | $8.7991 \times 10^6$ |
| 3 - Volatility Threshold | $5.6 \times 10^7$ | $1.9970 \times 10^6$ |

Table 2: Turnover for the Three Different Strategies

Additionally, distinct patterns across different periods and the relationship between turnover and the volatility of SPTL are explored.

1. **Momentum Leveraged Trading Strategy**

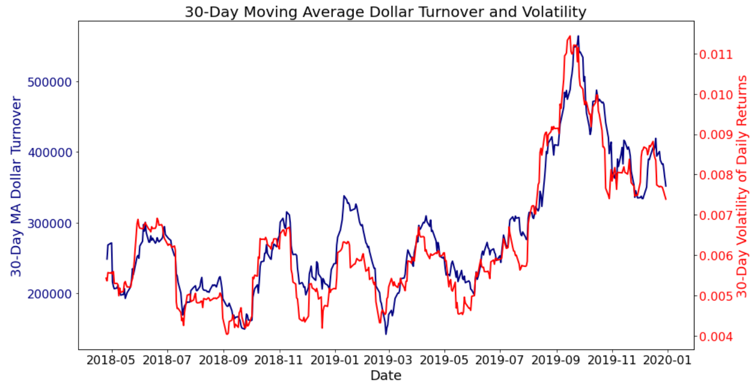


**Figure 5:** 30-Day Moving Average Dollar Turnover and Volatility for Strategy 1.

2. **Machine Learning-Enhanced Mean Reversion Trading Strategy**

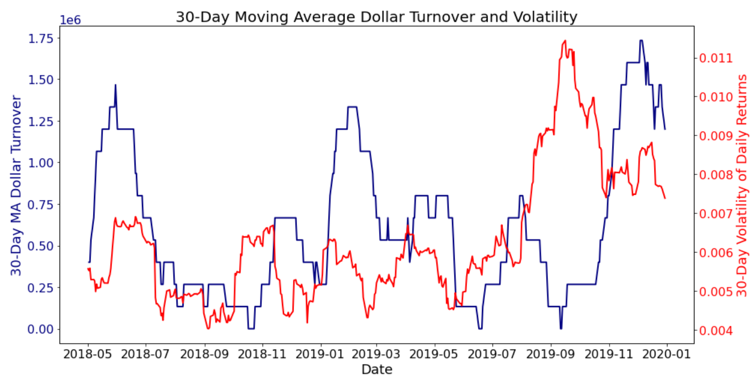


**Figure 6:** 30-Day Moving Average Dollar Turnover and Volatility for Strategy 2.

3. **Volatility Threshold-based Leveraged Trading Strategy**

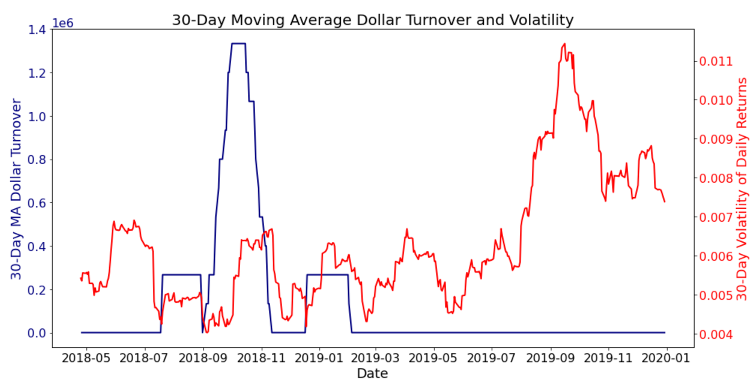


**Figure 7:** 30-Day Moving Average Dollar Turnover and Volatility for Strategy 3.

The figures above demonstrate a clear pattern of correlation between trading units and market volatility, varying according to the strategy employed.

In Figure 5, Strategy 1 (Momentum) shows a direct correlation with market volatility, meaning its activity increases with the ups and downs of the market. This strategy capitalizes on existing market trends, increasing its trading during volatile periods to maximize profits. The synchronized peaks in turnover and volatility highlight the strategy's effectiveness in exploiting market trends. In contrast, in Figure 6, Strategy 2 (Machine Learning-Enhanced Mean Reversion) doesn't closely mirror the immediate volatility of the market. It looks for opportunities where prices are expected to return to their historical average, emphasizing a longer-term view over reacting to short-term volatility. The strategy relies more on predictive analytics to identify trading opportunities, and therefore it prioritizes statistical patterns and mean reversion. In Figure 7, Strategy 3 (Volatility Threshold) initiates trading actions exclusively when market volatility exceeds an established threshold. This approach is specifically designed to capitalize on significant market movements. The notable increase in trading activity during increased volatility demonstrates a targeted strategy, engaging in the market under conditions of high volatility. It exploits the effects of large market fluctuations through a predefined threshold.

## Total Profit and Loss (PnL) Series

In the total PnL series analysis, unused capital is invested in a money-market account, growing at the risk-free rate. Plotting $\Delta V_t$, $\Delta V_{\text{cap}}$, and $\Delta V_{\text{total}}$ shows how the strategy performs over time.

1. **Momentum Leveraged Trading Strategy**

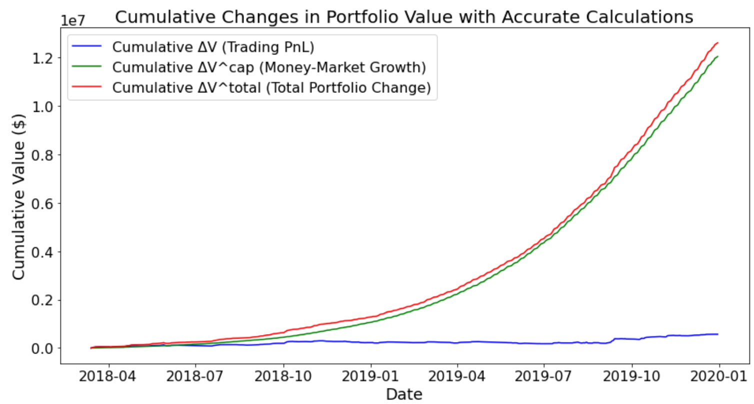


**Figure 8:** Cumulative Changes in Portfolio Value using Strategy 1.

2. **Machine Learning-Enhanced Mean Reversion Trading Strategy**

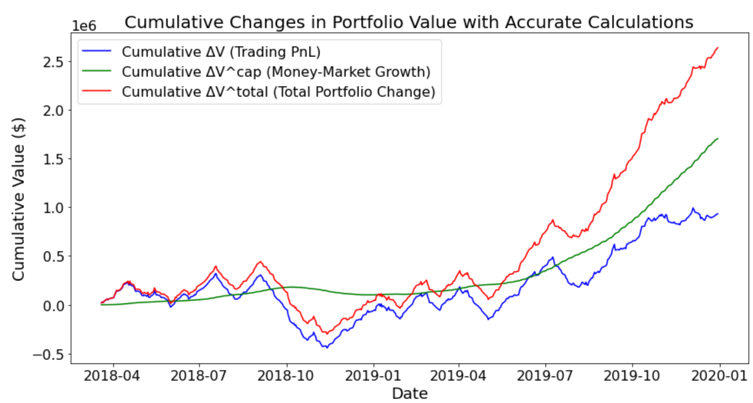


**Figure 9:** Cumulative Changes in Portfolio Value using Strategy 2.

3. **Volatility Threshold-based Leveraged Trading Strategy**

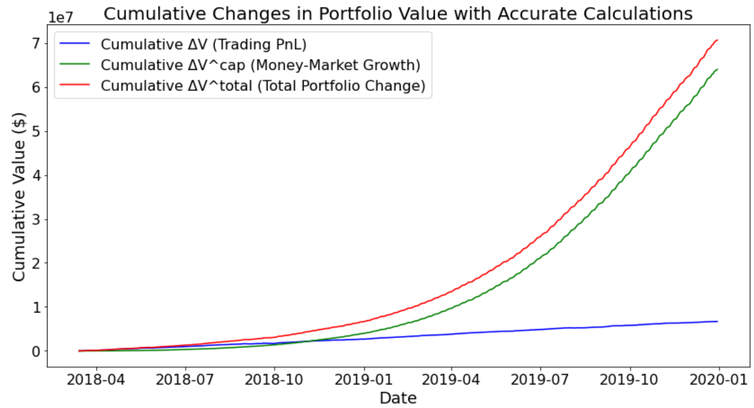


**Figure 10:** Cumulative Changes in Portfolio Value using Strategy 3.

In figures 8, 9, and 10, distinct outcomes are observed for each trading strategy. Figure 8 demonstrates a consistently positive trajectory across all components indicating a successful strategy that enhances the portfolio's value over time. Figure 9 demonstrates fluctuations with both ups and downs, ultimately indicating a strategy that appears profitable by the end of the observed period. Figure 10, while similar to Figure 8 in showing significant growth, does so on a much larger scale. The analysis also includes a comparison of these plots by increasing the funding costs by 1.5 times, which clearly influences the overall strategy performance. The table below shows the final cumulative values of $\Delta V_{total}$ under normal trading fund rates ($r_t^f$) and the adjusted rates ($1.5 * r_t^f$) for each strategy.

| **Strategy** | **Final Portfolio Value** ($r_t^f$) | **Final Portfolio Value** ($1.5 * r_t^f$) |
|---|---|---|
| Strategy 1 - Momentum | $\$1.2602 \times 10^7$ | $\$7.2903 \times 10^7$ |
| Strategy 2 - ML-Enhanced Mean Reversion | $\$2.634 \times 10^6$ | $\$4.46 \times 10^7$ |
| Strategy 3 - Volatility Threshold | $\$7.0605 \times 10^7$ | $\$4.5767 \times 10^8$ |

Table 3: Last values of Cumsum $\Delta V_{total}$ for each strategy

Increasing funding costs by 1.5 times clearly influences the overall strategy performance. As anticipated, the higher costs lead to a decrease in the trading PnL, since rising expenses associated with increased funding costs would naturally compress margins and reduce net trading gains. In contrast to the trading PnL, the performance of the money-market capital account shows a positive trajectory due to the increase of the interest rate on unused capital in this account, which enhances the returns from the money-market capital account, providing a significant counterbalance to the reduced trading PnL.

In the context of Strategy 1 (Momentum), this dual-faceted scenario leads to an overall enhancement in strategy performance. While there is a reduction in the Sharpe Ratio, indicating a decrease in risk-adjusted returns, the strategy still maintains positive performance. Strategy 2 (Machine Learning-Enhanced Mean Reversion) exhibits also an overall improvement using increased funding costs. There is an observable enhancement in risk-adjusted performance metrics such as the Sharpe Ratio and an increase in the strategy's total portfolio value. Under standard funding conditions, Strategy 3 (Volatility Threshold) demonstrates adequate performance with reasonable risk management, but the introduction of higher funding costs not only improves the risk-adjusted returns, evidenced by an increase in the Sharpe Ratio, but also in absolute financial performance, with dramatic growth in total value. This strategy has the exceptional ability to capitalize on adverse conditions.

## Risk Metrics

Below are the risk metrics for the three strategies:

Strategy 1 - Momentum:

| Metric | Training Set | Test Set |
|---|---|---|
| Sharpe Ratio | 5.532 | 2.6756 |
| Sortino Ratio | 0.9217 | 0.3501 |
| Maximum Drawdown | -7.0032 | -7.7682 |
| Calmar Ratio | 0.779 | 1.93 |

Table 4: Performance Metrics for Strategy 1

Strategy 2 - Machine Learning-Enhanced Mean Reversion:

| Metric | Training Set | Test Set |
|---|---|---|
| Sharpe Ratio | 5.08 | 1.6283 |
| Sortino Ratio | 0.5767 | 0.1804 |
| Maximum Drawdown | -0.3737 | -2.5431 |
| Calmar Ratio | 1.569 | 0.1007 |

Table 5: Performance Metrics for Strategy 2

Strategy 3 - Volatility Threshold

| Metric | Training Set | Test Set |
|---|---|---|
| Sharpe Ratio | 3.3201 | 16.8146 |
| Sortino Ratio | 0.3581 | 1.8951 |
| Maximum Drawdown | -31.8786 | -0.0783 |
| Calmar Ratio | 0.0122 | 23.7852 |

Table 6: Performance Metrics for Strategy 3

Strategy 1 demonstrates solid performance with a decrease in Sharpe Ratio from training to testing (5.532 to 2.6756), reflecting reduced but still effective risk-adjusted returns. Even though Maximum Drawdown decreases slightly from training to testing, the improved Calmar Ratio indicates better performance relative to risk in real-world conditions. Strategy 2's performance declines from training to testing, as seen in the drop in both Sharpe (5.08 to 1.6283) and Sortino Ratios, reflecting reduced effectiveness in risk-adjusted returns. The increase in Maximum Drawdown and significant decrease in Calmar Ratio highlight greater losses and lower performance stability under real-world conditions. Strategy 3 shows remarkable improvement from the training to the test set, with a significant increase in Sharpe (3.3201 to 16.8146) and Sortino Ratios. The drastic reduction in Maximum Drawdown and a substantial increase in Calmar Ratio underscore the strategy's superior risk management and adaptability in the test phase.

Risk investigation is a critical component in assessing the effectiveness of a trading strategy. The table below displays the 95% Confidence Level Value at Risk (VaR) across the different strategies and phases. Strategy 3 exhibits a reduction in risk from the training to the testing phase, suggesting better performance during the testing period. In contrast, Strategy 1 and Strategy 2 present an increased risk in the testing phase compared to the training phase, indicating potential issues with overfitting or an inability to adapt to changing market conditions.

| Strategy | Training Set 95% VaR | Test Set 95% VaR |
|---|---|---|
| Strategy 1 | -$3,903.01 | -$6,847.83 |
| Strategy 2 | -$18,438.69 | -$30,415.19 |
| Strategy 3 | -$20,993.69 | -$9,266.54 |

Table 7: 95% Confidence Level VaR for Different Strategies

## Rolling Sharpe Ratio & Drawdowns Chart

Below are the rolling sharpe ratio plots for both the training and test sets.

1. **Momentum Leveraged Trading Strategy**

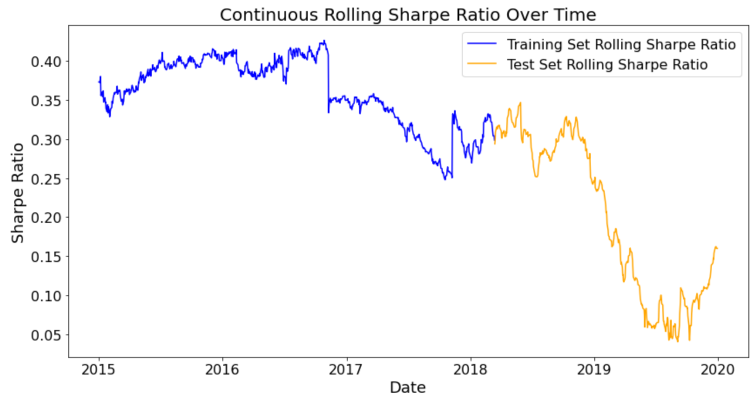


**Figure 11:** Continuous Rolling Sharpe Ratio Over Time for Strategy 1.

2. **Machine Learning-Enhanced Signal-Based Trading Strategy**

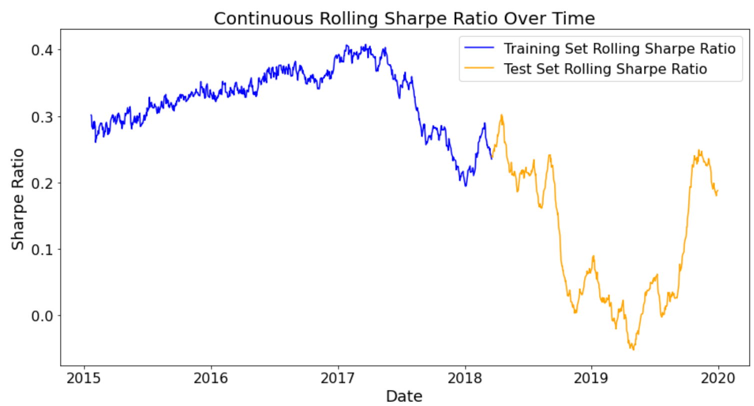


**Figure 12:** Continuous Rolling Sharpe Ratio Over Time for Strategy 2.

3. **Volatility Threshold-based Leveraged Trading Strategy**

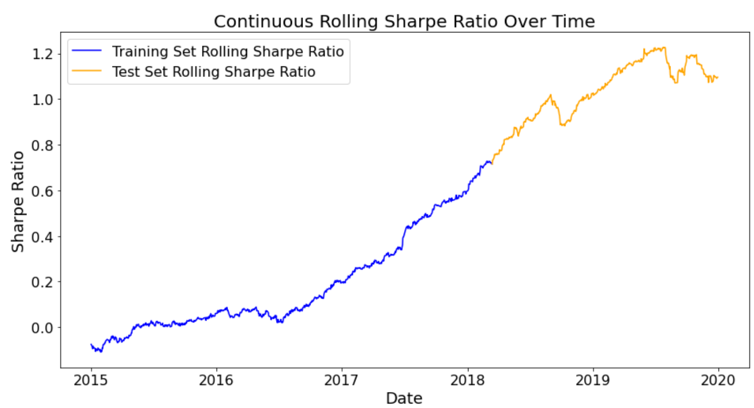


**Figure 13:** Continuous Rolling Sharpe Ratio Over Time for Strategy 3.

Next, the drawdown charts for each strategy are presented over time alongside the historical rolling 90-day volatility of the underlying asset.

1. **Momentum Leveraged Trading Strategy**

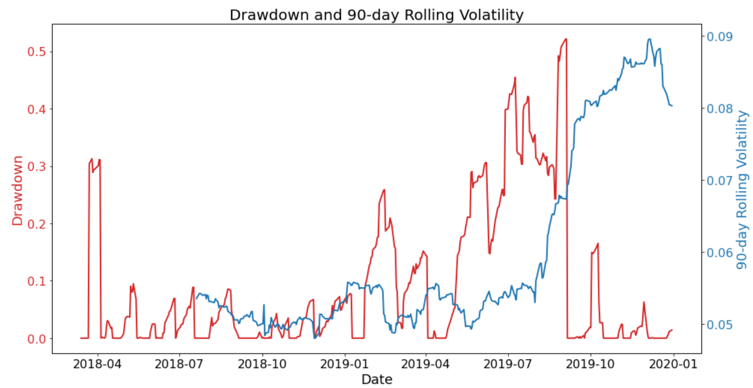


**Figure 14:** Drawdown and 90-day Rolling Volatility for Strategy 1.

2. **Machine Learning-Enhanced Signal-Based Trading Strategy**

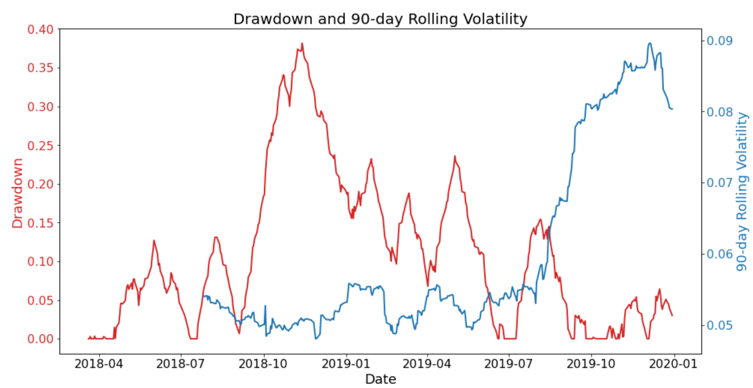


**Figure 15:** Drawdown and 90-day Rolling Volatility for Strategy 2.

3. **Volatility Threshold-based Leveraged Trading Strategy**

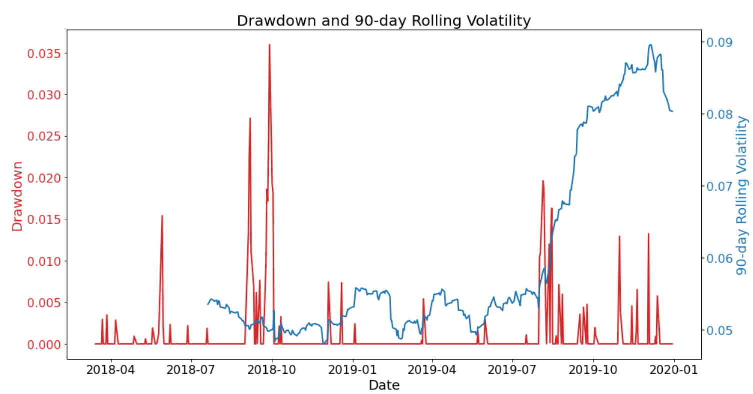


**Figure 16:** Drawdown and 90-day Rolling Volatility for Strategy 3.

The content and implications of the figures presented above will be thoroughly analyzed and discussed in the following discussion section.

# Discussion

Strategy 1 (Momentum), demonstrates a solid performance during training but a noticeable drop in the test phase, which could be due to overfitting or changes in market conditions not captured during the training period. The drawdowns for this strategy are relatively modest, yet the most significant drawdowns appear to occur in periods of increased volatility. Towards the end of the observed period, despite ongoing high volatility, the strategy's drawdowns significantly decrease, indicating that the risk management mechanisms are adapting and becoming more effective. In order to make the model more adaptable to new data and market conditions, one way is to implement rolling cross-validation to ensure that the model is tested on multiple periods, reducing the chance of overfitting to a specific market phase. Antoher way to improve is to incorporate a trend-strength indicator, such as the Average Directional Index (ADI), to better assess the reliability of momentum signals and to exit trades when the trend weakens.

Strategy 2 (Machine Learning-Enhanced Mean Reversion) shows volatility in training performance, which performs slightly better in the train set, and thus the strategy adapts better to training conditions than to real-world conditions. Initially, this strategy shows moderate drawdowns, indicating steady performance. Later, an increase in volatility points to a greater risk from market changes, but is followed by a decrease and stabilization in drawdown levels. Enhancing this strategy could involve adding multiple Bollinger Bands with different standard deviations to create a more refined range of mean reversion, helping to identify different levels of price extremes. Also, another improvement is to implement a stop-loss mechanism to limit losses on each trade, reducing the impact of large drawdowns and further utilize a machine learning model to dynamically adjust the parameters of the Bollinger Bands based on market conditions.

Strategy 3 (Volatility Threshold) demonstrates significant progress and enhanced performance throughout both the training phase and in the test set, characterized by performance gains and minimal drawdowns. Notably, during periods of high market volatility, the strategy exhibits smaller drawdowns compared to earlier phases. This observation is expected for a volatility threshold strategy, which is designed to capitalize on or mitigate risks associated with market volatility. Improving this strategy could involve regularly updating the volatility threshold based on recent market conditions to ensure it is not based on outdated information. Also implement a graduated approach where the size of the position or the aggressiveness of the strategy is adjusted based on the level of detected volatility, meaning less exposure in higher volatility and vice versa. Another improvement is the usage of a real-time volatility forecasting model to anticipate market changes and adjust strategy parameters proactively rather than reactively.

Across all strategies, adopting a dynamic margin management approach based on market volatility and reducing leverage when the strategy experiences a drawdown and increase it during winning streaks is crucial for safer, more consistent investment outcomes. The consistent application of ten-fold leverage has largely amplified the returns of each strategy, demonstrating the power of leveraging in capitalizing on market movements. However, this comes with increased risk, as leverage can similarly magnify losses. Therefore, while the high portfolio values reflect the successful application of strategies under certain market conditions, they also underline the heightened risk exposure from leveraged trading.

In conclusion, while each trading strategy has its strengths, there is significant room for improvement and integration. In general, future work should emphasize in developing and integrating advanced risk management strategies to balance the potential for high returns against the risk of significant losses. Furthermore, continuous optimization and testing are crucial. As market conditions evolve, trading strategies should be regularly reviewed and updated to ensure they remain effective and relevant. This ongoing process can benefit from backtesting against new data sets, real-time monitoring, and adaptation to market feedback.

# Bibliography

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Yahoo Finance. (2023). Sptl - spdr portfolio long term treasury etf [Accessed: 2023-03-01].