Coursework 2 - COMP0051 Algorithmic Trading

Contents

1 Introduction

In this scholarly pursuit, three leveraged trading strategies were meticulously devised and evaluated using the time series data of the SPTL Exchange-Traded Fund (ETF)[1]. The selected strategies encompassed Buy-and-Hold, Momentum, and Mean Reversion methodologies. The Buy-and-Hold strategy, often deemed rudimentary due to its passive nature, was nonetheless integrated into this study as a critical benchmark. The juxtaposition of Momentum and Mean Reversion strategies provides an analytical dynamic, as these methodologies represent antithetical views on moving averages: Momentum aligns with the principle of trend continuation, whereas Mean Reversion postulates an inevitable return to the mean (Koijen et al., 2009).

This report is structured as follows: Initially, the methodology for time series data preparation is elucidated. Subsequently, the three leveraged trading strategies under consideration will be defined. The performance of each strategy will then be analyzed, utilizing metrics and evaluative criteria. These include but are not limited to, position, turnover, profit and loss (PnL), and other key metrics such as the Sharpe Ratio, and Sortino Ratio.

2 Data Preparation

For the purpose of this analysis, data pertaining to the SPDR Portfolio Long Term Treasury ETF (SPTL) was procured from Yahoo Finance, spanning a period from January 1st, 2014 to December 31st, 2019. Then the Effective Fed Funds Rate (EFFR Index) was used as a proxy for the risk-free rate and the annualised rate data over the same period was downloaded from the New York Fed [2]. To adjust this annual rate to a daily rate, simple calculation $r_t^f = EFFR(t) \cdot dc$ was applied where $dc \approx \frac{1}{252}$ was adopted as day-count. The subsequent step involved the computation of the daily excess return per unit Total Liability (TL), as financing at the risk-free rate is necessitated for the analysis.

$$r_t^e = \frac{\Delta p_t}{p_t} - r_t^f, \tag{1}$$

- r_t^e: Daily excess return per unit
- p_t: Price of EPTL at time t
- r_t^f: Daily risk-free rate

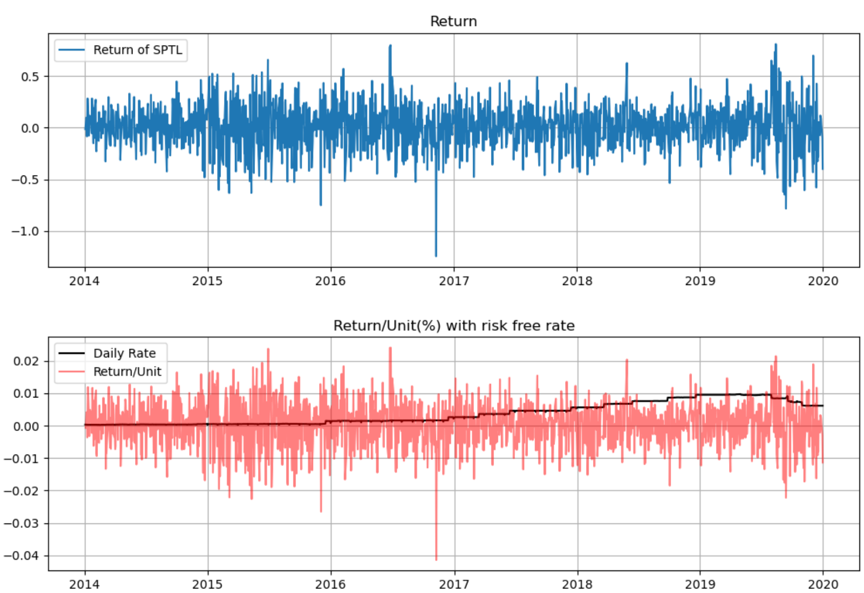


Figure 1: SPTL return time series, the EFFR daily rate and the excess return per unit of SPTL

[1] https://finance.yahoo.com/quote/SPTL/
[2] https://www.newyorkfed.org/markets/reference-rates/effr

Figure 1 presents the time series for the return of SPTL, which evidently oscillates around 0, indicating its stationarity. Additionally, the daily risk-free rate exhibits a stepped increase until the middle and latter part of 2019. Given that the daily risk-free rate is relatively small, the adjusted daily excess return per unit is not significantly influenced. However, a comparison of the daily returns of SPTL, the risk-free rate, and the excess return offers valuable insight into the performance of SPTL in relation to a "risk-free portfolio". This comparison is a crucial step in understanding the relative performance and potential risks associated with this ETF.

As a part of the analysis, backtesting is important to evaluate the performance of the trading strategies as well as hyperparameters tuning. The time series was divided into the training part and the testing part, accounting for 70% and 30% separately.

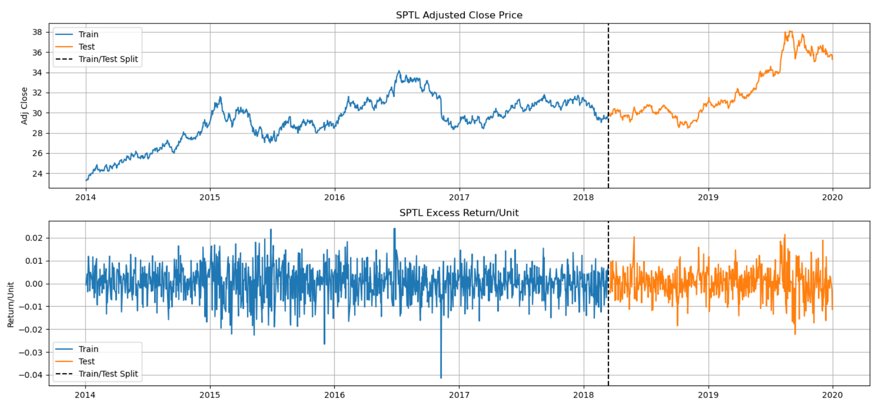


Figure 2: Train / Test Split for SPTL and Daily Excess Return Time Series.

The split is illustrated in Figure 2. The separation allows for training models on historical data and evaluation of unseen data, verifying the generalization abilities of trading strategies for future market features.

3 Methodology

As this mission is about leveraged trading strategies, some pre-defined assumptions are necessary to be clarified. First, the initial capital V_0 is $200,000 and the leverage L is 10. Besides, by a leveraged strategy it means a sequence $\{\theta_t\}_{t=1}^{T}$ of dollar values of SPTL which is constrained by

$$|\theta_t| \leq V_0 \times L, \tag{2}$$

which means that whenever the money is trading in, its absolute position should not exceed the initial amount. If the position exceeds $V_0 \times L$ due to a price increase, a portion of the position will be forced to unwind, with the excess being placed into a money market account that will grow at the risk-free rate. If the price decreases, the funds in the money market remain unchanged, with only the position experiencing a decrease. If the loss in position exceeds the margin, the trading will be halted. During a price drop, the margin remains unaffected until the loss equals the margin. These assumptions, while not realistic, help compare strategies under risk-management conditions for stop-loss. Transaction costs aren't considered.

3.1 Buy and Hold

The buy-and-hold strategy is the simplest method and only consists of holding a fully leveraged long position. Therefore, the signal for holding is $\{s_t = 1\}, \forall t$.

3.2 Momentum

The Momentum strategy, a trading paradigm premised on the recent price trend strength of assets, was initially propagated by Richard Driehaus. Subsequent empirical studies (Koijen et al., 2009; Hong & Stein, 1999; Jegadeesh & Titman, 1993) have corroborated its efficacy. The strategy's core tenet suggests that assets demonstrating strong historical performance will likely sustain this trajectory, and vice versa. Trading signals are discerned through various technical indicators to ascertain trend strength and direction. In this study, the moving average is utilized to generate signals. A long position is adopted when the short-term moving average surpasses the long-term one, while a short position is signalled when the short-term average falls below its long-term counterpart.

3.3 Mean-Reversion

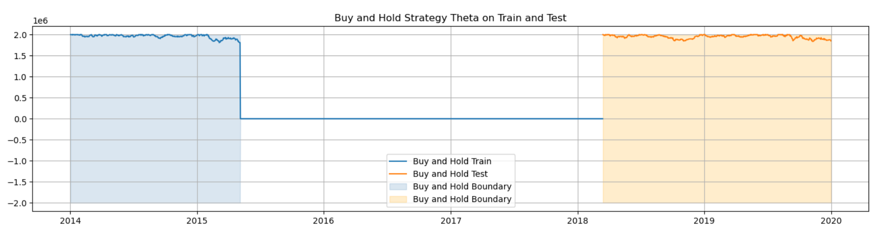
The Mean-Reversion strategy, predicated on the assumption that asset prices will gravitate towards their long-term mean, has been validated by researchers(Poterba & Summers, 1988; Lo & MacKinlay, 1988). This strategy employs moving averages to engender trading signals. Contrasting with momentum strategies, the underlying principle posits that an elevated short-term average relative to the long-term average implies an impending mean reversion, signaling a short position. Conversely, a depressed short-term average augurs a potential price elevation towards the mean, indicating a long position.

The momentum and mean-reversion strategies have hyper-parameters, which are the window size of the moving average. Therefore, the best window size will be selected with multiple trials on the training data, proving the experiment's effectiveness and generalization through the test dataset.

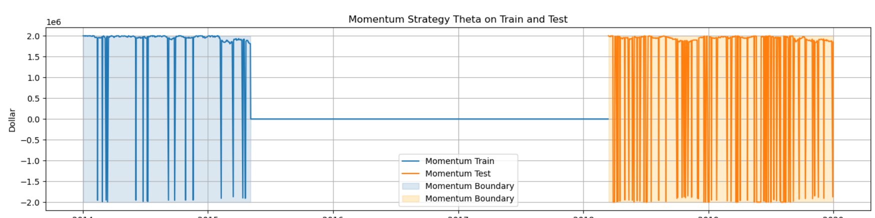
4 Results

4.1 Trading Position

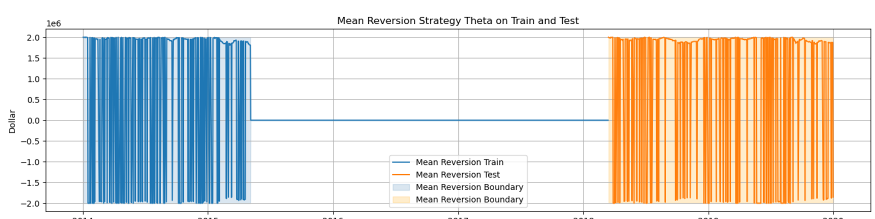
To reach the goal of the training set, different window sizes are applied to evaluate the final return performance of strategies. Short-term window sizes and long-term window sizes used are [1, 5, 10, 20] and [5, 20, 40, 60] respectively. The pair of (1, 5) and (1, 10) are chosen with the highest return for the momentum and the mean-reversion. Therefore the shift between the long/short signal will be frequent due to the small window size, which is illustrated in Figure 3.



(a) θ_t for the Buy-and-Hold Strategy



(b) θ_t for the Momentum Strategy (Short-term Window = 1, Long-term Window = 5)



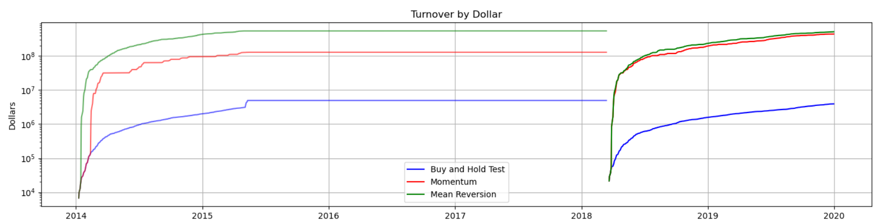
(c) θ_t for the Mean-Reversion Strategy (Short-term Window = 1, Long-term Window = 10)

Figure 3: Position $\{\theta_t\}$ of Three Strategies with Upper and Lower bound $[-V_0 \times L, V_0 \times L]$

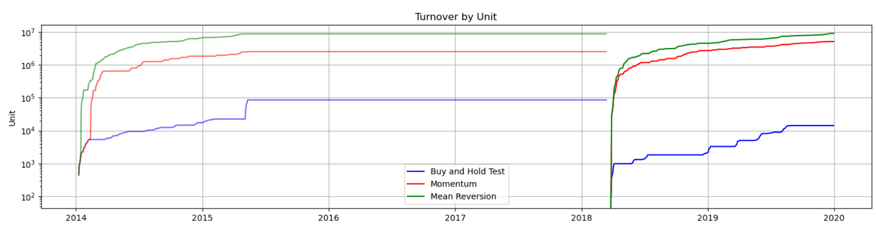
Besides, Figure 3 shows how the position changes and based on the pre-discussed condition, it is constrained by the initial position. Besides, all three strategies were closed near the middle of 2015 as there was a continuous price decrease there shown in Figure 2. This makes the training incomplete especially when the length of the test set is longer than the practical training set. Therefore, the hyperparameters chosen cannot be proved enough while the leveraged principle forced trading close. Additionally, we can also observe that the position is oscillating around 0, meaning the long and short operation.

4.2 Turnover

The turnover dollars and units elucidate the efficacy and efficiency of a trading strategy, representing the aggregate value and quantity of SPTL transacted over a given period, respectively. These metrics, highlighting trading frequency, suggest the active strategy's potential for exploiting market inefficiencies, contrasting with a passive Buy-and-Hold approach.



(a) Turnover Dollars for Three Leveraged Strategies



(b) Turnover Unit for Three Leveraged Strategies

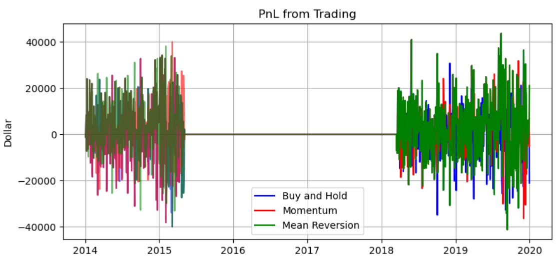
Figure 4: Moving Average (window size = 5) of Turnover in Dollar and Number of Units Traded over Time

Figure 4 depicts temporal variations in turnover dollars and units for the three strategies. The Buy-and-Hold strategy, due to its passive nature, exhibits the least turnover, whereas the mean-reversion strategy surpasses momentum in both training and testing sets. The discrepancy between momentum and mean-reversion is attributable to price time series' volatility and range-bound characteristics.

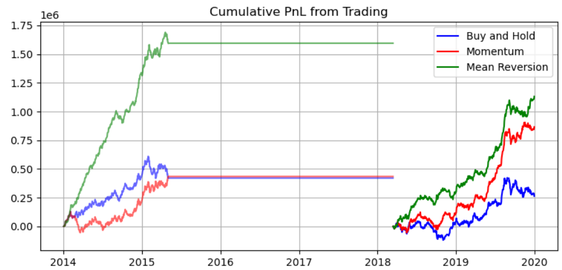
4.3 Profit and Loss

The profit and loss (PnL) metrics serve as a robust measure for assessing algorithmic trading strategies, offering a comprehensive and direct perspective on temporal profitability. Specifically, daily PnL values provide a fine-grained depiction of the strategies' susceptibility to market volatility. In this section, the total PnL, an amalgamation of trading market PnL and money market PnL—where idle funds were allocated—is evaluated.

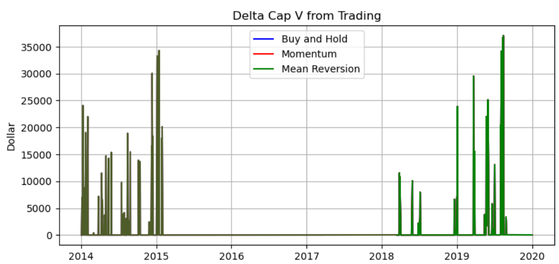
Figure 5 shows the daily and cumulative PnL for three leveraged trading strategies and the capital growth for the unused money in the money market.



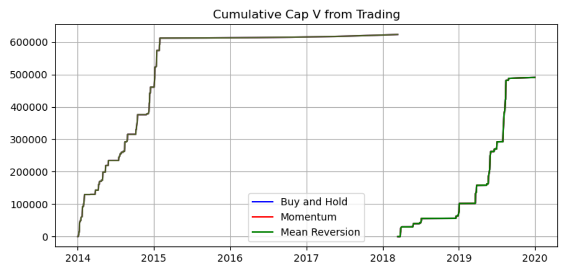
(a) PnL of the Three Strategies



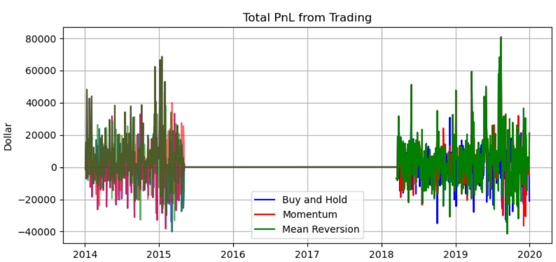
(b) Cumulative PnL of the Three Strategies



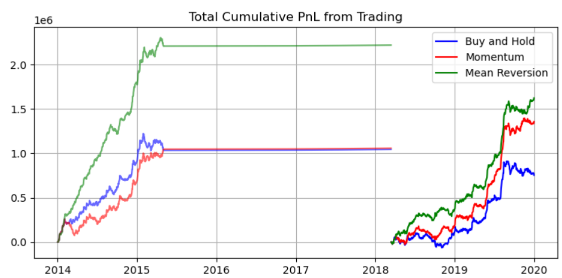
(c) Change in the Growth of Money-Market Capital



(d) Cumulative Change in the Growth of Money-Market Capital



(e) Total PnL for Three Leveraged Strategies



(f) Cumulative Total PnL for Three Leveraged Strategies

Figure 5: PnL and Change in the Growth of the Money-Market Capital Account

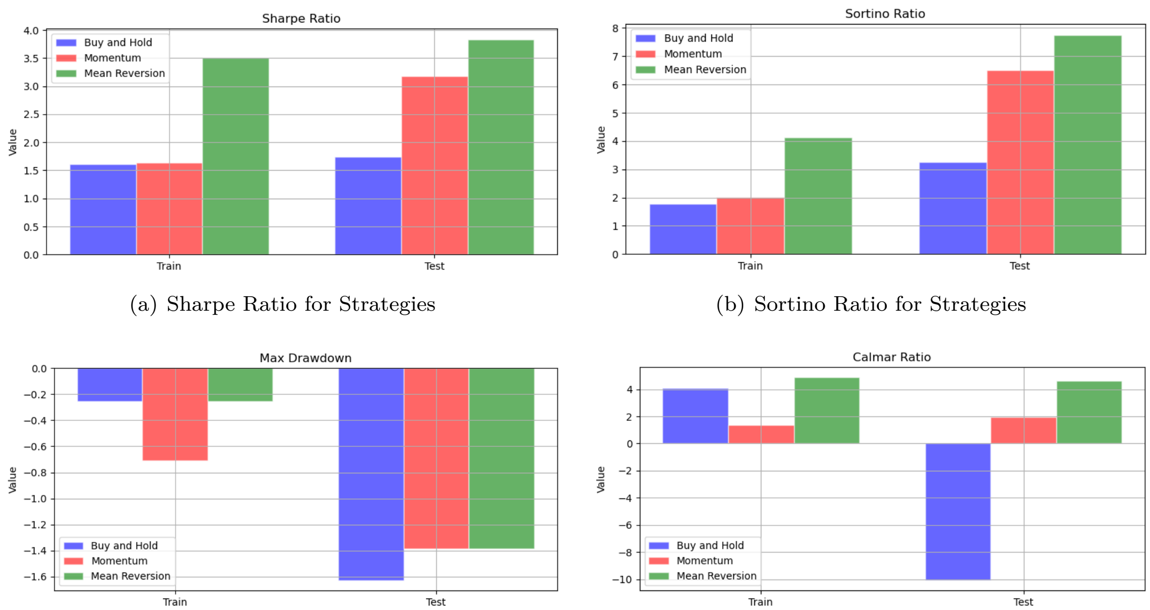
The Buy-and-Hold strategy, represented by the blue line, underscores conservative investing and outperforms momentum on the training set. Given the significant price volatility and stationarity during this period, the mean-reversion strategy yields the best performance for PnL on the training set, while momentum underperforms despite it being a growth period. The mean-reversion strategy successfully identifies more signals indicating price reversals towards the mean of the window, thereby generating higher profits. Conversely, due to the discontinuity of the trend, the momentum strategy proves ineffective.

However, performance on the test set underscores that determining the superior strategy is contingent on the characteristics of the time series. For the test set, characterized by less stationarity and long-term growth with a pronounced trend, momentum outperforms and surpasses the buy-and-hold strategy. Nevertheless, given the market's limited change and high volatility, the mean-reversion strategy still emerges as the optimal choice with the highest PnL.

Interestingly, in the cumulative PnL figure, each increment in the mean-reversion strategy appears slightly delayed compared to the growth of the momentum strategy. This can be attributed to the fact that the momentum strategy reaps profits during the upward phase of the trend, while the mean-reversion strategy may profit from the downward phase.

4.4 Performance Indicators

While position and PnL plots serve as effective qualitative indicators for evaluating strategy performance, quantitative metrics such as the Sharpe Ratio, Sortino Ratio, Maximum Drawdown, and Calmar Ratio can also be instrumental in assessing the strategies. The results for both the training and testing sets are depicted in Figure 6. This analysis offers an additional perspective for evaluating the performance of each strategy.



(a) Sharpe Ratio for Strategies

(b) Sortino Ratio for Strategies

(c) Maximum Drawdown for Strategies

(d) Calmar Ratio for Strategies

Figure 6: Comparison of Indicators for Trading Strategies in Training and Testing Set

4.4.1 Sharpe Ratio

The Sharpe Ratio is a metric used to measure the risk-adjusted performance of an investment. It provides a means to assess the return of an investment relative to its risk. It is calculated by

$$Sharpe = \frac{\mu_{\Delta V_t} \times 252}{\sigma_{\Delta V_t} \times \sqrt{252}}, \tag{3}$$

where $\mu_{\Delta V_t}$ is the averaged annualised excess return and $\sigma_{\Delta V_t}$ is the standard deviation of it.

Figure 6(a) demonstrates that the Mean-Reversion strategy yields the highest Sharpe Ratio, exceeding 2 in both training and testing phases, thereby outperforming the benchmark and reinforcing its efficacy and risk robustness in this ETF. Conversely, the Buy-and-Hold strategy exhibits the lowest Sharpe Ratio, indicating its lack of effective risk management. The Momentum strategy, consistent with its performance in Figure 5(f), performs modestly in the training set but excels in the testing phase, suggesting its superior performance in more stable series.

4.4.2 Sortino Ratio

This indicator is similar to the Sharpe Ratio but it considers more "harmful" volatility of the series. Therefore, it can be calculated by

$$Sortino = \frac{\mu_{\Delta V_t} \times 252}{\sigma_{\Delta V_t[<0]} \times \sqrt{252}}. \tag{4}$$

In general, all three strategies exhibit higher Sortino Ratios compared to their respective Sharpe Ratios, yet maintain the same ordinal relationship. Notably, the Buy-and-Hold strategy experiences a more pronounced increase when transitioning from Sharpe to Sortino in the testing set. This can be attributed to its greater upside volatility relative to downside volatility, a phenomenon further explored in the subsequent price analysis.

4.4.3 Maximum Drawdown

Max Drawdown is a performance metric, that quantifies the maximum observed loss from peak to trough for an investment, expressed as a percentage of the peak value. This measure illuminates the conditionality in return increments, challenging the assumption that downside events are interchangeable. Specifically, it addresses the potential for consecutive negative returns to yield excessively high losses over a given period. It is calculated by

$$MaxDrawdown = \max\{\frac{\Delta V_t - \Delta V_{max}}{\Delta V_{max}}\}. \tag{5}$$

Typically, Max Drawdown ranges between [-1, 0]. However, as indicated in Figure 5(f), it can fall below -1 when cumulative total PnL is negative, as reflected in the test performance in Figure 6(c). In the testing set, both Momentum and Mean-Reversion strategies exhibit smaller maximum drawdowns, suggesting that positive trading strategies may contribute to more stable investments.

4.4.4 Calmar

Finally, the Calmar Ratio is a hybrid risk-adjusted performance metric that combines the ideas of the Sharpe and Sortino ratio and the Max Drawdown, calculated by

$$Calmar = \frac{\mu_{\Delta V_t}}{MaxDrawdown}. \tag{6}$$

A higher Calmar Ratio signifies that an investment has delivered superior returns relative to its associated risk level, thus deeming it a more favorable investment. In this context, the Buy-and-Hold strategy exhibits a negative Calmar Ratio in the testing set, indicating poor performance due to its substantial maximum drawdown. Conversely, the Mean-Reversion strategy once again demonstrates its robustness and stability in terms of returns.

5 Discussion

5.1 Turnover in Certain Period

As shown in 4, there are some periods that the turnover suffered a faster growth: Start 2014 - Mid 2014, End 2014 - Start 2015, Mid 2018 - End 2018 and so on. By viewing the trend and volatility of the return series (Figure 7), the value is larger than the other period, creating more opportunities to grow the turnover value. (Volatility between Mid 2015 and 2018 is ignored as it triggered the risk-management setting, and closed the trading)

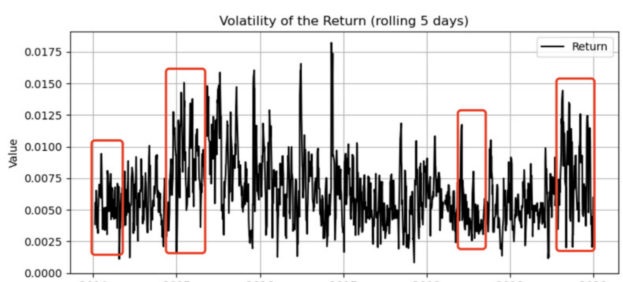
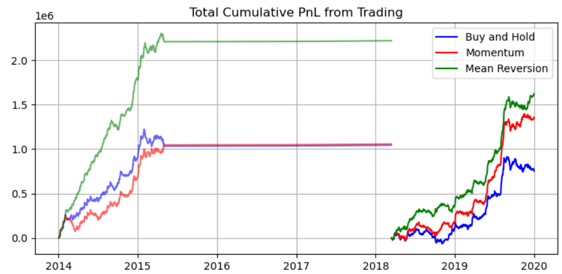


Figure 7: Volatility of the Return (rolling 5 days)

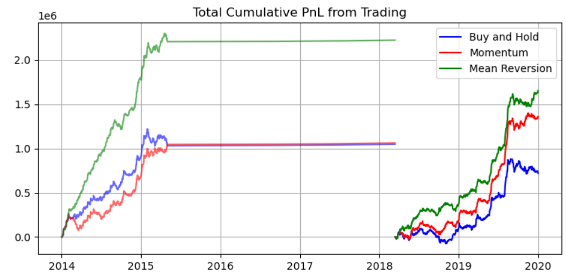
5.2 Increased Daily Risk-Free Rate

A pertinent question to consider is the impact of a high risk-free rate. Directly, this leads to a lower daily excess return per unit of SPTL, as per Equation 1. Theoretically, a high risk-free rate increases the cost of borrowing money to finance positions, which could render some trading strategies less profitable. This effect is particularly pronounced for strategies that involve holding positions for extended periods or those that rely heavily on leverage.

When the risk-free rate, r_t^f, increases by 150%, it's expected to have a substantial impact on trading strategies, potentially rendering some strategies less effective. However, through practical calculations, it's observed that the percentage change in price is typically over 100 times the daily risk-free rate. This suggests that changes in the risk-free rate do not significantly influence actual performance. This is corroborated by Figure 8, where no notable difference can be discerned.



(a) Cumulative Total PnL for Three Leveraged Strategies



(b) Cumulative Total PnL for Three Leveraged Strategies when Risk-Free Rate Increase

Figure 8: Comparison between Cumulative Total PnL for Different Risk-Free Rate

Indeed, the specific impact resulting from changes in the risk-free rate would hinge on a multitude of factors. These include the nature of the trading strategy, the types of assets involved, and the prevailing market conditions.

5.3 Sharpe Ratio behaves on Train Set and Test Set

Figure 6(a) demonstrates that even identical trading strategies can yield different performances across different segments of the time series. Notably, the momentum strategy shows a significant improvement, with the Sharpe Ratio doubling on the testing set. The other two strategies also exhibit growth, albeit within a reasonable range. This observation suggests that the momentum trading strategy lacks robustness and struggles in handling high-volatility ETFs due to its unstable performance. Consequently, a method that concentrates on enhancing strategy robustness is needed.

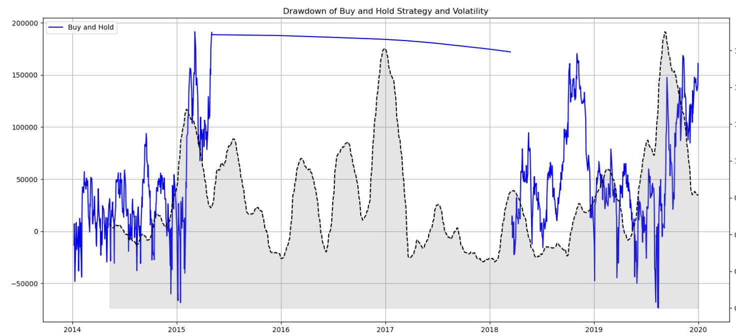
One method is given by Markowitz (1952), that diversification can be applied for momentum strategy. Instead of focusing on a single asset or a small group of assets, consider broadening the scope of the momentum strategy to include a wider range of assets. This can help to reduce the impact of any one asset's performance on the overall results. Another is using proper risk management (Jorion, 2000). Implementing strict risk management rules can help to limit losses and improve the robustness of the momentum strategy. This could include setting stop-loss and take-profit levels, limiting the size of any one position, and regularly rebalancing the portfolio.

5.4 Drawdown Analysis

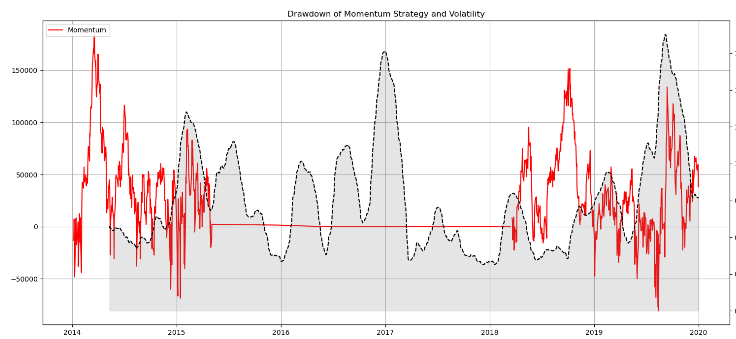
Figure 9 indeed provides valuable insights into the relationship between drawdowns and the volatility of the stock price, which can aid in understanding the performance of each trading strategy. For the buy-and-hold strategy, it is evident that the largest drawdowns are proportional to the historical volatility of SPTL, as these drawdowns typically occur near volatility spikes. In contrast, for the momentum and mean-reversion strategies, the highest drawdowns occur both at the valleys and peaks of volatility.

This observation provides an opportunity to devise a safer investment strategy by dynamically adjusting the use of margin in accordance with market volatility levels. By doing so, it is possible to limit the size of drawdowns during periods of high or low volatility and maximize returns during periods of low or high volatility, depending on the strategy in use. This approach effectively leverages the unique characteristics of each strategy under different volatility conditions, potentially enhancing overall portfolio performance and risk management.

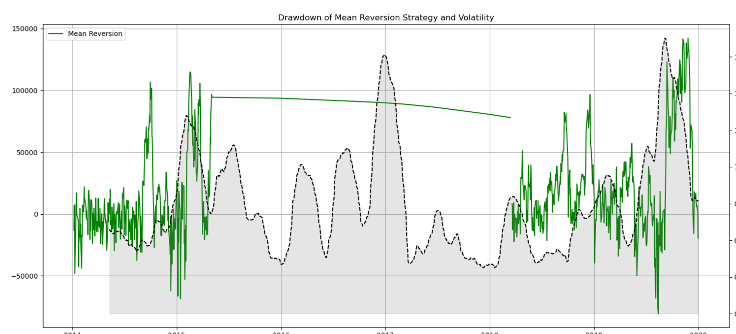
Moreover, none of the three strategies shows stable performance under the risk. Therefore, more risk management is necessary to mitigate the risk associated with market volatility, improving the robustness of the strategies.



(a) Drawdown of Buy-and-Hold



(b) Drawdown of Momentum



(c) Drawdown of Mean-Reversion

Figure 9: Comparison between the Drawdown to the Historic Rolling 90-Days Volatility of Asset Price

6 Conclusion

This report presented a comprehensive evaluation of three algorithmic trading strategies: buy-and-hold, momentum, and mean-reversion. The performance of each strategy was assessed under various market conditions and leverage policies, leading to the selection of the most effective strategy. However, it is acknowledged that the analysis contains limitations and does not encompass all possible scenarios. For example, the assumption of zero slippage and transaction costs, while convenient for theoretical analysis, does not reflect real market conditions and may overstate the profitability of the strategies.

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